Research progress in mechanized and intelligentized pollination technologies for fruit and vegetable crops

Panliang Wu[1,2], Xiaohui Lei[2*], Jin Zeng[2], Yannan Qi[2], Quanchun Yuan[2], Wanxi Huang[2], Zhengbao Ma[3], Qiyang Shen[3], Xiaolan Lyu[1,2*]

(1. *School of Agricultural Engineering, Jiangsu University, Zhenjiang 212013, Jiangsu, China*;
2. *Institute of Agricultural Facilities and Equipment, Jiangsu Academy of Agricultural Sciences/Key Laboratory of Modern Horticultural Equipment, Ministry of Agriculture and Rural Affairs, Nanjing 210014, China*;
3. *Jiangsu Agricultural Machinery Development and Application Center, Nanjing 210017, China*)

Abstract: With the rapid advancement of modern agriculture, mechanized and intelligent pollination has emerged as a crucial focus for enhancing agricultural efficiency and minimizing labor expenses. Traditional pollination methods, limited by environmental factors and high labor costs, fail to adequately address the production demands of large-scale orchards and vegetable gardens. Consequently, researchers have integrated mechanized equipment, drone technology, robotics, and deep learning algorithms to achieve accurate identification and precise pollination on inflorescences. The research on mechanized and intelligent pollination has not only injected new momentum into the field of fruit and vegetable pollination but also provided key technological support for addressing global agricultural labor shortages and increasing crop yields. This review summarizes recent advances in mechanized and intelligent pollination, focusing on deep learning's role in object recognition, improvements in pollination equipment, and the effectiveness of intelligent pollination across various fruits or vegetables. Studies indicate that mechanized and intelligent pollination significantly enhances working efficiency and fruit yields, though it continues to face challenges such as technical complexity and high implementation costs. Looking ahead, as robotics and artificial intelligence algorithms continue to advance, mechanized and intelligent pollination is poised for broader adoption in agricultural management practices. This review systematically summarizes the research progress in mechanized and intelligent pollination technologies for fruit and vegetable crops, providing significant theoretical support and reference value for future studies in crop pollination techniques.

Keywords: fruit and vegetable pollination, mechanization, deep learning, drone technology, object recognition
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1 Introduction

With rapid advancements in modern agricultural technologies, mechanization and automation have become essential trends for improving agricultural productivity. Pollination, a critical phase in fruit and vegetable production, directly impacts both yield and quality. Traditionally, fruits and vegetables rely on natural wind and bees for pollination[1-4]. However, these methods are vulnerable to weather conditions. In recent years, declining bee populations have reduced pollination capacity, making it increasingly difficult to meet the rising demand for pollination. This has led to financial losses for producers and higher costs for pollination services[5-8]. Additionally, issues such as improper plant arrangements and the harmful effects of pesticides on bees further complicate pollination[9]. Given the economic and sustainability demands of fruit and vegetable production, there is an urgent need for efficient and reliable pollination alternatives.

To address these challenges, researchers have investigated various artificial pollination methods. Currently, point pollination and dusting are the most common techniques. Unlike bee pollination, artificial methods allow greater control over pollen sources and are unaffected by weather changes[10]. These techniques can improve fruit set rates and increase economic returns[11-14]. However, artificial pollination is labor-intensive and not suited for large-scale operations[15]. With the advancement of urbanization and industrialization, the issues of high labor costs and low efficiency associated with traditional pollination methods have become increasingly pronounced, posing significant obstacles to artificial pollination[16,17]. As modern agricultural technologies evolve, particularly with the integration of drones, IoT, and AI, pollination techniques are advancing toward mechanization and automation.

This study will provide a comprehensive review of pollination techniques from the following perspectives: First, it will introduce

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Biographies: Panliang Wu, Research Assistant, research interest: orchard management machinery and its application, Email: wpl15312051215@163.com; **Jin Zeng**, Research Assistant, research interest: orchard management machinery and its application, Email: j-zeng@jaas.ac.cn; **Yannan Qi**, Research Assistant, research interest: orchard management machinery and its application, Email: qiyn1020@163.com; **Quanchun Yuan**, Research Assistant, research interest: orchard management machinery and its application, Email: yuanquanchun@jaas.ac.cn; **Wanxi Huang**, Engineer, research interest: orchard management machinery and its application, Email: 597774265@qq.com; **Zhengbao Ma**, Researcher, research interest: orchard management machinery and its application, Email: 13851780516@163.com; **Qiyang Shen**, Senior Engineer, research interest: orchard management machinery and its application, Email: 13913990904@163.com.
***Corresponding author: Xiaohui Lei**, Research Associate, research interest: orchard management machinery and its application. Institute of Agricultural Facilities and Equipment, Jiangsu Academy of Agricultural Sciences, Nanjing 210014, China. Email: leixiaohui.2008@163.com; **Xiaolan Lyu**, Researcher, research interest: orchard management machinery and its application. Institute of Agricultural Facilities and Equipment, Jiangsu Academy of Agricultural Sciences, Nanjing 210014, China. Email: lxlanny@126.com.

methods of pollen collection to supply the raw material required for pollination. Next, it will explore various current methods of artificial pollination, along with their suitable cultivation models, specific applications, and actual benefits. Following that, it will analyze the challenges mechanized and automated pollination face in modern agriculture and propose feasibility outlooks based on development trends. Finally, a summary will be provided based on the review. With the advancement of precision and smart agriculture technologies, mechanized and automated pollination is expected to become a core component of modern agriculture in the future, further driving agricultural efficiency and sustainability. By systematically reviewing and synthesizing the aforementioned aspects, this study aims to provide a theoretical foundation and technical support for related research and practical applications. The ultimate goal is to contribute to increasing yields, reducing pesticide use, and optimizing agricultural production practices.

2 Pollen collection and utilization

2.1 Pollen collection

The quantity of pollen required for artificial pollination varies considerably depending on the type of crop and the specific pollen delivery mechanisms employed. Certain plants, like date palms, naturally produce abundant pollen, making collection relatively straightforward. However, for crops such as kiwifruit, apples, citrus, and pears, the limited pollen production of their flowers demands substantial labor input for effective collection[18]. This highlights the increasingly specific objectives and requirements for artificial pollination, which include ensuring a high-quality and reliable source of pollen, maintaining economic viability, and minimizing pollen consumption throughout the process. To prevent flower loss post-bloom and ensure pollen viability, the collection is typically carried out just before the blossom[19]. Presently, three principal methods are widely employed for pollen collection: positioning pollen traps at hive entrances to collect pollen harvested by bees, manually or mechanically harvesting and purifying flowers, or utilizing specialized equipment to directly extract pollen from male flowers.

Manual collection is suitable for small-scale operations or crops that produce high pollen yields[20]. Branches are vibrated to release open male flowers or pollen onto plastic sheeting beneath the trees, or a moistened cloth is used to gently tap the inflorescences. The collected pollen is then rinsed with water and filtered. This method is highly labor-intensive, costly, and often results in incomplete pollen collection[21]. In contrast, mechanized pollen collection enables large-scale operations and has already demonstrated notable success in kiwifruit and apple orchards[19,22]. This method produces dry pollen by grinding and separating the anthers from surrounding structures, followed by filtering the pollen under controlled conditions. If the anthers contain excess moisture, they must be dehydrated using specialized drying equipment. Notably, pollen loses its viability at temperatures exceeding 35°C, making precise temperature regulation critical during the dehydration process[23]. The variability in flower maturity obtained through mechanized methods can result in inconsistent pollen quality, but this approach significantly reduces collection costs[24].

While current technologies are unable to purify bee-collected pollen, using such pollen remains a viable cost-reduction strategy. Researchers have successfully implemented artificial pollination using bee-collected pollen in kiwifruit[25,26], apples[27], and pears[28], achieving satisfactory fruit setting rates. Given that bee-collected pollen is mixed with nectar and bees forage across different plant species, the purity is relatively low. Compared to pure pollen, bee-collected pollen requires pre-washing to reduce its sugar concentration[29,30]. Current technologies have not yet advanced to the point of extracting bee-collected pollen for large-scale artificial pollination.

Beyond the aforementioned techniques, pollen can be directly extracted through mechanical suction. For example, a dual-cyclone pollen extractor can be utilized to directly harvest pollen from kiwifruit vines, achieving high efficiency and purity in pollen collection[19,31]. Once pollen is successfully collected, it requires proper storage to maintain its viability. Studies have demonstrated that storing pollen at –20°C is the optimal method for preserving its viability, significantly alleviating the challenge of synchronizing pollen collection with pollination and enhancing the reliability of the pollination process[32-34]. The methodologies for pollen collection, along with the associated purification processes, are illustrated in Figure 1.

