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Artificial Pollination by Nano drone Technology: A review

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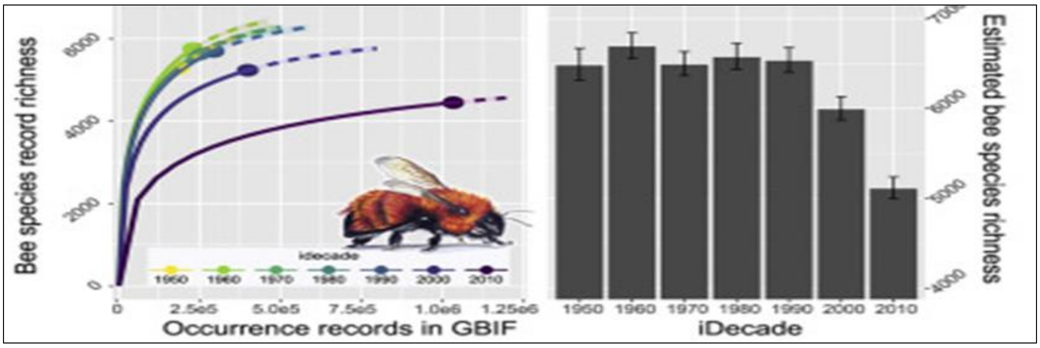
Abstract
Pollination is a critical process for crop production and ecological balance. However, the decline in natural pollinators, such as bees and other insects, due to habitat loss, pesticide use, climate change, and diseases, has raised concerns. To address these challenges, researchers are exploring the concept of artificial pollination, with a particular focus on drone-based technology. Effective autonomous pollination necessitates drones that can proficiently navigate their environment, detect target flowers, and transfer pollen without causing harm. This multifaceted approach involves various modules: environment sensing for obstacle detection and mission-critical data collection, flower perception for locating and mapping flowers, path planning to optimize pollination routes, flight control for precise drone maneuvering between waypoints, and specific pollination mechanisms tailored to different crops. Nano drones hold significant promise in revolutionizing precise pollination in agriculture by identifying flowers, navigating to them, pollinating, and even cooperating with other drones. To enhance their efficacy, the development of diverse end effectors customized for various flower types is essential. Nevertheless, practical deployment faces challenges, including payload limitations and sensitivity to adverse weather conditions. Overcoming these hurdles is imperative to advance this innovative technology towards broader and practical implementation, addressing pressing pollination issues in agriculture and ecosystems.

Keywords: Pollination, artificial pollination, drone, nano drone, flower detection

Introduction

Pollination is the biological process which transfer of pollen from an anther the male part of the plant to the stigma, which is the female part of the plant, leading to fertilization and the formation of seeds. Pollination is crucial for the production of crops, plays a significant role in both agriculture and the ecosystem, contributing to the balance of our surroundings. This process directly impacts on crop production, resulting in higher yields, improved quality, and increased genetic diversity for enhanced resilience. Simultaneously, pollinators are essential for maintaining biodiversity, which contributes to ecosystem stability by ensuring the health and survival of plant communities, which provide habitat, food, and shelter to a multitude of animal species. This intricate web of interactions driven by pollination sustains the harmony of our surroundings, making it a key service vital for human well-being and sustains the delicate balance of natural ecosystems (Meeuse, 2023) [14].

Unlike animals plants cannot move in search of the partner and rely on the help of external forces (wind, water, and insects) known as pollinators. The Food and Agriculture Organisation of the United Nations estimates that 90% of the world's food is produced from 100 crop species, 71 of which are pollinated by bees (Pinheiro *et al.*, 2023) [17]. Insects constitute the majority of pollinating animals, with honey bees (*Apis mellifera* L.) being the principal pollinators of several crop species (Sluijs *et al.*, 2016). However, this species' foraging behaviour is distinctive because bees are sensitive to several factors. This behaviour is closely related to the bee colony and the environment. Unfortunately, over the past few years, there has been a growing concern about the global decrease in pollinators, especially bees. With increases in pesticide use, parasites, and other diseases, the declining bee population became a concern in 2006 with the onset of Colony Collapse Disorder (CCD), which caused a significant decrease in colonies.



Source: Zattara and Aizen, 2021

Fig 1: Worldwide decreasing trend of bee population

To overcome this decline and ensure the continued pollination of plants, researchers have been exploring the concept of artificial pollination. Artificial pollination involves using innovative techniques, such as hand pollination by tools or hand held devices like brush, needle, electric brush, vehicle mounted devices like blowers, sprayers, drones equipped with pollen-carrying devices, to mimic the natural pollination process. By supplementing the work of natural pollinators with these advanced technologies, artificial pollination could help maintain crop yields, preserve biodiversity, and support the health of our ecosystems in the face of declining pollinator populations.

Pollination techniques

Hand Pollination

This is the simplest and most common form of artificial pollination. It involves physically transferring pollen from the stamen to the stigma with a paintbrush, stick, or pole tipped with a feather-brush (Pratap and Ya, 2012; Gianni and Vania, 2018) [5]. This method is tedious and labour- intensive. This cost can be sustained by some high-value crops, particularly when pollen does not need to be collected (e.g., tomato), the pollen is produced in abundance and collection costs are low (e.g., date), or the market value of the crop is very high (e.g., vanilla). Where mechanisation is available (even if only in the form of a vibratory wand), it is often more effective and economical than manual pollination (Peet and Welles, 2004; Sakamoto, 2009; Gianni and Vania, 2018) [5, 16, 20].

Hand Held devices

Hand-held devices have revolutionized artificial pollination, offering increased efficiency and cost savings compared to manual methods. Devices like blowers, sprayers, and vibratory wands enable precise pollen application. Directed broadcast of pollen using a handheld leaf blower has been estimated to deliver only 1% of pollen to stigmatic surfaces (Goodwin and McBrydie, 2013) [7]. Vibratory wands are ideal for indoor tomatoes, while pneumatic devices with brush tips suit orchard crops. Additionally, electrostatic hand spray methods have shown success in certain scenarios, but further research and development are necessary for practical integration into modern agricultural practices. Technical challenges, such as accurate targeting and potential flower damage, require attention for wider commercial adoption (Vera-Chang *et al.*, 2016; Giles, 2021; Lukose *et al.*, 2022) [6, 13, 21].

Vehicle mounted devices

Vehicle-mounted devices are employed in large-scale agricultural settings to expedite the pollination process over vast crop areas. Various types of equipment, such as sprayers, blowers, and fans, have been developed for this purpose. Compared to equivalent hand-held devices, these vehicle-mounted options significantly reduce the need for labor, making the process more efficient. The devices are typically attached to tractors or other farm vehicles, enabling the dispersal of pollen over a wide area in an effective manner. However, a limitation of these systems is that they often require a larger quantity of pollen due to their non-targeted approach, potentially leading to increased pollen consumption (Bullock and Overley, 1949; Williams and Legge, 1979; Torres *et al.*, 2021; Hi *et al.*, 2003; Gan-Mor *et al.*, 2003; Law, 2001; Whiting, 2019.) [1, 4, 12, 22, 23].

Vehicle mounted electrostatic device

Non-targeted systems in artificial pollination can be inefficient, leading to wastage of pollen grains that settle on leaves, orchard structures, and branches without fertilizing the flower. A significant portion of pollen grains landing on petals may not be effectively redistributed by bees. To address this issue, researchers have explored directed broadcasts of electrostatically charged pollen. By directing the pollen into the canopy, the amount of pollen lost to the surrounding environment is reduced. Moreover, positively charging the pollen increases its attraction to pointed structures like styles, enhancing pollen deposition and improving overall pollination efficiency. This innovative approach aims to minimize pollen wastage and optimize pollination success in artificial pollination methods (GanMor *et al.*, 2003; Law, 2001; Whiting, 2019) [4, 12, 23].

Challenges in Traditional Artificial pollination Over Drone Pollination: There are various challenges occurs during the pollination process and are need to be addressed with the proper solutions otherwise it leads to the reduction of crop yield. The major challenges were mentioned in the table.

Table 1: Various challenges in traditional artificial pollination over drone pollination

Sl. No.	Challenges	Description
1	Labor-Intensive	Traditional artificial pollination methods, such as hand pollination and hand-held devices are labour-intensive and time-consuming. They require manual efforts from workers, which can increase costs and make them less practical for large-scale agricultural operations.
2	Inefficient Pollen Transfer	Some artificial pollination techniques may not achieve efficient pollen transfer compared to natural pollinators like bees.
3	Limited Scale	Certain artificial pollination methods, like hand pollination or hand-held devices, may not be feasible for

		large-scale crops or vast agricultural fields due to the need for extensive labour and time.
4	Environmental Impact	Vehicle-mounted devices used in artificial pollination may have environmental impacts, such as soil compaction and greenhouse gas emissions, especially when applied on a large scale.
5	Lack of Precision	Some artificial pollination methods may lack precision in pollen delivery, leading to uneven pollination and potential fertilization issues.
6	Pollen Storage and Viability	Maintaining the viability of stored pollen for extended periods can be difficult. Pollen may lose its potency or become contaminated, affecting the success of artificial pollination efforts.
7	Lack of Pollinator Behaviour	Artificial pollination may not replicate the complex behavior and interactions of natural pollinators, which can have broader ecological implications beyond just fertilization, such as the conservation of biodiversity.

To overcome all these challenges, researches started advanced method called pollination by drone technology. Drone based pollination technology has received considerable attention. The use of drones to pollinate crops is an attractive proposition both because drones have a good aesthetic fit for the job they are airborne pollinators, like bees and because drone technology has a lower barrier to entry than other forms of robotics. These devices are either directly controlled by a pilot, follow a set path defined by the layout of orchard rows, or utilise a 3 D model of the environment built from an earlier pass by scouting drones. Many drone pollinators are modifications of commercially available drones, particularly those designed for agrichemical sprays, but a number are also being custom designed for pollination. Several pollination modes are being explored, including aerial broadcast distribution of pollen, as well as utilising the drone's air vortices for pollination directly for hybrid grain production and greenhouse grown self-compatible crops such as strawberry, tomato, pepper, and eggplant.

Drone Pollination

Drone pollination is a method of artificial pollination that involves using drones equipped with spray systems to disperse pollen over crops. Instead of relying on natural pollinators like bees or wind, drones are deployed to carry and release pollen, mimicking the action of pollinators to facilitate fertilization in plants.

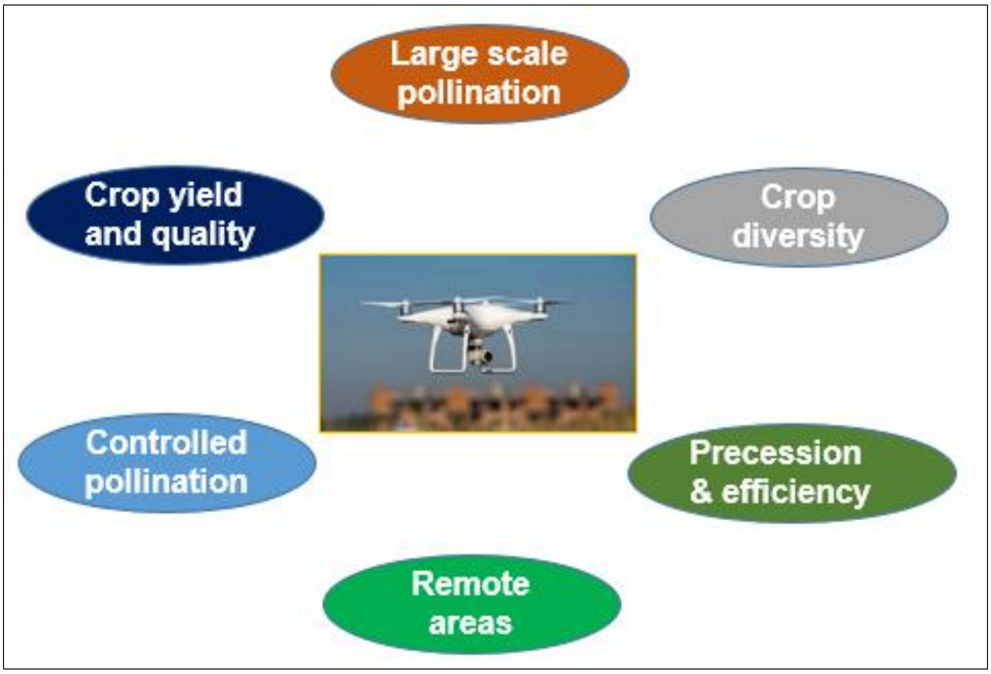


Fig 2: Scope of Drone for Pollination

Table 2: Different scopes of drone pollination

Sl. No.	Scope	Description
1	Crop Diversity	Drone pollination can facilitate the pollination of a wide range of crops, including those with complex flower structures or crops grown in challenging environments.
2	Large-Scale Pollination	Drones can cover large agricultural fields quickly and efficiently, making them suitable for large-scale pollination efforts in commercial farming.
3	Precision and Efficiency	Drone pollination can deliver pollen with high precision directly to targeted flowers, ensuring efficient use of pollen and minimizing wastage.
4	Remote and Inaccessible Areas	Drones can reach remote or difficult-to-access areas, including steep terrains or areas where traditional pollination methods are not feasible.
5	Reduced Labour Costs	By automating pollination, drones can significantly reduce the need for manual labor, leading to cost savings for farmers.
6	Supplementing Natural Pollinators	In regions facing declining bee populations or other natural pollinator challenges, drone pollination can serve as a valuable supplement to ensure sufficient pollination.
7	Crop Yield and Quality	Improved and consistent pollination through drone technology can lead to enhanced crop yields and improved fruit quality.

Drone spray pollination is considered a potential solution for large-scale pollination in agriculture, particularly in situations where natural pollinators are scarce or infeasible due to large fields, remote locations, or specific crop requirements. It offers advantages such as increased speed, efficiency, and reduced labor compared to manual pollination methods. However, drone spray pollination also comes with challenges and limitations such as:

Table 3: Challenges in conventional drone pollination

Sl. No.	Challenge	Description
1	Non-Targeted Pollen Dispersion	Drones may not precisely deliver pollen to specific flowers, leading to wastage and inefficiency.
2	Inconsistent Pollen Distribution	Environmental factors like wind or varying drone flight patterns can result in uneven pollen distribution.
3	Risk of Cross-Contamination	Pollen from one variety may contaminate other crops, affecting the genetic purity of seeds and harvest quality.
4	Limited Precision	The larger size and less agile nature of traditional drones may hinder precise targeting of flowers in dense crop canopies.
5	Environmental Impact	The use of pollen sprays may have unintended effects on non-target organisms and surrounding ecosystems.

To address these challenges and optimize the pollination process, researchers and farmers are exploring nano drone pollination, where smaller and more agile drones can deliver pollen with higher precision, ensuring efficient and accurate pollination of targeted flowers while minimizing environmental impacts and maximizing crop yield potential.

Nano-drone Pollination

Unmanned Aerial Vehicles (UAVs) are often applied to diverse agriculture activities. Several classifications are used based on size, weight, speed, and altitude, among others. The class selected classifies UAVs according to their weight and wingspan (Hassanalian and Abdelkefi. 2017) [8]. The chosen class must be able to balance the weight that can be placed onboard and the size of the propellers (which cause the movement of pollen). The Nano drone class is the most suitable for the intended pollination functions, with a weight of 3 to 50 g and a wingspan of 2.5 to 15 centimetres. However, Nano drones are still underutilised in this context, although they can perform tasks more precisely than conventional UAVs.