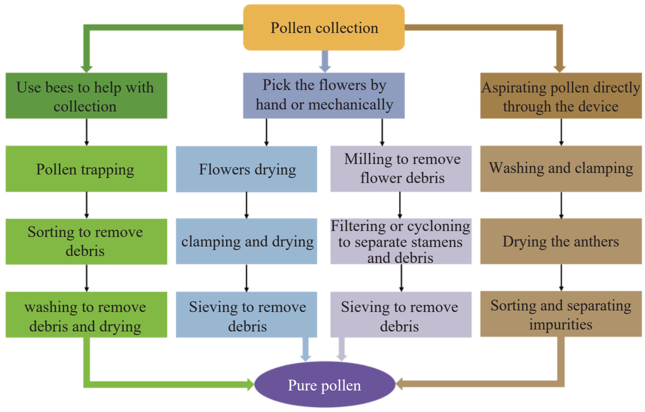


Figure 1 Pollen collection flowchart

2.2 Pollen utilization

Mechanical pollination involves the use of pollen in both dry and wet forms, each with distinct advantages and applications. In practical applications, dry pollen is typically mixed with diluents such as talc, starch, or charcoal to prevent pollen clumping, thereby enhancing its flowability and dispersal during mechanical spraying and ensuring effective pollination[35,36]. In the case of wet pollen, it is commonly suspended in aqueous solutions for spraying. Additives are incorporated into the aqueous solution to enhance pollen suspension while maintaining osmotic pressure and pH levels compatible with pollen cell physiology, thereby preserving pollen viability during pollination[37-41].

Given the respective advantages and limitations of dry and wet pollen, some mechanical pollination systems employ a combined approach. Dry pollen is more convenient to apply compared to wet pollen, as the majority of fruit trees can be pollinated using dry pollen without the need for specialized solutions. Dry pollen exhibits higher viability than wet pollen and, when coupled with electrostatic application, adheres more effectively to the stigma[42-44]. Dry pollen that does not initially reach the stigma may still be transferred through secondary mechanisms, such as wind or insect pollinators[45]. The application of dry pollen is often more diffuse, resulting in lower precision. However, wet pollen not only prevents the pollen from being dispersed by wind but also avoids negatively impacting pollination efficiency. Most studies currently measure pollination effectiveness by fruit setting rate[15,46-49]. Regardless of whether dry or wet pollen is used, various factors influence the outcome of pollination, such as the composition of diluents, weather conditions during operation, as well as stigma viability[40,50-53].

3 Pollination equipment

Artificial pollination is primarily employed as a supplement to bee pollination, particularly in scenarios such as cross-pollination, high humidity environments, or where pollinating insects are scarce. To ensure effectiveness, pollen often needs to be applied two or more times[54]. Currently, artificial pollination has shown to be highly effective in fruit crops such as kiwifruit[14,55,56] and apple[57]. In areas with limited natural pollinators, the proper use of artificial pollination can enhance fruit setting and increase seed production[58]. The current methods of artificial pollination are summarized in Table 1.

Table 1 Artificial pollination methods

Pollination method	Technical example	Pollination effectiveness	Crops	Application context
Manual pollination[46,59-63]	Brushes, feathers	Low pollination efficiency, low fruit set rate, lower fruit quality.	Jujube, dragon fruit, kiwifruit, apple, tomato	Suitable for small-scale to medium-scale orchards.
Handheld semi-mechanized pollination[42,43,64-66]	Vibration rods, electric brushes, air-supply machines	Low pollination efficiency, moderate fruit set rate, lower fruit quality.	Tomato, pepper	Applicable for medium-scale or non-standard orchards.
	Pneumatic brushes, sprayers	Low pollination efficiency, moderate fruit set rate, moderate fruit quality.	Kiwifruit, cherimoya, apple	
Ground-based mechanized pollination[67-72]	Mobile blowers and sprayers	High pollination efficiency, high fruit set rate, higher fruit quality.	Kiwifruit, apple, date palm	Suitable for large-scale to medium-scale standardized orchards.
	Mobile blowers and sprayers with electrostatic devices		Kiwifruit, date palm	
Drone pollination[73-78]	Agricultural drones	High pollination efficiency, moderate fruit set rate, moderate fruit quality.	Kiwifruit, apple	Suitable for medium-scale to large-scale orchards with aerial access.
Intelligent pollination[79-89]	Pollination robotic arms, pollination robots	High pollination efficiency, high fruit set rate, high fruit quality.	Kiwifruit, watermelon, fragrant pear, apple, tomato	Mostly tested on single varieties in structured environments.

3.1 Handheld semi-mechanized pollination

Manual pollination is a labor-intensive task, wherein fruit growers utilize brushes, feathers, and similar implements to perform the process[11,60,62]. For high-value fruits, the costs associated with manual pollination are considered acceptable, but significant discrepancies remain in efficiency and cost control when compared to the use of handheld devices.

In medium-scale to large-scale orchards, handheld devices offer a more efficient approach to pollination. Semi-mechanized tools such as blowers, vibrating rods, and sprayers operate more efficiently than traditional methods like brushes and feathers, significantly reducing labor costs. Commonly used handheld semi-mechanized equipment includes vibrating rods for self-pollination, handheld air-assisted pollinators, pneumatic devices with brushes or feathers, and sprayers. The operational site is illustrated in Figure 2. Notably, although the handheld air-assisted pollinator exhibits lower targeting precision, it can achieve over 50% pollen coverage on the stigma when wind speed is increased[65,66]. Currently, handheld electrostatic pollinators equipped with electrostatic devices are also available to enhance pollen adhesion to stigmas[44,90].

a. Hand-held electric pollinator[91] b. Pollen battery dry dispenser[68]

c. Backpack dry pollen pollination blower[68] d. Backpack liquid pollen pollination diaphragm pump[68]

Figure 2 Semi-mechanized handheld pollination

3.2 Terrestrial mechanized pollination

The field of terrestrial mechanized pollination has evolved significantly, primarily driven by the need to enhance efficiency and offset limitations associated with traditional pollination methods. Early mechanized approaches focused on adapting blowers and sprayers to supplement natural pollination, particularly in large-scale orchards where labor-intensive manual pollination was not feasible. Initial efforts[36,91-93], such as the development of spray planes and tractor-mounted spraying systems in regions like the USA and Italy[94,95], offered scalable alternatives[68]. However, the effectiveness of these devices in increasing fruit set rates remained limited due to early technological constraints and environmental dependencies, such as wind and humidity.

Building on these early methods, advancements in mechanized pollination have sought to improve targeting accuracy and pollen adherence to stigmas. For instance, to address issues with pollen deposition and reduce the inefficiencies caused by overloading, researchers introduced electrostatic pollination systems. By charging pollen particles, these systems enhanced the attraction to stigmas, thereby improving yield per unit area and reducing pollen waste[96-98]. Such innovations in electrostatic technology, exemplified by devices used in crops like date palms and kiwifruit, highlight the shift towards more precise and resource-efficient pollination solutions.

Recent advancements have further refined these technologies. For example, the application of airflow-guided pollen release models enables precise control over pollen dispersion, maximizing adherence to target structures while minimizing drift[99]. Additionally, the development of dual-fan systems and vortex-based distribution methods has allowed for more consistent coverage across crops with complex floral arrangements, such as kiwifruit[69-71]. By integrating these advancements, mechanized pollination systems are increasingly capable of achieving higher fruit set rates under varied agricultural conditions[100]. An introduction and analysis of common mechanized pollination equipment are summarized in Table 2, while the structural diagram of the pollination equipment is shown in Figure 3.

Despite these improvements, challenges remain. Many terrestrial mechanized pollination technologies are in experimental stages, with economic and operational constraints slowing widespread adoption. Factors such as high development costs and the limited commercial incentives for lower-value crops hinder broader implementation[69]. Furthermore, the irregular growth patterns of fruit trees in orchards necessitate the standardization of planting patterns to fully leverage mechanized solutions. Addressing these issues requires continued innovation and increased investment to adapt mechanized pollination systems for diverse agricultural environments.

Table 2 Mechanical pollination methods

Category	Operating principle	Assessment
Air-assisted liquid sprayer for pollination[68]	The tractor-towed spraying system operates between crop rows, utilizing a spray pump to uniformly distribute the stored pollen suspension onto the flowers of the crops.	This machine offers high efficiency, extensive coverage, uniform pollination, low labor input, and precise control. However, it incurs high acquisition and maintenance costs and is vulnerable to wind interference.
Vehicle-mounted powder applicator[91]	The fan system generates high-pressure airflow, dispersing pollen from the storage unit through the nozzle onto the plants, with the vehicle moving to facilitate extensive coverage.	This mechanism offers rapid pollination speed and high operational efficiency. However, it is characterized by excessive pollen consumption and limited applicability in large-scale operational settings.
Dual-fan dry pollen pollination tractor[68]	The dual fans generate strong airflow through high-speed rotation, directing pollen onto fruit tree flowers for effective pollination, with adjustable wind speed to meet different pollination requirements.	This machine offers high efficiency, wide coverage, and uniform pollination for large-scale orchards but is sensitive to wind, humidity, and consumes significant pollen.
Electrostatic pollen applicator[70]	A high-voltage electrostatic generator charges the pollen, which is then aerosolized into a charged cloud by a blower, facilitating quicker adherence to the stigma.	This system enables precise pollination, reduces pollen consumption, and enhances yield, yet incurs high costs, requires frequent calibration, and is less effective for most fruit tree species.
Electrostatic field pollinator[71]	A blower ejects pollen using high-velocity airflow, charging the pollen through a corona electrode, thereby utilizing the charge-focusing effect to concentrate pollen on designated flowers.	This machine provides high pollen efficiency, rapid pollination, and wide coverage. However, it is costly, unsuitable for long-distance pollination, and requires strict operational standards.

a. Air-assisted liquid sprayer for pollination[68] b. Vehicle-mounted powder applicator[92]1 c. Dual-fan dry pollen pollination tractor[68] d. Electrostatic field pollinator[71]

Figure 3 Structural diagram of pollination equipment

As robotics and automated control systems continue to advance, terrestrial mechanized pollination stands on the cusp of achieving greater commercial viability. Continued research and development in these technologies promise to enhance adaptability and efficiency, establishing a foundation for modern, sustainable pollination practices across diverse agricultural contexts.

3.3 Drone-assisted pollination

Drone-assisted pollination, an emerging agricultural innovation, has increasingly been applied to hilly and mountainous orchards, leveraging drones for precise pollen delivery and optimized resource use. Initial applications primarily focused on addressing geographical constraints in manual pollination. Equipped with thermal imaging and multispectral cameras, early drones aimed to facilitate detection, localization, and targeted pollination, thus reducing pollen waste and labor costs. However, limitations in weather adaptability, technological constraints, and plant species compatibility initially hindered broader application, especially in economically underdeveloped regions[101].

Subsequent research focused on mimicking natural pollination mechanisms. Researchers have developed small drones with adhesive-coated bristles to simulate bee pollination. Through remote control, the drone can collect pollen from stamens via adhesion and subsequently use the gathered pollen to perform targeted pollination tasks[74]. Hiraguri et al. developed a drone capable of emulating insect pollinators[102], employing artificial intelligence to automate flower detection and pollination. This system achieved an impressive fruit setting rate of over 60%, demonstrating the potential for automated pollination in controlled environments. Jia et al. furthered this by proposing swarm-based drone methods[103], using algorithms to tackle target allocation, collision, and path planning when operating multiple drones simultaneously. Despite their promise, these systems are largely limited to virtual simulations, and practical efficacy remains to be validated[104].

More recent developments have focused on specific pollination techniques and intelligent automation, including direct contact and spray pollination. Alyafei et al. used remote-controlled drones to perform timed and quantified liquid pollination on target fruit trees at preset altitudes[75]. This study demonstrated that drone-assisted pollination can reduce pollen usage and increase pollination speed without compromising fruit quality. China Agricultural University developed a targeted pollination device mounted on drones[78], equipped with an anti-clogging spray mechanism that enables rapid and efficient pollination in large-scale orchards. Shandong University of Technology introduced an electrostatic pollination device for drones[72], which enhances pollen adhesion and reduces waste, especially effective for high-value flowering crops. Additionally, Hulens et al. designed a compact drone integrated with an optimized convolutional neural network[105], capable of accurately identifying and approaching flowers, achieving a high pollination success rate. Nevertheless, the technical complexity of coordinating multiple drones and the high operational costs remain major obstacles to large-scale application.

Researchers have also explored the use of drone-generated airflow to facilitate pollen distribution through vibration or vortex effects, enhancing pollination efficiency without direct contact. Shi et al. investigated using downwash airflow generated by drone rotors to create flower vibration[77], a technique validated through Computational Fluid Dynamics (CFD) simulations and field trials. This method not only reduced costs but also enhanced fruit yield and operational efficiency. Lin et al. employed lattice Boltzmann-based numerical simulation methods to analyze the impact of rotorinduced downwash airflow on pollination efficiency[106]. By optimizing airflow parameters and developing a system to monitor pollen density, they achieved significant improvements in autonomous pollination effectiveness and crop yield. Ongoing innovations in drone capacity, including enhanced payload and autonomous navigation, are anticipated to advance drone-assisted pollination, enabling its practical application in diverse agricultural settings. The models of drone pollination systems currently under research are summarized in Table 3 and the drone model structure for pollination is illustrated in Figure 4.

Table 3 Drone models for pollination

Pollination method	Working principle	Assessment
Bubble pollination[73]	The drone carries a bubble generator that precisely controls the emission of bubbles. When the pollen-filled bubbles reach the stigma, they burst and release pollen, completing the pollination process.	This system offers low pollen consumption, minimal labor, and high efficiency without damaging flowers, but has poor targeting accuracy, unstable performance, environmental issues, and high maintenance costs.
Contact pollination[74]	A hummingbird-sized drone with a bottom surface coated in ion liquid gel (ILG) bristles brushes the stigma of flowers as it hovers, facilitating pollination.	This system provides high adaptability, efficient pollen use, and combined pollination, but risks flower damage, has low drone efficiency, requires skill, and is unsuitable for large-scale use.
Liquid pollination[75]	The drone sprays a pollen suspension onto target plants at preset intervals and heights, increasing pollination success through repeated applications.	This system offers simple operation, high efficiency, improved fruit quality, and reduced labor costs, but is ineffective for certain species and requires high technical skills.
Autonomous recognition pollination[76]	The drone identifies flower position, size, and angle, navigates to the target, and approaches the flower. Pollination is achieved through a visual servo network that controls the drone interaction with the flower.	This system reduces labor costs, offers high adaptability and operational precision, and ensures a high pollination success rate. However, it is affected by wind, sensitive to target distance, and limited by a simplistic pollination rod design.
Wind pollination[106]	The drone, equipped with a high-precision navigation system, flies along a predetermined route. Its rotors create a wind field that disperses pollen to the female parent plants, ensuring effective pollination.	This system features long flight endurance, high efficiency, precise navigation, minimal pollen waste, and uniform pollination. However, it incurs high equipment costs, is susceptible to wind, and is unsuitable for large-scale production.

a. Bubble pollination[73] b. Liquid pollination[75] c. Autonomous recognition pollination[76] d. Wind pollination[106]

Figure 4 Drone model structure for pollination

3.4 Intelligent pollination

With the dramatic increase in computational power and the growing availability of big data, deep learning has emerged as a powerful tool for improving recognition accuracy and enhancing the autonomy of robotic systems. In the realm of recognition systems, cascade convolutional neural networks (CNN) and the YOLO series models have demonstrated exceptional capabilities in object feature extraction, enabling highly accurate recognition and detection. In robotic arm control, deep learning has been utilized to develop intelligent pollination techniques that recognize objects of various shapes, orientations, and sizes while autonomously selecting optimal operational paths tailored to specific conditions. This section analyzes recent advancements in recognition systems and robotic arm design for pollination, aiming to refine models and foster innovations that advance intelligent pollination systems and equipment.

3.4.1 Recognition system

Advancements in deep learning and image recognition technologies have significantly enhanced the capabilities of automated pollination. Early work focused on basic Convolutional Neural Networks (CNNs) to detect and locate flowers in orchard environments. However, these early CNN frameworks struggled with accuracy under complex and variable lighting conditions. To improve robustness in dynamic environments, researchers introduced preprocessing techniques such as data augmentation and Gaussian filtering. For instance, Hiraguri et al. expanded their training dataset through data augmentation and applied Gaussian filtering to simulate motion blur caused by drone or robotic movement[84], thereby substantially increasing system accuracy in dynamic image processing.