Fig 3: Representation of Nano Drone in pollination (Source: AI-generated)

The scope of nano drone pollination are: Nano drones are significantly smaller and lighter than traditional UAVs, reducing the risk of injury to people, animals, and property in the case of an accident or other malfunction. These characteristics make them more manoeuvrable and they can operate in tight spaces and near crops. Nano drones can fly closer to crops, which allows for more precise guidance and application such as fertiliser or pest control chemicals. Nano drones are typically quieter and cause fewer changes in their surroundings, which can be important in certain applications such as tree pollination. Nano drones equipped with advanced sensors and imaging technology can navigate through crop canopies more effectively, achieving uniform and consistent pollen distribution.

Requirement of Nano drone for pollination

To achieve effective autonomous pollination, a nano drone must be able to traverse and autonomously navigate its environment, detecting and targeting flowers to pollinate and transfer pollen between targeted flowers. It should localize itself relative to a home position and fly within a designated area using its onboard flight controller (Craigie *et al.*, 2021) [2].

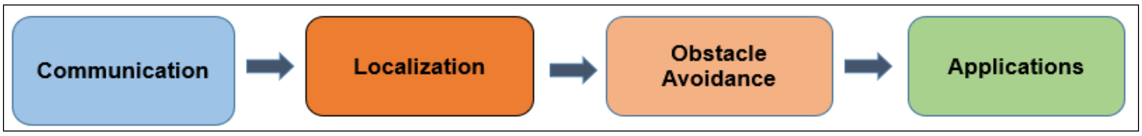


Fig 4: Requirement of Nano drone for pollination

Communication

The main aim of Nano drone is to capable of moving and pollinating autonomously. The crazy file 2.1 is the core component of communication module and this hardware provides low latency, long range radio communication and low energy Bluetooth.

Localization

The location of the nano drone can be determined using an approach based on Simultaneous Location and Mapping (SLAM). By placing a camera on the nano drone, it is possible to collect images of the environment. This information is transmitted to the ground station and used by SLAM to map the surrounding environment. The Robotic Operating System (ROS) is a framework for developing robotics algorithms. The computer vision algorithms required for SLAM are developed using the ROS tool (Esfahlani, 2019; Pinheiro *et al.*, 2023) [3, 17].

Obstacle avoidance: Obstacle avoidance can be achieved using the localisation provided by SLAM. This approach maps the environment around the NAV, allowing the determination of the positions of the surrounding obstacles and, consequently, leads to obstacle avoidance (Esfahlani, 2019) [3].

Application: The nano drones were developed as per the application and requirement need to design the nano drone.

Basic Components of Nano copter for Pollination

The overall design of the nano drone relies on a flight controller to control and stabilize the drone, a primary computer (Raspberry Pi 3B running ROS Noetic) to manage higher-level decisions and communicate between the different parts of the drone system, a camera to detect flowers, a servo-driven end-effector to make contact with the flowers to pollinate them, and a GPS for position estimation.

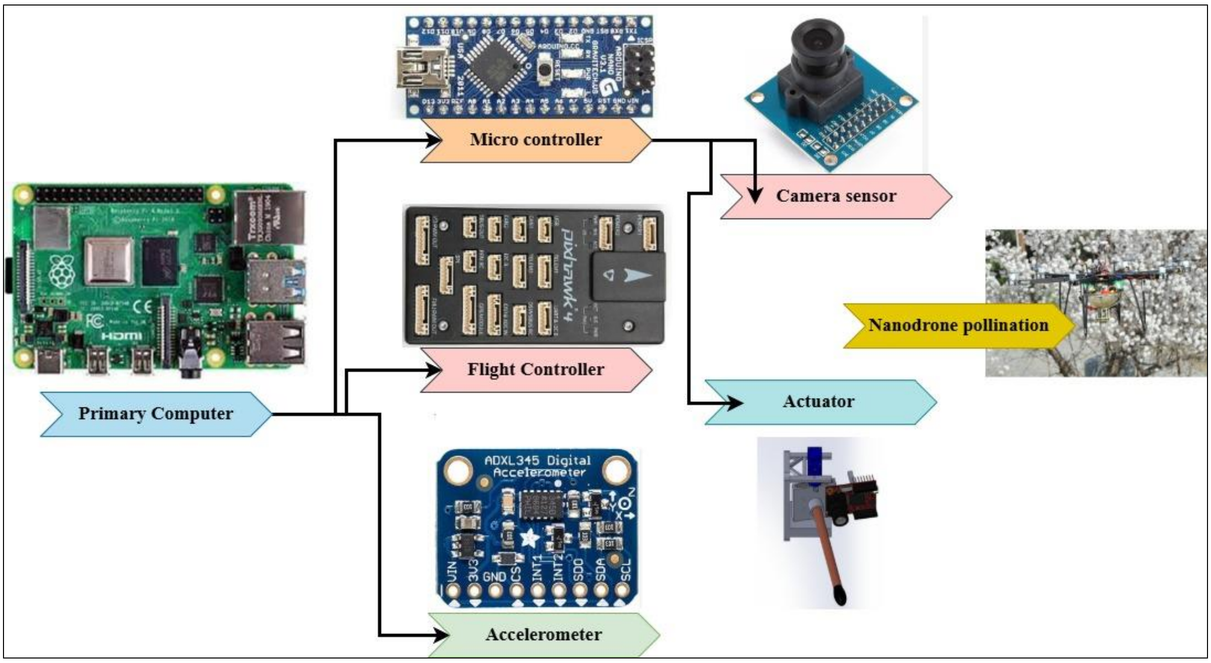


Fig 5: Components of nano drone for pollination

The software system is organized into multiple subsections: end-effector control, vision processing, flight control, and optical flow/altitude detection. These subsections all interact with the primary onboard computer, the Raspberry Pi 3B. End effector positioning is handled by an Arduino Nano. This microprocessor communicates to a Python node within primary computer's ROS architecture. Target end effector angles are transmitted over a USB cable using UART communication and received directly by the Arduino, which commands a servo to move the end effector. Onboard vision processing is delegated to a camera. This camera runs a custom flower detection algorithm and returns the centroids of detected flowers. The Raspberry Pi communicates directly with the camera through UART protocol communicating over the Raspberry Pi's dedicated RX and TX GPIO pins. These pins are accessed similarly to a standard serial bus port. This allows for lightweight signal cables to carry data transmission to the camera, lessening the physical load that would be placed on the servo actuator by a full USB cable.

The Raspberry Pi communicates to the flight controller by sending MAVLink commands through a USB to UART adapter. The generated MAVLink commands converts the high-level ROS messages to the MAVLink control messages that the flight control understands. This MAVROS Bridge is used to receive positional data from the flight control which is used to generate the target position and velocity set points. The final subsection is handled by a second camera. This separate camera performs optical flow to calculate a body velocity estimate. The integrated microchip on the camera communicates with a time of flight sensor and IMU using I2C which is used to estimate flight altitude and attitude. The velocity, altitude, and attitude estimates are sent directly with the flight controller through a UART connection.

End effector design

The end-effector refers to the dynamic platform that houses a camera and a pollen collector. It is designed to collect and deposit pollen and dynamically track flowers as they move within the end effector. The choice of end effector and its design parameters can significantly impact the success of pollination. The requirement of end effector was mentioned in the table 4.

Table 4: Requirement of end effector

Sl. No.	Requirement	Description
1	Pollination Efficiency	The end effector should be designed to mimic the natural pollination process, ensuring efficient transfer of pollen from one flower to another. It should maximize the probability of successful pollination.
2	Gentle Handling	The end effector should not damage the flowers during the pollination process. It should be gentle to prevent harm to the plants and flowers.
3	Adaptability	The end effector should be adaptable to various types of flowers and plants. Different flowers may require different approaches to pollination, so the end effector should be versatile.
4	Pollen Collection	The end effector should be able to collect and dispense pollen effectively. Efficient pollen collection and distribution are essential for successful pollination.
5	Stability	The end effector should be stable and able to maintain its position in windy conditions or while hovering over flowers.
6	Precision	Precision in terms of placement and timing is crucial. The end effector should accurately place pollen on the pistils of flowers and do so at the right moment in the flower's reproductive cycle.
7	Payload Capacity	The end effector should have a suitable payload capacity to carry an adequate amount of pollen for multiple pollination cycles before refilling.
8	Power Efficiency	It should be designed to consume minimal power to maximize flight time and reduce the need for frequent recharging.

Design parameters of nano drone for pollination

Designing an effective end effector for drone pollination involves a combination of engineering, robotics, and plant biology knowledge. It's essential to tailor the end effector to the specific plant species you intend to pollinate and consider the environmental conditions in which the drone will operate. Additionally, continuous testing and refinement of the end effector design are critical to achieving successful pollination outcomes. The design requirements were mentioned in table 5.

Table 5: Design parameters of nano drone for pollination

Sl. No.	Design parameter	Description
1	Shape and Size	The shape and size of the end effector should be optimized for the type of flowers intend to pollinate.
2	Material	The material used for the end effector should be lightweight yet durable. Materials like lightweight plastics or composites are often suitable.
3	Pollen Storage	Design the end effector to store and dispense pollen efficiently. This may involve the use of chambers, brushes, or other mechanisms to ensure controlled pollen release.
4	Actuation Mechanism	The end effector should have a reliable actuation mechanism, such as servo motors or pneumatic systems, to control the movement of the pollen dispensing mechanism.
5	Sensors and Imaging	Integrate sensors and imaging technology, such as cameras and proximity sensors, to detect flowers and accurately target the pistils for pollination.
6	Control System	Develop a robust control system that allows for precise control of the end effector's movements and pollen dispensing.
7	Communication	Ensure the end effector can communicate with the drone's flight controller to coordinate its actions and monitor pollen levels.
8	Feedback Mechanisms	Include feedback mechanisms to monitor the success of pollination efforts and make real-time adjustments as necessary.

Craigie *et al.,* 2021 [2] designed an end effector using an eye shadow brush as the pollen collector, aligning the camera's optical axis parallel to the collector. This configuration simplifies path computation for the drone, as there's a constant offset between the camera and brush. To ensure a consistent horizontal position during flight, they added a hard stop behind the rotating plate, enabling compensation for servo errors. This design minimizes gravitational effects on the servo and maintains the drone's center of mass stability.

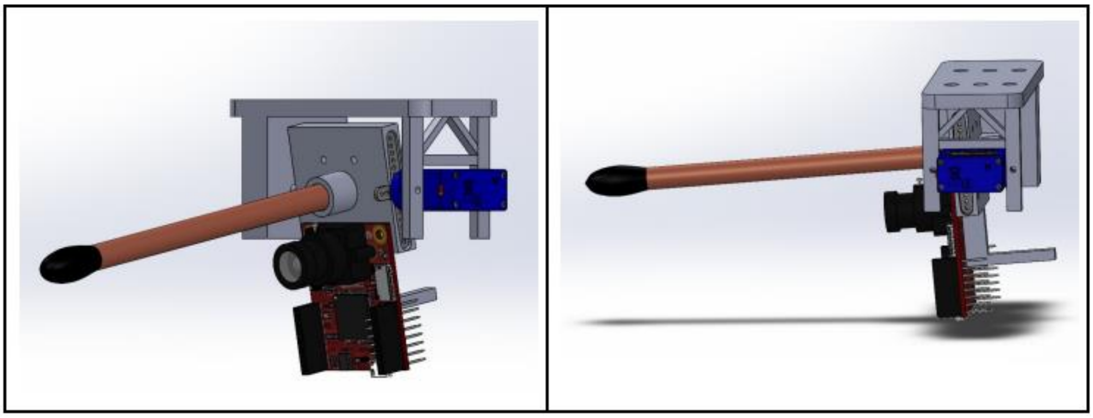


Fig 6: End effector design (Craigie *et al.*, 2021) [2]

End effector tracking

A proportional controller is used to track the end-effector to track a flower for pollination. The effectiveness of this flower tracking algorithm was evaluated by placing a flower within the view of the camera and moving it up and down, which tested the end-effector's ability to track the flower as it moved. This test found that the end-effector can successfully track flowers between 0 and 90 degrees before hitting the physical limitations of the end-effector. This test proved that a proportional control could be used to accurately track a flower moving relative to the camera frame to properly align the pollen collector with the center of the flower (Craigie *et al.*, 2021) [2].

Nano copter for Pollination

Pollination by nano drone will be complex. The system will need to identify flowers, fly to them, pollinate, cooperate with other drones, etc. These steps are best described in a series of modules, the chief of which are environment sensing, flower perception, path planning, flight control, and pollination mechanisms.

Fig 7: End effector tracking

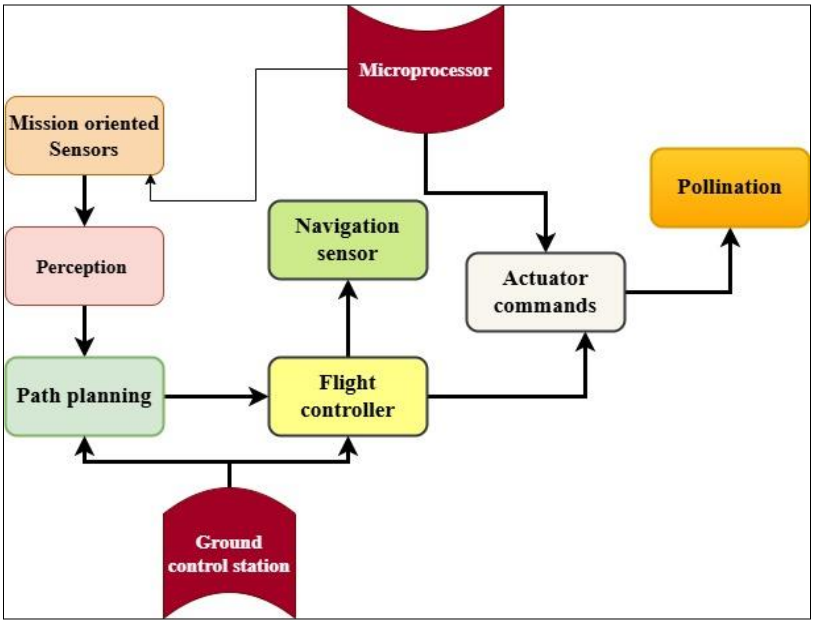


Fig 8: Flow chart of Nano copter pollination (Source: Rice *et al.*, 2022

The artificial pollination by nano drone modules are broadly defined as follows. Environment sensing involves the system sensing its environment, searching for obstacles and other mission critical information. Flower perception, following from environment sensing, requires the system to detect and locate the flowers in the environment and then describes these flowers' locations as waypoints in a map. Path planning refers to finding the optimal path or sequence of waypoints (flowers or flower clusters) in which to pollinate. Flight control refers to the maneuvering of the nano drone from one waypoint to the next in a closed-loop manner. Finally, the pollination mechanism is used to physically pollinate the flower. The pollination mechanism will vary depending on the crop being pollinated (Rice *et al.*, 2022) [18].

Flower Perception

Since the nano drone goal is pollination, it must be able to recognise flowers and execute commands to approach them. Identification is possible using perception algorithms to process the images a camera acquires (Pinherio *et al.*, 2023). Flower perception provides the input to the path planning module, which in turn provides the input to the flight control module (Rice *et al.*, 2022) [18]. For this purpose, it is necessary to develop a Deep Learning Neural Network (DLNN) for flower recognition and implement an algorithm that defines the command to be executed by the nano drone based on the position of the flower detected in the frame.