Building upon these foundations, multi-scale CNN architectures were developed, including the MC-AlexNet model, which leveraged multi-scale input and color balancing techniques to improve robustness under varying illumination conditions. Liu et al. proposed the MC-AlexNet model and further applied binocular stereo vision combined with grayscale deformation template matching[107], significantly enhancing the three-dimensional localization accuracy of flower centers, thereby optimizing pollination efficiency. Meanwhile, Mu et al. enhanced the detection capability for flowers of varying sizes by employing Mask R-CNN for instance segmentation and integrating it with a feature pyramid network[108]. Their research also utilized data augmentation and transfer learning techniques to accelerate model convergence and developed a 2D flower density mapping algorithm that prioritizes the identification of the first fully bloomed flower, enhancing pollination efficiency. The recognition results of non-YOLO models are presented in Figure 5.

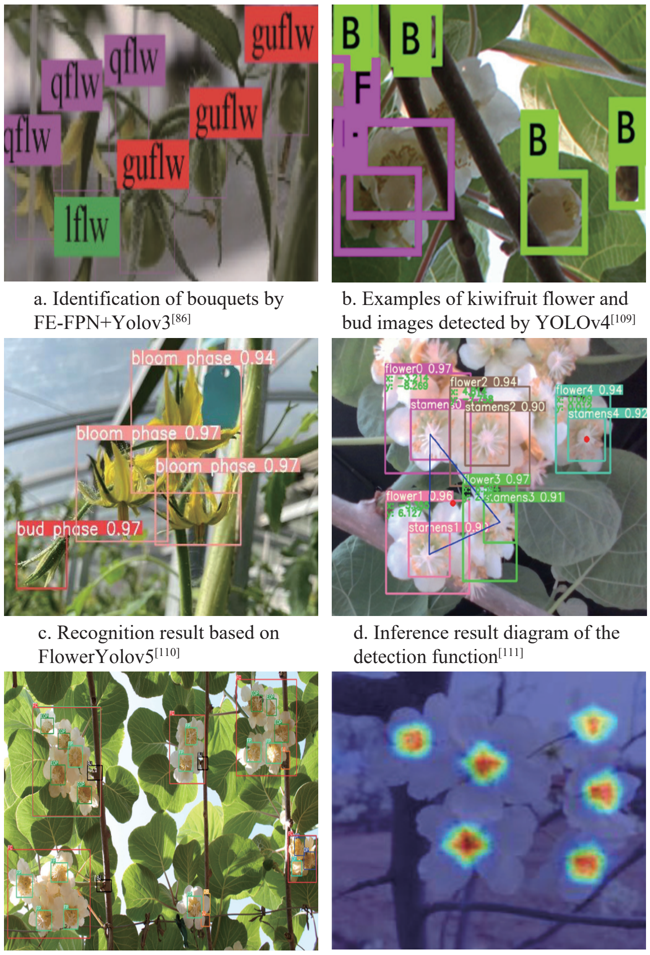
a. Recognition results of improved MC-AlexNet under illumination[107] b. Mask R-CNN based instance segmentation of apple flowers[108]

Figure 5 Recognition results of non-YOLO models

Recent developments have shifted toward integrating attention mechanisms and feature fusion layers within YOLO models, particularly YOLOv4 and YOLOv5, which greatly enhance the ability to recognize small, complex objects within cluttered backgrounds - crucial for high-precision flower detection. For example, Zhao et al. improved upon the YOLOv3 network by combining it with a feature pyramid network and the Prim minimum spanning tree algorithm[86], which prioritized extracted flower clusters and substantially increased recognition accuracy and efficiency across various flowering stages. Similarly, Li et al. enhanced YOLOv4's receptive field by incorporating spatial pyramid pooling and path aggregation networks[109], aggregating parameters across multiple detection layers to improve feature extraction in complex environments.

YOLOv5 has made significant advances in lightweight model design and inference speed, making it particularly suitable for resource-constrained environments. Xu et al.[110] integrated a convolutional attention module and feature fusion layers into the YOLOv5 network, balancing parameter size with detection accuracy to meet real-time application needs in practical production. Zhou et al.[111] optimized anchor box configurations in YOLOv5, introduced the CBAM attention mechanism, and employed the CIOU loss function to improve the model's ability to suppress background noise. Additionally, they incorporated a flower tilt angle estimation module and proposed a pollination strategy based on polygonal edge points, further refining pollination accuracy. Ren et al. significantly optimized the YOLOv5n model[82], achieving a more lightweight architecture while maintaining high accuracy. Additionally, the model incorporates the PfAAMC3 attention module within the backbone network, substantially enhancing the recognition accuracy of kiwifruit stamen features. Gao et al.[112] employed a YOLOv5I-based deep learning model to detect kiwifruit flowers at various developmental stages. By integrating RGB-D cameras to capture color and depth information, and synchronizing with control and spraying systems, they achieved automated pollination. The recognition results of YOLO models are presented in Figure 6.

The latest YOLOv7 models combine frequency domain data augmentation with lightweight design features. For instance, Zheng et al. integrated MobileNetv3 as the backbone for YOLOv7-S[89], applying Fourier transform for frequency domain data augmentation and incorporating a coordinated attention mechanism in the feature fusion layer. This approach reduced computational demands while preserving high accuracy. These advancements lay a strong foundation for achieving real-time recognition and pollination capabilities in complex agricultural environments. The improvements and recognition accuracy comparisons of current recognition models applied in pollination are summarized in Table 4.



a. Identification of bouquets by FE-FPN+Yolov3[86]

b. Examples of kiwifruit flower and bud images detected by YOLOv4[109]

c. Recognition result based on FlowerYolov5[110]

d. Inference result diagram of the detection function[111]

e. Results of multi-class kiwifruit flowers detection with rectangles marked in different colors[112]

f. Heat map visualization based on FPG-YOLO[82]

Figure 6 Recognition results of YOLO models

Table 4 Comparison of recognition model improvements and accuracy rates

Model name/(Base model)	Small object	Multi-scale input	Attention	Offline data	Loss function	Feature pyramid network	Contour detection	Weighted box fusion	Recognition accuracy
Polli-CNN/(CNN)	√	-	-	√	-	-	√	-	87.3%
MC-AlexNet/(AlexNet)	√	√		√	-	-		√	96.2%
ABD-Net/(Mask R-CNN)	√	√		√	-	√	√	√	78.1%
FE-FPN+Yolov3/(YOLOv3)	√	√	√	-	-	√	√	-	85.2%
Kiwi-YOLOv4/(YOLOv4)				√	-	√	√	√	97.6%
FlowerYOLOv5/(YOLOv5)		√	√	√	√	-	-	-	94.2%
Kiwifruit-YOLOv5/(YOLOv5)	-	-	√	√	√	-	-	√	89.1%
Selective-KiwiYOLO/(YOLOv5I)	√	√	√	-	-	-	√	-	96.1%
FPG-YOLO/(YOLOv5n)		√	√	-		-	-	-	94.1%
M-YOLOv7-SCSN+F/(YOLOv7)	√	-	√	-	√	-	√	-	97.2%
Binocular-YOLOv4/(YOLOv4)	√	-	-	-	-	√	-	√	95.3%
PSTL-Orient/(YOLOv5)	√			√	-	-	-	√	91.1%
Pro-FlowerNet/(YOLOv5I)	√	-	√	√	-	-	√		98.4%
ACW-YOLOv5s/(YOLOv5s)	√	-	√	√	-	-	√	√	95.7%
AWFP-YOLOv8/(YOLOv8)	-	-	-	√	√	-		√	90.9%

3.4.2 Intelligent pollination robotic arms

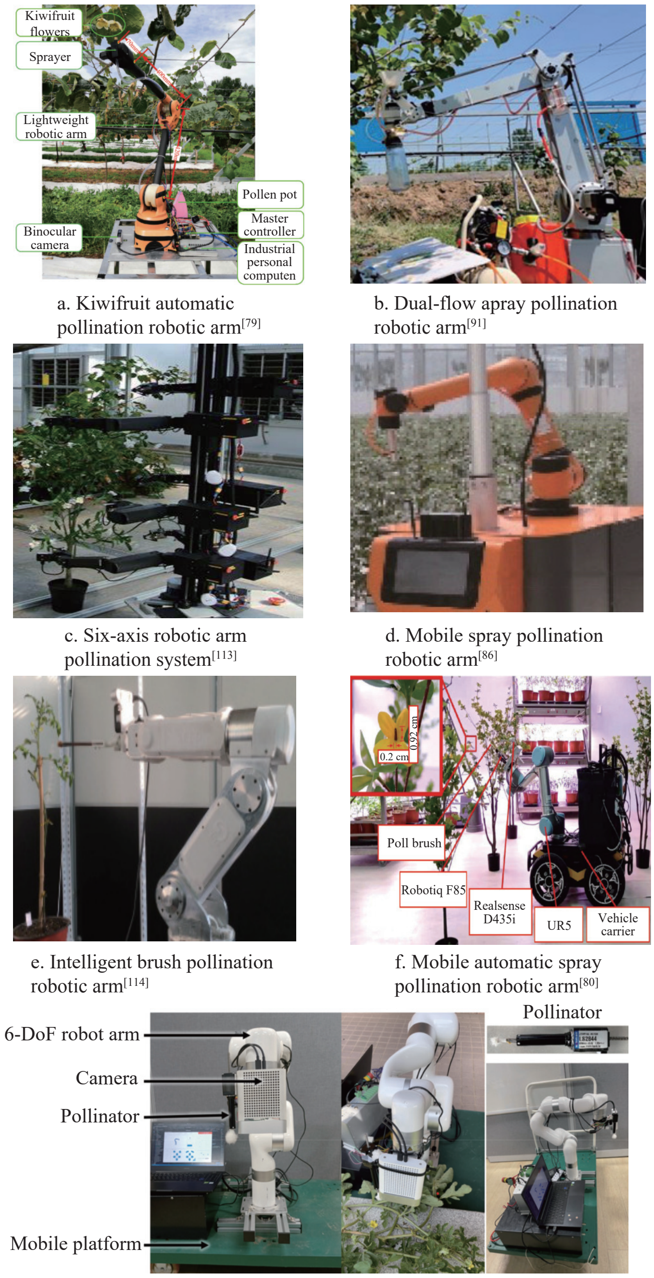
The progressive development of robotic arm-based pollination systems has aimed at increasing precision and efficiency in agricultural pollination tasks[113]. Initially, simple robotic arms were developed to address the need for accuracy in pollen application, which is particularly challenging in complex orchard environments. Early systems incorporated basic recognition capabilities and manual control to deliver pollen through contact or spraying, providing a foundation for automated pollination.

As technology advanced, researchers integrated depth-sensing cameras and machine learning algorithms, enhancing the robotic arms' ability to detect flowers and optimize pollination angles. For example, Li et al. introduced a six-degree-of-freedom robotic arm equipped with a binocular camera[79], enabling 3D positioning for targeted pollen delivery. However, limitations in speed and detection accuracy, especially under varying light conditions, underscored the need for further enhancements.

To address detection precision, Yang et al. developed a system using the PSTL_Orient algorithm[80], which improved the robotic arm's capacity to locate pistils and adjust the pollination angle. This adaptation enabled more accurate pollen placement, yet the system faced limitations when dealing with plants of varying heights due to the restricted movement range of the robotic arm.

More recent developments have incorporated advanced deep learning models, such as YOLOv5, to detect specific flower features and stages. Li et al. employed YOLO-based models to identify target flowers[91], using dual-flow spray mechanisms that adapt to different growth stages, thereby enhancing pollination precision and significantly reducing labor required for post-pollination thinning.

Further innovations include the work of Yu et al.[114], who combined the YOLOv5 framework with EfficientNetV2 for real-time classification of blossoms and posture recognition, allowing for more efficient flower detection and positioning. Additionally, Ahmad et al. incorporated depth cameras with a YOLOv8 system[81], enabling robotic arms to adjust for flower depth and orientation. This latest system demonstrates robustness in complex conditions, handling occlusions and changes in flower shapes, thus extending the practical applicability of intelligent pollination robotic arms in diverse agricultural environments. The operational environment of the intelligent pollination robotic arm is presented in Figure 7.



a. Kiwifruit automatic pollination robotic arm[79]
b. Dual-flow apray pollination robotic arm[91]
c. Six-axis robotic arm pollination system[113]
d. Mobile spray pollination robotic arm[86]
e. Intelligent brush pollination robotic arm[114]
f. Mobile automatic spray pollination robotic arm[80]
g. Vision-guided intelligent automatic pollination robotic arm[81]

Figure 7 Intelligent pollination robotic arms

While intelligent pollination technologies have achieved notable advancements in enhancing efficiency and precision, significant challenges persist in adapting to complex environmental variations and minimizing hardware costs. Through ongoing refinement in visual recognition algorithms and control systems, intelligent pollination robotic arms are expected to become more versatile and widely applicable across various agricultural settings.

4 Summary and prospects

4.1 Pollen viability

Pollen collected under natural conditions quickly loses viability, and some pollen types require specific desiccation to break dormancy, making effective pollen storage a key challenge. Generally, pollen must be stored in a dry environment at temperatures below 0°C to reduce viability loss. For mechanical pollination systems reliant on external pollen sources, precise viability assessments are essential prior to pollination. Currently, pollen viability analyzers offer high-throughput, non-invasive testing, providing critical data on pollen viability, concentration, and quantity. This information helps mitigate risks of reduced fruit set and lower fruit quality associated with low pollen viability. Additionally, regular monitoring of stored pollen is crucial to observe viability changes, enabling assessment of storage conditions' effects on pollen vitality. Such practices enhance pollination success rates, improve fruit quality, and ultimately boost agricultural productivity and economic efficiency.

4.2 Drone intelligence

The use of drone technology in agriculture, especially in assisted pollination, has advanced significantly. However, current data indicates that while drone-assisted pollination improves operational efficiency, it has yet to meet expected outcomes, suggesting substantial room for enhancement. Achieving precise positioning and collaborative functions is essential for future intelligent applications, and integrating technologies like remote sensing and IoT will be critical for high-precision pollen spraying. Current limitations in real-time data feedback prevent drones from fully monitoring pollination, as data processing and parameter extraction lag behind phenotyping platforms. Real-time image processing technologies could address this issue, enabling drones to adjust during pollination. Additionally, given the complex agricultural environments, there is considerable scope to improve drones' autonomous navigation and obstacle avoidance capabilities. Strengthening operational resilience in adverse weather through waterproof and wind-resistant designs is another necessary enhancement. These optimizations will make drones more effective in complex agricultural settings, advancing their practical application.

4.3 Recognition system

Current recognition systems rely primarily on deep learning algorithms, leveraging data from depth cameras for feature extraction and object detection. Optimizing the YOLO model to improve small-flower recognition accuracy while minimizing computational load has become a central goal. Key enhancements include suppressing background noise and strengthening the model's capacity to capture relevant features. Additionally, traditional spectral imaging requires further research to better understand spectral relationships for more accurate data. Thermal imaging for flower detection also shows promise as a means to reduce errors from light dispersion in spectral imaging. Integrating shape and posture analysis with edge pixel detection to identify flower contours offers a practical pathway to improve recognition accuracy. Enhancing model generalization to reduce overfitting remains essential for improving system adaptability in complex environments. These measures collectively aim to boost detection precision and adaptability, ensuring the system's effectiveness in diverse agricultural settings.

4.4 Robotic structure

High manufacturing and development costs currently hinder the economic viability of robots. Two strategies can address this issue while maintaining functionality. First, enhancing crop yield and quality (especially for high-value crops) requires optimizing robot structure and components to maximize productivity and improve fruit quality in real-world applications. Second, adopting a modular design will increase decomposability and simplify maintenance. Adjustable height, width, and weight will further enable robots to adapt to different fruit types and agricultural environments. Additionally, integrating data feedback and real-time control systems will enhance monitoring of movement and pollination outcomes. These improvements will boost robot flexibility, reduce maintenance costs, and broaden applicability across diverse agricultural settings.

5 Conclusions

This review underscores the critical role of mechanized and intelligent pollination in overcoming the limitations of natural and traditional manual pollination methods to meet the demands of modern agriculture. The article systematically examines current technologies, starting with foundational methods in pollen collection and utilization, followed by detailed advancements in various pollination devices, including handheld equipment, ground-based machinery, drones, and intelligent robotic arms. Each of these technologies presents unique advantages and challenges, with a common goal of enhancing operational efficiency, improving crop quality, and reducing labor costs.

Despite the promising applications of mechanized and intelligent pollination in specific crops such as kiwifruit, date palms, apples, and watermelons, many technologies remain in the experimental stage due to significant technical hurdles and limited commercial incentives for lower-value crops. Additionally, the irregular growth patterns of orchard trees pose further challenges for large-scale mechanized implementation, emphasizing the importance of standardized orchard management practices.