From data collection to autonomous flower detection, includes three steps (Pinherio *et al.*, 2023). Data collection: Collecting and storing images to build the input dataset; Dataset generation: Annotating images by drawing bounding boxes around the flowers. Each annotation contained a bounding box around each object, representing its area, position, and class. Next, the dataset needs to duplicate by converting the images from RGB to grayscale. Further, after generating the flower detection dataset it needs to divide into three sets like 60% for training, 20% for validation, and 20% for test. Model training: The final step is the training the DL models to be deployed in the nano drone for real-time flower detection.

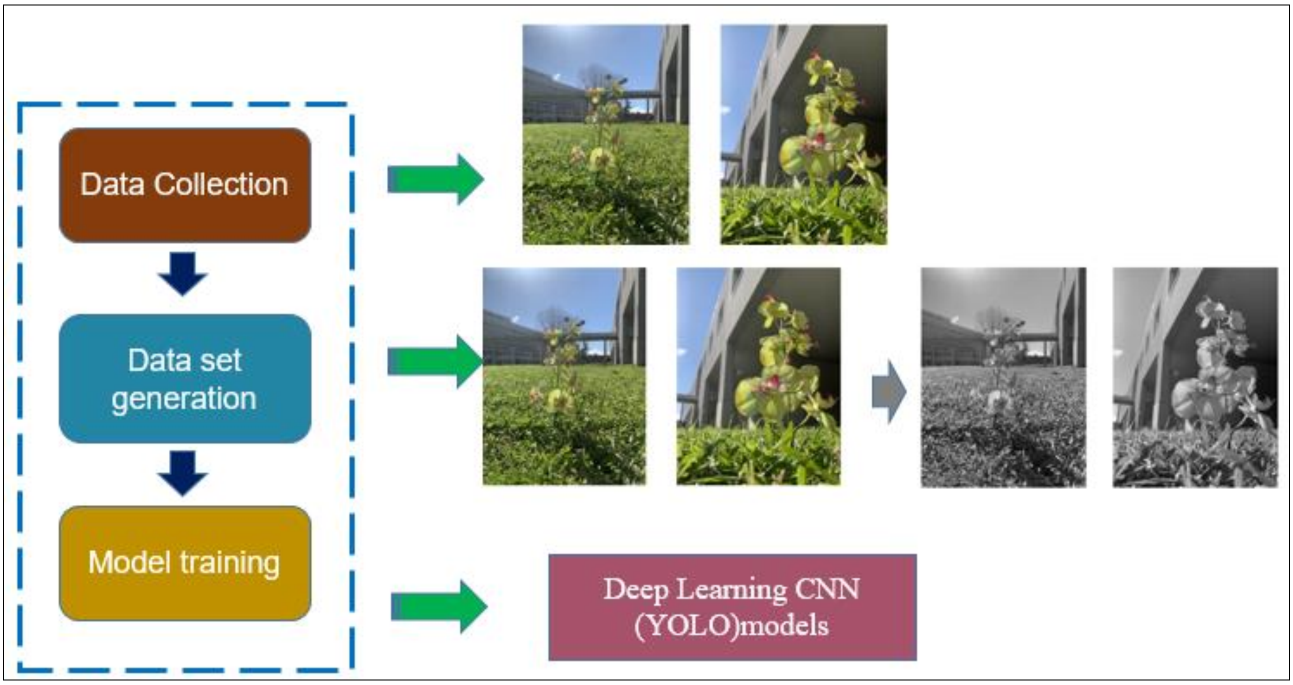


Fig 9: Flower Perception steps (Pinherio *et al.*, 2023)

In 2023, Pinheiro *et al.* [17] collected 103 flower images using an iPhone X, generated a flower dataset with Computer Vision Annotation Tool (CVAT), and identified 499 flowers. They augmented the dataset by converting images to grayscale (320 × 240 pixels). The dataset included 206 images (RGB and grayscale), split into training (60%), and validation (20%), and test (20%) sets. YOLO models (YOLOv5, YOLOv7, and YOLOR) were trained on this dataset for 300 epochs, with a batch size of 64 images and an input resolution of 320 × 320 pixels.

Since the precise steering the drone has to perform, processing of the video feed should happen on-board such that the delay between receiving images and correcting the drone's position is minimal. This implies the need for a small and light-weight processing board capable of performing real-time image processing. The camera feed is directly read by the processor and communicates with the drone via microcontroller. In addition to the camera, a depth sensor is required to measure the distance from the flower in the final approach (Huelns *et al.*, 2022).

Algorithm for flower detection

The algorithm analyses each frame and acts according to the information it has collected so far. To begin with, the algorithm checks the detections in each frame. If there are flower detections, the algorithm must calculate the centre of each detection and its distance to the centre of the frame. After performing the calculations for all detections, the algorithm determines the area that is closest to the centre of the image. Finally, the command that the nano drone should follow is determined (Pinheiro *et al.*, 2023) [17]. Flow chart for the flower detection is shown below in Fig.10.

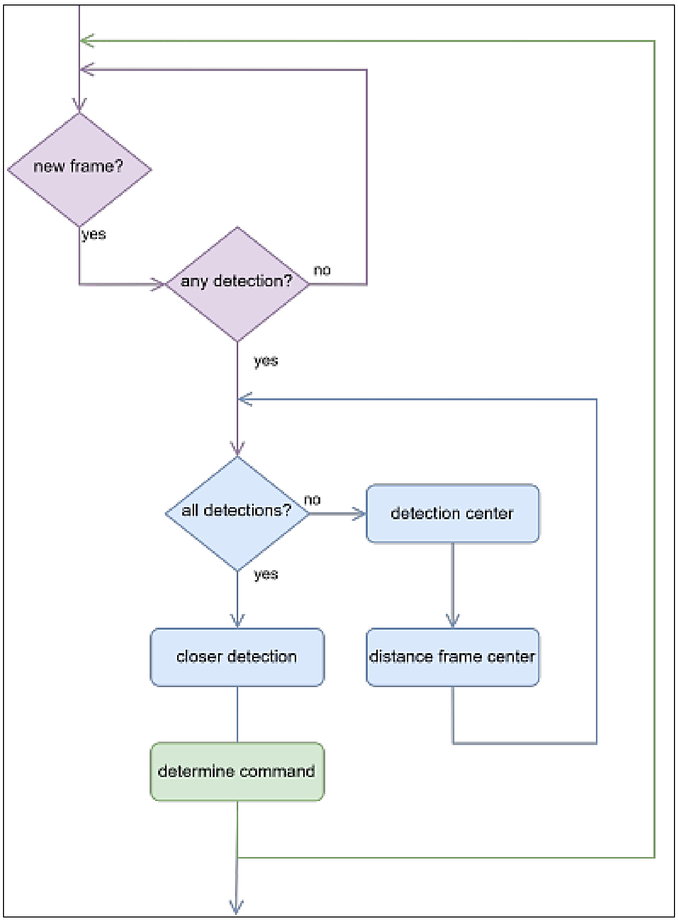


Fig 10: Flowchart of flower detection (Pinheiro *et al.*, 2023) [17]

Search Pattern: After proper initialization, the drone's main node enters the search pattern generation state. Here, it commands the Search Region node to generate a list of target set points for flower detection. The drone remains idle until switched into off-board mode by the user, initiated by the off-board switch on the radio controller. Upon entering off-board mode, the drone follows the generated search set points at a fixed frequency while constantly scanning for flowers using its onboard vision system. If a flower is detected, the drone switches to the stabilization state, using a local body velocity controller to center itself over the flower. Once stabilized and centered, the drone descends to the flower's set altitude, marking the completion of pollination. After pollination, the camera briefly halts its search to prevent repeated detection of the same flower. This cycle of searching, detecting, centering, and lowering continues until all set points are covered. The system autonomously lands when the search pattern is completed, or the user can manually intervene for landing (Craigie *et al.*, 2021) [2].