With the continued advancements in robotics, drones, automated control systems, and artificial intelligence, the commercial viability of efficient pollination machinery is gradually increasing. Looking forward, expanding research and development efforts in pollination technologies, particularly those aimed at enhancing adaptability to diverse agricultural environments, will be crucial. Supported by ongoing innovation and investment, mechanized and intelligent pollination technologies are expected to play a transformative role in future orchard production systems, accelerating agricultural modernization and promoting sustainable food production.

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[References]

[1] Miñarro M, Twizell K W. Pollination services provided by wild insects to kiwifruit (*Actinidia deliciosa*). Apidologie, 2015; 46: 276–285.

[2] Breeze T D, Bailey A P, Balcombe K G, Potts S G. Pollination services in the UK: How important are honeybees? Agriculture, Ecosystems & Environment, 2011; 142(3): 137–143.

[3] Abrol D P. Honeybees and rapeseed: A pollinator-plant interaction. Advances in Botanical Research, 2007; 45: 337–367.

[4] Eeraerts M, Smagghe G, Meeus I. Bumble bee abundance and richness improves honey bee pollination behaviour in sweet cherry. Basic and Applied Ecology, 2020; 43: 27–33.

[5] Reilly J R, Artz D R, Biddinger D, Bobiwash K, Boyle N K, Brittain C, et al. Crop production in the USA is frequently limited by a lack of pollinators. Proceedings of the Royal Society B, 2020; 287(1931). doi: 10.1098/rspb.2020.0922.

[6] Aizen M A, Harder L D. The global stock of domesticated honey bees is growing slower than agricultural demand for pollination. Current Biology, 2009; 19(11): 915–918.

[7] Mashilingi S K, Zhang H, Garibaldi L A, An J D. Honeybees are far too insufficient to supply optimum pollination services in agricultural systems worldwide. Agriculture, Ecosystems & Environment, 2022; 335: 108003.

[8] Molina-Montenegro M A, Acuña-Rodríguez I S, Ballesteros G I, Baldelomar M, Torres-Díaz C, Broitman B R, et al. Electromagnetic fields disrupt the pollination service by honeybees. Science Advances, 2023; 9(19). doi: 10.1126/sciadv.adh1455.

[9] Cappellari A, Malagnini V, Fontana P, Zanotelli L, Tonidandel L, Angeli G, et al. Impact of landscape composition on honey bee pollen contamination by pesticides: A multi-residue analysis. Chemosphere, 2024; 349: 140829.

[10] Wurz A, Grass I, Tscharntke T. Hand pollination of global crops - A systematic review. Basic and Applied Ecology, 2021; 56: 299–321.

[11] Pereira M C T, Nietsche S, Crane J H, Montas W. Gibberellic acid combined with hand pollination increases 'Red' and 'Lessard Thai' sugar apple fruit quality and produced parthenocarpic 'Gefner' atemoya fruits. Ciência Rural, 2019; 49(9). doi: 10.1590/0103-8478cr20180353.

[12] Li X T, Bao J P. Effects of different pollination combinations on stone cells, lignin, and related enzyme activities in fragrant pear fruit. HortScience, 2022; 57(5): 652–656.

[13] Toledo-Hernández M, Tscharntke T, Tjoa A, Anshary A, Cyio B, Wanger

T C. Hand pollination, not pesticides or fertilizers, increases cocoa yields and farmer income. Agriculture, Ecosystems & Environment, 2020; 304: 107160.

[14] Abbate A P, Campbell J W, Williams G R. Artificial pollination of kiwifruit (*Actinidia chinensis* Planch. var. *chinensis*) (Ericales: Actinidiaceae) results in greater fruit set compared to flowers pollinated by managed bees (*Apis mellifera* L. (Hymenoptera: Apidae) and *Bombus impatiens* Cresson (Hymenoptera: Apidae)). Journal of Economic Entomology, 2023; 116(3): 674–685.

[15] Fan G J. The Impact of Pollination on the Fruit Set and Quality of Pear Trees and Measures for Improvement. Applied Engineering Technology, 2021; 41(14): 35–36.

[16] Sharma A, Kaur S. Future prospects of artificial pollination in tree crop production: A review. International Archive of Applied Sciences and Technology, 2019; 10(2): 181–187.

[17] Huang J X, Ma W H, Shen J S, Guo C J. On pear tree bee pollination technology. Apiculture of China, 2020; 71(12): 31–32.

[18] Valiente J M, Juan-Borrás M, López-García F, Escriche I. Automatic pollen recognition using convolutional neural networks: The case of the main pollens present in Spanish citrus and rosemary honey. Journal of Food Composition and Analysis, 2023; 123: 105605.

[19] Yu M, Chen Y, Ding K, Ma J, Li Y Y. Study on the relationship between airborne pollen concentration and vegetation spatial structure in Beijing in spring based on CART decision tree model. Journal of Beijing Forestry University, 2023; 45(1): 121–131.

[20] Salomón-Torres R, Krueger R, García-Vázquez J P, Villa-Angulo R, Villa-Angulo C, Ortiz-Uribe N, et al. Date palm pollen: features, production, extraction and pollination methods. Agronomy, 2021; 11(3): 504.

[21] Girijashankar V. Effect of Eucalyptus pollen isolation methods on pollen viability, debris content, quantity isolated and pollen density per stigma. Journal of Plant breeding and Crop Science, 2010; 2(9): 273–279.

[22] Eyles A, Close D C, Quarrell S R, Allen G R, Spurr C J, Barry K M, et al. Feasibility of mechanical pollination in tree fruit and nut crops: A review. Agronomy, 2022; 12(5): 1113.

[23] Wang L M, Wu J F, Chen J Z, Fu D W, Zhang C Y, Cai C H, et al. A simple pollen collection, dehydration, and long-term storage method for litchi (*Litchi chinensis* Sonn.). Scientia Horticulturae, 2015; 188: 78–83.

[24] Schilling M. Bayer licenses PowerPollen corn seed pollination technology. Successful Farming, 2021. Available: https://www.agriculture.com/technology/bayer-licenses-powerpollen-corn-seed-pollination-technology. Accessed on [2024-09-10].

[25] Sáez A, Negri P, Viel M, Aizen M A. Pollination efficiency of artificial and bee pollination practices in kiwifruit. Scientia Horticulturae, 2019; 246: 1017–1021.

[26] David M A, Yommi A, Sánchez E, Martinez A, Murillo N, Marcellán O, et al. Strategic use of honey bees (*Apis mellifera* L.) to increase the number and size of fruits in kiwifruit (Actinidia chinensis var. deliciosa) . European Journal of Agronomy, 2022; 133: 126420.

[27] Bernauer O M, Tierney S M, Cook J M. Efficiency and effectiveness of native bees and honey bees as pollinators of apples in New South Wales orchards. Agriculture, Ecosystems & Environment; 2022; 337: 108063.

[28] Zhang X F, Wu M, Guo L N, Guo Y. Analysis and countermeasures of the current situation of pear pollination industry in shanxi. Apiculture of China, 2023; 74(9): 31–33.

[29] Hirsche J, García Fernández J M, Stabentheiner E, Großkinsky D K, Roitsch T. Differential effects of carbohydrates on arabidopsis pollen germination. Plant and Cell Physiology, 2017; 58(4): 691–701.

[30] Liu S S, Li Z W, Wu S W, Wang X Y. The essential roles of sugar metabolism for pollen development and male fertility in plants. The Crop Journal, 2021; 9(6): 1223–1236.

[31] Collection, preparation, pollination methods, and techniques of kiwi pollen. 2020. Available: https://www.pujiangmihoutao.com/58958.html. Accessed on [2024-9-20]. (in Chinese)

[32] Abreu I, Oliveira M. Fruit production in kiwifruit (*Actinidia deliciosa*) using preserved pollen. Australian Journal of Agricultural Research, 2004; 55(5): 565–569.

[33] Lora J, de Oteyza M A P, Fuentetaja P, Hormaza J I. Low temperature storage and in vitro germination of cherimoya (*Annona cherimola* Mill.) pollen. Scientia Horticulturae, 2006; 108(1): 91–94.

[34] Quinet M, Jacquemart A L. Troubles in pear pollination: Effects of collection and storage method on pollen viability and fruit production. Acta Oecologica, 2020; 105: 103558.

[35] Pacini E, Hesse M. Pollenkitt - its composition, forms and functions. Flora - Morphology, Distribution, Functional Ecology of Plants, 2005; 200(5): 399–415.

[36] Broussard M A, Coates M, Martinsen P. Artificial pollination technologies: A review. Agronomy, 2023; 13(5): 1351.

[37] Lee S-H, Kim W-S, Han T-H. Effects of post-harvest foliar boron and calcium applications on subsequent season's pollen germination and pollen tube growth of pear (*Pyrus pyrifolia*). Scientia Horticulturae, 2009; 122(1): 77–82.

[38] Sakamoto D, Kusaba S, Nakamura Y. Addition of forchlorfenuron to spray pollination media increases fruit set in 'Hosui' Japanese pear. HortTechnology, 2016; 26(2): 185–190.

[39] Karimi H R, Mohammadi N, Estaji A, Esmaeilizadeh M. Effect of supplementary pollination using enriched pollen suspension with Zn on fruit set and fruit quality of pistachio. Scientia Horticulturae, 2017; 216: 272–277.

[40] Ji R, Wang L, Wang Z, Gou C Q, Hao H T, Feng H Z. Effects of chitosan to pollination solution on fruit setting rate and fruit quality of Korla Fragrant Pear-All Databases. Xinjiang Agricultural Sciences, 2023; 60(5): 1208–1215.

[41] Liu L M, Liu Z Y, Han H, Jiang Y L, He X K, Liu Y J, et al. Influence of different liquid spray pollination parameters on pollen activity of fruit trees-pear liquid spray pollination as an example. Horticulturae, 2023; 9(3): 350.

[42] Lukose R, Dhalin D, Suresh D, Jayan P R, Vidhu K, Subhagan S R. Electrostatic pollen collector for tomato under greenhouse condition. Ama, Agricultural Mechanization in Asia, Africa & Latin America, 2021; 51(1): 1079–1092.

[43] Wu S, Liu J Z, Lei X J, Zhao S Y, Lu J J, Jiang Y X, et al. Research progress on efficient pollination technology of crops. Agronomy, 2022; 12(11): 2872.

[44] Khatawkar D S, James S P, Dhalin D. Role of electrostatics in artificial pollination and future agriculture. Current Science, 2021; 120(3): 484–491.

[45] Ito S, Gorb S N. Attachment-based mechanisms underlying capture and release of pollen grains. Journal of The Royal Society Interface, 2019; 16(157). doi: 10.1098/rsif.2019.0269.

[46] Zhu H X. Korla fragrant pear manual assisted pollination technology. Forestry of Xinjiang, 2006; 4: 24.

[47] Zhang D, Liu C, Liu Y C, Wei X, Yang Y M, Sun B, et al. Effects of different pollination modes on fruit setting rate and fruit quality of blueberry. China Fruits, 2023; 6: 54–58.

[48] Fu J, Qin Y Y Deng Y W, Huang D, Zhu Z H. Effect of artificial pollination on fruit setting rate of camellia oleifera. Journal of Fujian Forestry Science and Technology, 2023; 50(1): 66–70.

[49] Niu L J, Zhang D H, Ji G P, Jiang J Y, Wu Y R. Effects of different pollination techniques on fruit setting and fruit quality of fragrant pear. Northern Horticulture, 2022; 2: 40–46. (in Chinese)

[50] Zhai X D. A special liquid adjuvant for kiwifruit artificial pollination. 2023; CN202211313283.6. (in Chinese)

[51] Sakamoto D, Hayama H, Ito A, Kashimura Y, Moriguchi T, Nakamura Y. Spray pollination as a labor-saving pollination system in Japanese pear (*Pyrus pyrifolia* (Burm f.) Nakai): Development of the suspension medium. Scientia Horticulturae, 2009; 119(3): 280–285.

[52] Tacconi G, Michelotti V, Caciopp.O, Vittone G. Kiwifruit pollination: the interaction between pollen quality, pollination systems and flowering stage. Journal of Berry Research, 2016; 6(4): 417–426.

[53] Bee Research Institute. Bee-machine collaborative operation for efficient liquid pollination technology in pear orchards. China Beekeeping, 2021; 72(5): 11.

[54] Pathak H S. Effect of wet or dry pollen application methods on 'Hayward' kiwifruit production. New Zealand Journal of Crop and Horticultural Science, 2022; 1–13. doi: 10.1080/01140671.2022.2157447.

[55] Liu X F, Yao C C, Long Z X, Fan X F. Study on artificial pollination technique of Kiwifruit. Acta Agriculturae Boreali-occidentalis Sinica, 2002; 11(3): 91–93, 108.

[56] Hao W, Ding X T, He Z, Li K, Gong W X, Li Z X, et al. Development and evaluation of precision liquid pollinator for kiwifruit. Computers and Electronics in Agriculture, 2023; 213: 108193.

[57] Samnegård U, Hambäck P A, Smith H G. Pollination treatment affects fruit set and modifies marketable and storable fruit quality of commercial apples. Royal Society Open Science, 2019; 6(12): 190326.

[58] Oh E U, Kim S C, Lee M H, Song K J. Pollen application methods affecting fruit quality and seed formation in artificial pollination of yellow-fleshed kiwifruit. Horticulturae, 2022; 8(2): 150.

[59] Wang J G, Wang O F. Artificial pollination technology for pear trees. China Southern Fruits, 2002; 31(1): 40–42.

[60] Lin C X, Liu C Q, Wei J, Xu S L. High-efficiency artificial assisted pollination technology for korla fragrant pears. Northern Horticulture, 2021; 5: 175–177.

[61] Xue L Y, Li X H, Liu K. Artificial pollination technology during the blooming period of magnolia flowers. Xinjiang Farm Research of Science and Technology, 2010; 33(4): 21–23.

[62] Liu L. Exploration of artificial assisted pollination technology for fruit trees. Modern Agricultural Science and Technology, 2021; 15: 94–95.

[63] Li S F. Technical analysis of artificial pollination assistance for wei county pears. Northern Fruits, 2017; 3: 40–41.

[64] Zhang S L, Xie Z H. Current status, trends, main problems and the suggestions on development of pear industry in China. Journal of Fruit Science, 2019; 36(8): 1067–1072.

[65] Mahadik A S, Kushwaha H L, Kumar A, Bhowmik A, Singh A K. Pulsating air pollinator for greenhouse cultivation. Journal of Scientific & Industrial Research, 2021; 80(6): 477–485.

[66] Ding S M, Xue X Y, Cai C, Qin C W, Fang J B, Sun Z. Design and experiment on handheld air-assisted pollination device. Transactions of the CSAE, 2014; 30(13): 20–27.

[67] Pinillos V, Cuevas J. Artificial pollination in tree crop production. Horticultural Reviews, 2007; 34. doi: 10.1002/9780470380147.ch4.

[68] Gianni T, Vania M. Artificial pollination in kiwifruit and olive trees. Pollination in Plants, 2018. doi: 10.5772/intechopen.74831.

[69] Gan-Mor S, Ronen B, Vaaknin Y, Glik Y, Samocha Y, Eisikowitch D. Further studies on electrostatic date pollination from the laboratory bench to field unit performance test. Applied Engineering in Agriculture, 2009; 25(5): 643–646.

[70] Gan-Mor S, Bechar A, Ronen B, Eisikowitch D, Vaknin Y. Electrostatic pollen applicator development and tests for almond, kiwi, date, and pistachio - an overview. Applied Engineering in Agriculture, 2003; 19(2): 119–124.

[71] Shi F X, Xu X R. A Dual-Fan Electric Static Pollinator. 2024; CN202321752374. X. (in Chinese)

[72] Lan Y B, Zhao D N, Han X, Liu Q, Yu Q Y, Kong H, et al. A drone-enabled static pollination device and method. 2020; CN201910034995.6. (in Chinese)

[73] Yang X, Miyako E. Soap bubble pollination. iScience, 2020; 23(6): 101188.

[74] Lallensack R. Could this pollinating drone replace butterflies and bees? Science, 2017. doi: 10.1126/science.aal0730.

[75] Alyafei M A S, Dakheel A A, Almoosa M, Ahmed Z F R. Innovative and effective spray method for artificial pollination of date palm using drone. HortScience, 2022; 57(10): 1298–1305.

[76] Rice C R, McDonald S T, Shi Y, Gan H, Lee W S, Chen Y, et al. Perception, path planning, and flight control for a drone-enabled autonomous pollination system. Robotics, 2022; 11(6): 144.