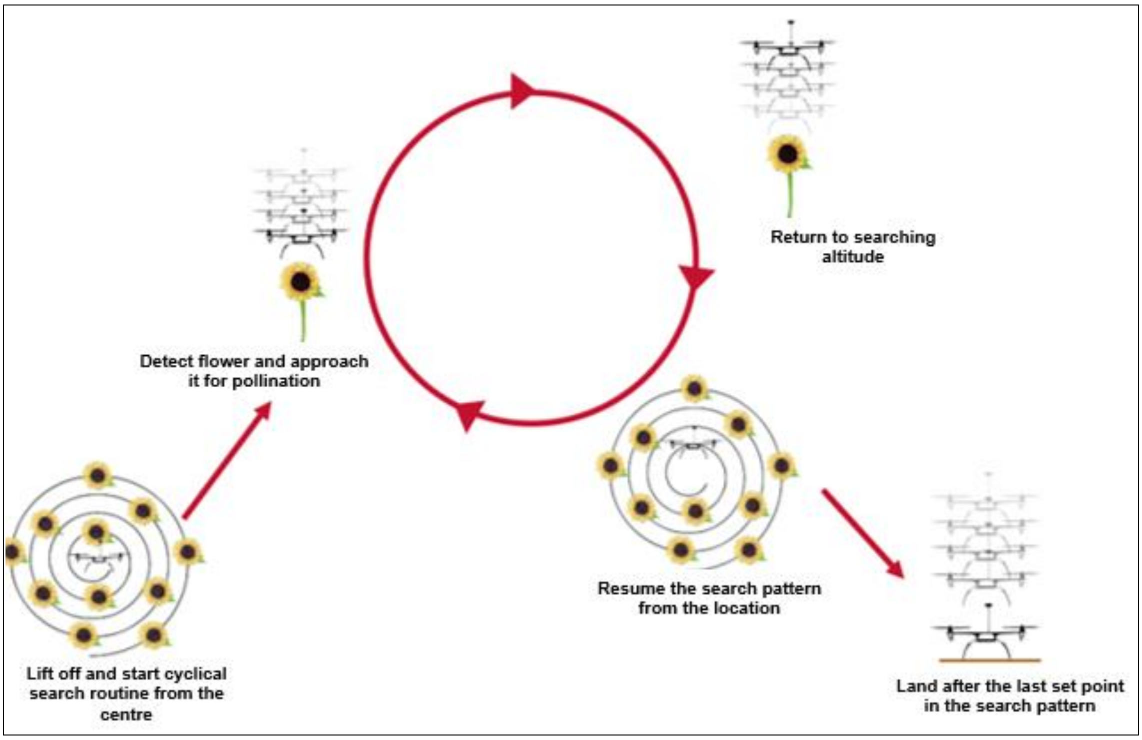


Fig 11: Visual Depiction of State Objectives (Craigie *et al.*, 2021) [2]

Flower Detection and targeting

The flower detection process consists of two stages (Fig. 11). In the first stage, a CNN is employed for flower pose estimation, determining the flower's position, size (indicative of distance), and orientation. This model guides the drone to approach a position approximately 80 cm from the flower, directly facing it. This stage comprises three steps: (i) forward movement until the drone reaches the correct distance from the flower, (ii) altitude adjustment to match the flower's height, and (iii) circular motion around the flower until the drone is facing it directly.

In the second stage, an image-based visual servoing network is used in an end-to-end approach, directly providing steering commands toward the sunflower's position. This model is applied during the final approach, leading to pollination touchdown (Hulens *et al.*, 2022) [10].

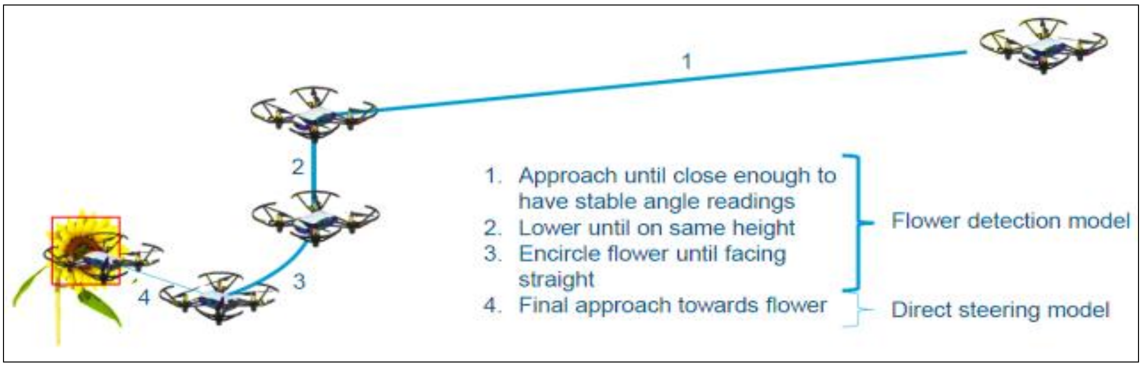


Fig 12: Visual servoing approach for flower detection (Hulens *et al.*, 2022) [10]

Detection stage

During this stage, which covers distances ranging from 8 meters to 0.8 meters, the primary objective is to train the detector using a custom flower dataset. This training enables the drone to effectively track and approach the flower. The flower's position information is crucial in this phase, as it guides the drone to keep the flower consistently at the center of its field of view. Additionally, the size of the detected flower serves as a valuable distance measurement metric. Figure 12 provides an illustrative representation of the flower properties detected by the detector, along with their associated steering dimensions (Hulens *et al.*, 2022) [10].

Furthermore, a significant enhancement has been made to the Convolutional Neural Network (CNN) architecture, enabling it to predict the horizontal angle of the flower (as depicted in Fig. 16). This predicted angle plays a pivotal role in directing the drone to maintain a 0° angle relative to the flower. As the drone approaches the flower and the flower's size grows beyond 60% of the frame-height, making it challenging to reliably detect, the system seamlessly transitions to the second stage of visual servoing.

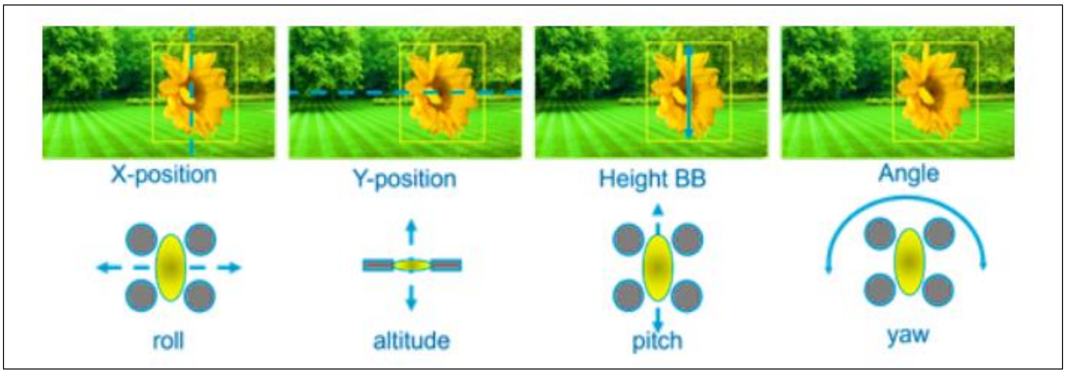


Fig 13: The four properties that the detection model perceives of the flower and their related steering dimension (Hulens *et al.*, 2022) [10].