[77] Shi Q. Study on mechanism and method of wind-induced vibration pollination of greenhouse tomato based on UAV downwash flow field. PhD dissertation. Jiangsu: Jiangsu University, 2021; 120–140. 162 p. (in Chinese)

[78] Liu Y J, Han H, Qiao B Y, Liu Z Y. A targeted pollination device for fruit trees mounted on an agricultural drone. 2023; CN202223253242.0. (in Chinese)

[79] Li K, Huo Y J, Liu Y N, Shi Y G, H Z, Cui Y J. Design of a lightweight robotic arm for kiwifruit pollination. Computers and Electronics in Agriculture, 2022; 198: 107114.

[80] Yang M H, Lyu H C, Zhao Y J, Sun Y C, Pan H, Sun Q, et al. Delivery of pollen to forsythia flower pistils autonomously and precisely using a robot arm. Computers and Electronics in Agriculture, 2023; 214: 108274.

[81] Ahmad K, Park J-E, Ilyas T, Lee J-H, Lee J-H, Kin S, et al. Accurate and robust pollinations for watermelons using intelligence guided visual servoing. Computers and Electronics in Agriculture, 2024; 219: 108753.

[82] Ren R, Sun H X, Zhang S J, Zhao H M, Wang L J, Su M, et al. FPG-YOLO: A detection method for pollenable stamen in "Yuluxiang" pear under non-structural environments. Scientia Horticulturae, 2024; 328: 112941.

[83] Tai N D, Trieu N M, Thinh N T. Modeling positions and orientations of cantaloupe flowers for automatic pollination. Agriculture, 2024; 14(5): 746.

[84] Hiraguri T, Kimura T, Endo K, Ohya T, Takanashi T, Shimizu H. Shape classification technology of pollinated tomato flowers for robotic implementation. Scientific Reports, 2023; 13(1): 2159.

[85] Wen C W, Long J H, Zhang Y, Guo W Z, Lin S, Liang X T. Positioning method of tomato pollination flowers based on 3D vision. Transactions of the CSAM, 2022; 53(8): 320–328.

[86] Zhao C J, Wen C W, Lin S, Guo W Z, Long J H. Tomato florescence recognition and detection method based on cascaded neural network. Transactions of the CSAE, 2020; 36(24): 143–152.

[87] Zhang H H. Design and implementation of an automatic pollination system for kiwifruit based on deep learning. Master dissertation. Shanxi: Xidian University, 2022; 31–76. 98 p. (in Chinese)

[88] Sapkota R, Ahmed D, Khanal S R, Bhattarai U, Mo C, Whiting M D, et al. Robotic pollination of apples in commercial orchards. arXiv: 2311.10755, 2023; doi: 10.48550/arXiv.2311.10755.

[89] Zheng W X, Yang Y. Mature Stage pear detection method based on frequency domain data augmentation and lightweight YOLO v7 model. Transactions of the CSAM, 2024; 55(5): 244–253.

[90] Shu C R, Xiong H L, Chen G F, Lei Y H, Zhan M, Chen F. Current situation and development of the research and application of the electrostatic spraying- dusting technique. Journal of Shenyang Agricultural University, 2002; 33(3): 211–214.

[91] Li G. Accurate pollination device of kiwifruit based on vision perception and air-liquid spray. Master dissertation. Shanxi: Northwest A&F University, 2023; 15–41. 85p. (in Chinese)

[92] Hedhly Afif, Hormaza J I, Herrero M. Global warming and sexual plant reproduction. Trends in Plant Science, 2009; 14(1): 30–36.

[93] Huang H W. Domestication and commercialization of *Actinidia*. In: Huang H W (Ed.). Kiwifruit. Valencia: Academic Press. 2016; 191–210. doi: 10.1016/B978-0-12-803066-0.00004-6.

[94] Ahi K D, Sönmez E, Argaç A, Erturk U. An unmanned aerial vehicle based artificial pollination in frost-affected walnut (*Juglans regia*) orchard. Plant Physiology, 2023. doi: 10.15832/ankutbd.1163150.

[95] Mangena P, Mokwala P W. Introductory chapter: Pollination. In: Mokwala P W (Ed.). Pollination in Plants. IntechOpen. 2018. doi: 10.5772/intechopen.77227.

[96] Vaknin Y, Gan-Mor S, Bechar A, Ronen B, Eisikowitch D, Grunewaldt J. Effects of supplementary pollination on cropping success and fruit quality in pistachio. Plant Breeding, 2002; 121(5): 451–455.

[97] Gan-Mor S, Bechar A, Ronen B, Eisikowitch D, Vaknin Y. Improving electrostatic pollination inside tree canopy via simulations and field tests. Transactions of the ASAE, 2003; 46(3): 839–843.

[98] Liu X L. The role of electrostatic in the pollination of wind-pollinated plants. Master dissertation. Shandong: Shandong University, 2013; 49–56. 76 p. doi: 10.7666/d.Y2331489. (in Chinese)

[99] Liu S Y, Zhang X M, Wang X Y, Feng R B, Wu J X, Zhang S J, et al. Vibration inducing and airflow guiding coupled tomato pollination method research based on gas-solid two-phase flow model. Computers and Electronics in Agriculture, 2024; 216: 108472.

[100] Vaknin Y V Y, Gan-Mor S G S, Bechar A B A, Ronen B R B, Eisikowitch D E D. Improving pollination of almond (*Amygdalus communis* L. Rosaceae) using electrostatic techniques. The Journal of Horticultural Science and Biotechnology, 2001; 76(2): 208–212.

[101] Ahmad A, Ordoñez J, Cartujo P, Martos V. Remotely piloted aircraft (RPA) in agriculture: A pursuit of sustainability. Agronomy, 2020; 11(1): 7.

[102] Hiraguri T, Shimizu H, Kimura T, Matsuda T, Maruta K, Takemura Y. Autonomous drone-based pollination system using ai classifier to replace bees for greenhouse tomato cultivation. IEEE Access, 2023; 11: 99352–99364.

[103] Jia Y L, Wang X J, Wang R Y, Yue X. Simulation study on multiple unmanned aerial vehicles for precise stereotactic in orchard. Journal of Agricultural Mechanization Research, 2023; 45(6): 24–29.

[104] Potts S G, Neumann P, Vaissière B, Vereecken N J. Robotic bees for crop pollination: Why drones cannot replace biodiversity. Science of The Total Environment, 2018; 642: 665–667.

[105] Hulens D, Van Ranst W, Cao Y, Goedemé T. Autonomous visual navigation for a flower pollination drone. Machines, 2022; 10(5): 364.

[106] Lin Z H. Electric multi-rotor drones can extend the study of key technologies for auxiliary pollination. Master dissertation. Guangdong:

South China Agricultural and University, 2021; 68 p. (in Chinese)

[107] Liu S Y, Zhang X M, Wang X Y, Hou X N, Chen X A, Xu J, et al. Tomato flower pollination features recognition based on binocular gray value-deformation coupled template matching. Computers and Electronics in Agriculture, 2023; 214: 108345.

[108] Mu X Y, He L, Heinemann P, Schupp J, Karkee M. Mask R-CNN based apple flower detection and king flower identification for precision pollination. Smart Agricultural Technology, 2023; 4: 100151.

[109] Li G, Suo R, Zhao G, Gao C Q, Fu L S, Shi F X, et al. Real-time detection of kiwifruit flower and bud simultaneously in orchard using YOLOv4 for robotic pollination. Computers and Electronics in Agriculture, 2022; 193: 106641.

[110] Xu T Y, Qi X Y, Lin S, Zhang Y H, Ge Y H, Li Z L, et al. A Neural network structure with attention mechanism and additional feature fusion layer for tomato flowering phase detection in pollination robots. Machines, 2022; 10(11): 1076.

[111] Zhou H L, Ou J L, Meng P H, Tong J H, Ye H B, Li Z, et al. Reasearch on kiwi fruit flower recognition for efficient pollination based on an improved YOLOv5 algorithm. Horticulturae, 2023; 9(3): 400.

[112] Gao C Q, He L L, Fang W T, Wu Z C, Jiang H H, Li R, et al. A novel pollination robot for kiwifruit flower based on preferential flowers selection and precisely target. Computers and Electronics in Agriculture, 2023; 207: 107762.

[113] Jin T T, Han X Z. Robotic arms in precision agriculture: A comprehensive review of the technologies, applications, challenges, and future prospects. Computers and Electronics in Agriculture, 2024; 221: 108938.

[114] Yu X H, Kong D Y, Xie X X, Wang Q, Bai X W. Deep learning-based target recognition and detection for tomato pollination robots. Transactions of the CSAE, 2022; 38(24): 129–137.