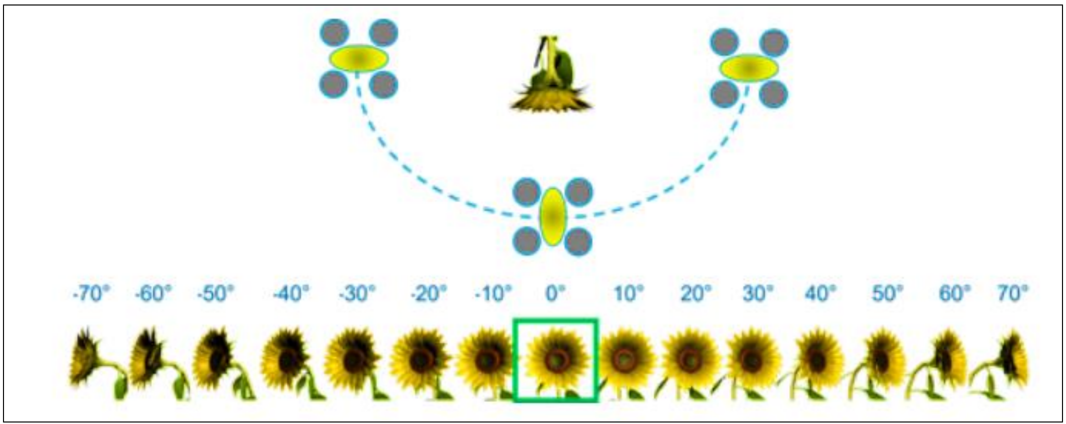


Fig 14: Horizontal angle detection of the flower (Hulens *et al.*, 2022) [10].

When the drone approached the flower close enough for the final descent, detection model of the previous phase does not work anymore. That is because the flower's size exceeds the field-of-view of the camera. In this stage, we needs to train the architecture d for classification that directly outputs steering commands (up, down, left, right or center). This network is trained on zoomed-in images of a flower (fig.18). During the final approach to the flower, a distance sensor measures the distance between the drone and the flower with high accuracy. The pollination rod in front of the flower measures required distance (8 cm). When the distance becomes smaller than 8 cm we assume the rod touched the flower and the pollination took place (Hulens *et al.*, 2022) [10].

Fig 15: Example images from the direct visual servoing image dataset and the proposed direct visual servoing approach. (Hulens *et al.*, 2022) [10].

Evaluation of Flower Detection

The selection of appropriate metrics to evaluate deep learning models depends on the specific problem at hand. Metrics offer distinct perspectives on the performance of a deep learning model and are often used in combination to gain a comprehensive understanding of its behaviour. The metrics listed below are commonly used to evaluate the outcomes of object detection and classification (Pinheiro *et al.*, 2023) [17]. To determine the type of detection, it is necessary to understand the differences between a "correct detection" and an "incorrect detection". One way is to use the intersection over union (IoU). Intersection over Union (IoU) is based on the Jaccard Index, which measures the similarity coefficient for two datasets. Here, the IoU is used to measure the area of overlap between two bounding boxes using the ground-truth and predicted bounding boxes.

The classification of a detection as valid or invalid by comparing the IoU with a given threshold t. If the IoU ≥ t, the detection is considered valid and if the IoU < t, it is considered invalid. The type of detection is determined by following concepts:

- True Positive (TP): A valid detection of a ground-truth bounding box, i.e., IoU ≥ t;
- False Positive (FP): An invalid detection (incorrect detection of a non-existent object or incorrect detection of a ground-truth bounding box), i.e., IoU < t;
- False Negative (FN): An invalid detection of a ground-truth bounding box;
- True Negative (TN): Not applicable in object detection.

There is no need to find infinite bounding boxes in each image during object detection. The evaluation of the object detection methods mainly involved the concepts of precision and recall:

Accuracy calculates the ratio of the number of correct predictions to the total number of predictions:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad \ldots\ldots.\ (2)$$

Precision measures the ability of the model to identify only the relevant objects, i.e., the percentage of valid detections out of all detections and is calculated by

$$\text{Precision} = \frac{TP}{TP + FP} \quad \ldots\ldots.\ (3)$$

Recall measures the ability of the model to find all ground-truth bounding boxes, i.e., the percentage of valid detections out of all ground truths and is calculated by:

$$\text{Recall} = \frac{TP}{TP + FN} \quad \ldots\ldots.\ (4)$$

F1 score represents the harmonic mean between precision and recall and is used to evaluate performance; it is calculated by

$$\text{F1 score} = 2\times\frac{\text{Precession} \times \text{Recall}}{\text{Precession} + \text{Recall}} \quad \ldots\ldots.\ (5)$$

The precision × recall curve is a way to evaluate the performance of an object detector. This procedure plots a curve as confidence changes for each object class.

- A good object detector maintains high precision as recall increases. In other words, by varying the confidence threshold, precision and recall should remain high.
- A poor object detector for recovering all ground-truth objects (increasing recall) needs to increase the number of detected objects (increasing FP, which implies decreasing precision) to retrieve all ground truth objects (high recall).
- Therefore, an optimal detector identifies only the relevant objects (FP = 0, indicating high precision) while finding all ground-truth objects (FN = 0, implying high recall).
- The Average Precision (AP) is another way to evaluate the quality of the object detector. AP compares the performance of object detectors to calculate the area under the precision × recall curve. AP is the average precision of all recall values between 0 and 1. Therefore, a high area represents both high precision and recall.
- The mean Average Precision (mAP) is a metric used to measure the accuracy of object detectors across all classes. The mAP is the average AP across all classes

Table 6: Confidence threshold value that optimized the F1 score for each YOLO (Pinheiro *et al.*, 2023) [17].

Model	Confidence Threshold	F1 Score
YOLOv5	71%	94%
YOLOv7	70%	96%
YOLOR	69%	97%

The confidence threshold values presented led to the best balance between precision and recall, which maximised the number of true positives and minimised the number of false positives and false negatives. All three models had similar confidence threshold values and similar confidence in their predictions. Table 6 shows the confidence threshold value that maximised the F1 score for each model in the validation set (Pinheiro *et al.*, 2023) [17].

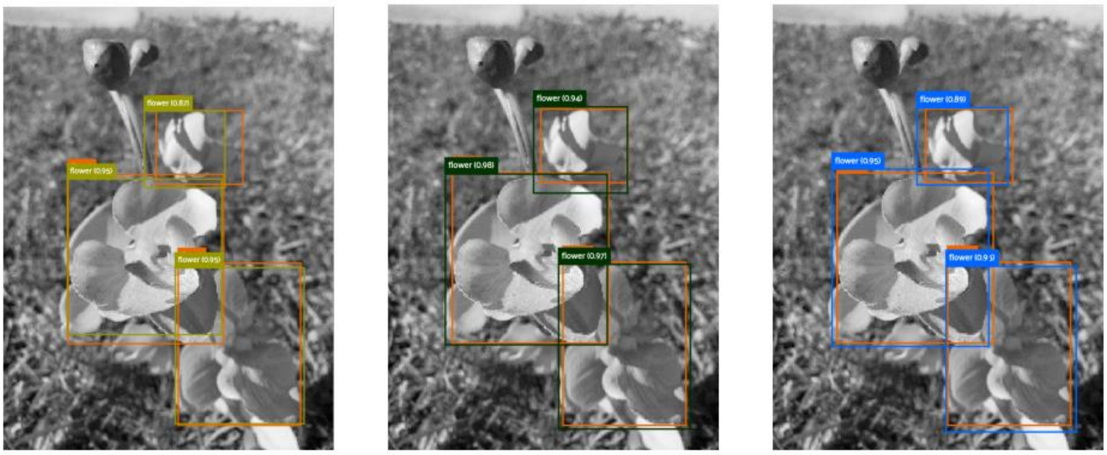
Table 7: Detection results of the testing set obtained from the Flower Detection data set (Pinheiro *et al.*, 2023) [17]

Model	Confidence threshold, %	Accuracy %	Precession %	Recall%	F1 score, %	mAP, %	Time per image, ms
YOLOv5	>0	25	25	99	40	71	1.9
	>71	92	97	95	96	69	2.0
YOLOv7	>0	15	15	100	26	81	3.4
	>70	97	98	99	98	80	2.3
YOLOR	>0	44	44	99	61	82	4. 6
	>69	97	98	99	98	81	2.7

Table 7 shows the results of the test set. The inference was performed for a 0% confidence threshold and the confidence threshold value that maximised the F1 scores in the validation set. The inference was performed with a batch size of 8 and an IoU threshold of 50%. In the test set, a batch size of 8 was used, as the processing capacity was smaller.

Lower confidence rates typically lead to an increase in false positives and a decrease in false negatives. As a result, precision decreases due to the increase in false positives and recall increases due to the decrease in false negatives. The results show that limiting the confidence threshold of the models resulted in a considerable increase in accuracy, precision, and F1 score at the cost of a slight decrease in recall and mAP. When the confidence threshold is set to maximise accuracy, precision and F1 score remain in the range of 90% to 99%.

Figure 18, shows two images (grayscale and RGB) from the test set and the ability of the models to detect flowers, (a-c) RGB example and (d-f) grayscale example. Orange bounding boxes present ground truth. Light green bounding boxes present the predictions from YOLOv5. Dark green bounding boxes present the predictions from YOLOv7. Blue bounding boxes present the predictions from YOLOR.



(d) Gray example - YOLOv5 (e) Gray example - YOLOv7 (f) Gray example - YOLOR

Fig 16: Detection of flowers in sample images from the test set of the Flower Detection Dataset (Pinheiro *et al.*, 2023) [17].

Flower stabilization/Centering

Once the camera detects a flower, the drone breaks free from the search routine and enters the flower stabilization state. This state implements a PD velocity controller that sends a velocity message to the flight controller. Because MAVROS sends velocity set points in the ENU frame, system transforms target velocities from the local body to the global ENU frame. To do this, we need to rotate the local body velocity vector by the current heading of the drone's compass. To center over the flower, the controller takes the centroid of the detected flower as input. Since the frame size of the camera is known, the desired center-point can be established. This allows the controller to calculate the error between the flower's current centroid and the desired center-point of the camera. The proportional and derivative terms of the controller are used to calculate the desired velocities based on this error. Once the error is smaller than a defined threshold, the drone begins to lower over the centered flower while running the PD controller (Craigie *et al.*, 2021) [2].

Flight control system

The drone employs a flight controller, typically a Pixhawk, to manage its position, heading, and velocity during flight within a designated region for flower search. This flight controller firmware offers various features, including data logging, an Extended Kalman Filter for sensor-based position estimation, and a MAVLink interface for onboard computer control and high-level decision-making, which is facilitated by a Raspberry Pi. The Raspberry Pi interfaces with the end effector and the flight controller, utilizing its multiple UART ports for this purpose (Craigie *et al.*, 2021) [2].

Drone flight control methods can be categorized into two main approaches: learning-based and model-based. Learning-based methods use flight data to train the flight controller, including fuzzy logic, human-based learning, and neural networks. These methods require data from pilot flights or previous system trials. Model-based flight control relies on an aircraft model to derive control inputs. Examples include feedback linearization, proportional integral derivative (PID), and model predictive control (MPC). Feedback linearization transforms nonlinear dynamics into a linear coordinate system for control problem solving before converting the solution back to the true coordinate frame. PID control operates in a closed-loop manner, applying controls based on the error between the actual and desired states. MPC formulates optimal control over a future horizon and applies the resulting controls (Kendoul, 2012) [11].

The pollination algorithm for the nano drone is a multi-step process to guide the drone accurately to a flower for pollination. It begins by analysing each captured frame for flower detections. For each detected flower, it calculates the center and distance to the frame center. The algorithm then selects the closest flower to the frame center as the target. Next, it determines the appropriate command for the drone based on the target's position, both vertically and horizontally. The goal is to center the flower in the frame and bring the drone closer to it for pollination when in proximity. This systematic approach ensures precise flower targeting and efficient pollination (Pinheiro *et al.*, 2023) [17].

Evaluation of nano drone for pollination

Craigie *et al.* (2021) [2] conducted an experiment to evaluate the effectiveness of their drone design for pollination. The experiment, conducted outdoors, involved placing three plastic sunflowers within a five-meter radius of the drone. This setup allowed them to assess the drone's performance while navigating in a flower-free region and pollinating. To avoid interference from drone propellers, the sunflowers were attached to fixed-height metal rods.

The experiment activated the drone's autonomous pollination routine, which involved searching for and attempting to pollinate every detected flower. Successful pollination was determined by checking for colored powder on flowers, representing pollen transfer. The team conducted this experiment 14 times over two days. Results showed that the drone could detect an average of 2.14 flowers per test and attempted to pollinate 96% of all detected flowers. The survival rate of tested flowers was 93%. However, the drone did not achieve successful pollination due to challenges in sensing the distance between the pollen collector and the flower's surface.

In summary, the drone system demonstrated the ability to detect and approach flowers reliably but faced difficulties in achieving successful pollination. The drone's flower survival rate was high, but it was unable to confirm pollination success due to technical challenges (Craigie *et al.*, 2021) [2].

Table 8: Evaluation of nano drone for pollination (Craigie *et al.*, 2021) [2].

Time stamp	Flower survival	Flower detections	Attempted Pollinations	Successful pollination	Cut shorts
4/24,00:11	TRUE	1	1	0	**
4/24,00:17	TRUE	1	1	0	**
4/24,00:24	TRUE	1	1	0	**
4/24,01:19	TRUE	2	2	0	
4/24,01:24	TRUE	1	1	0	
4/24,01:32	TRUE	1	1	0	
4/24,01:39	FALSE	2	2	0	
4/24,01:53	TRUE	2	2	0	
4/24,02:05	TRUE	3	3	0	
4/24,02:41	TRUE	3	3	0	
4/24,13:30	TRUE	3	3	0	
4/24,13:33	TRUE	5*	5*	0	
4/24,13:41	TRUE	2	2	0	
4/24,13:54	TRUE	1	1	0	
4/24,13:56	TRUE	1	1	0	**
4/24,14:04	TRUE	2	2	0	
4/24,14:10	TRUE	2	2	0	
4/24,14:13	TRUE	1	1	0	
Avg. including test cut short **			Attempted pollination given a flower detected (%)		
1.89	1.83		97.1		
Avg. excluding test cut short **			Attempted pollination given a flower detected (%)		
2.14	2.07		96.7		

Limitation of Nano Drone for Pollination: Nano drones for pollination are subject to limitations due to their strict size and weight restrictions, typically falling within 3 to 50 grams in weight and 2.5 to 15 centimeters in wingspan. These constraints give rise to several challenges given in table 9:

Table 9: Limitations of nano drone for pollination

Sl. No.	Limitations	Description
1	Limited Flight Endurance	Nano drones have small batteries, resulting in short flight times. This limits their ability to cover large areas or perform extended pollination missions before requiring recharging or battery replacement.
2	Aerodynamic Vulnerability	Their small size makes nano drones highly susceptible to aerodynamic factors like air currents, drift, and turbulence. Minor air disturbances can destabilize them, hindering their precise navigation within agricultural fields.
3	Flight Irregularities	Nano drones may exhibit asymmetries and inconsistencies in flight performance due to their delicate and miniature design. These irregularities can affect their maneuverability and overall effectiveness in pollination tasks.
4	Fragile Components	Nano drones often incorporate fragile and safety-critical components due to their size and weight constraints. Damage to these components can lead to system failures or malfunctions, reducing their reliability and durability for pollination operations.
5		

Conclusion

Nano drones hold significant promise for revolutionizing precise pollination in agriculture. These miniature aerial vehicles offer the potential to enhance crop production by efficiently identifying flowers, navigating to them, and conducting pollination while also facilitating cooperation among multiple drones. To optimize pollination success, the development of diverse end effectors customized for different flower types is essential. However, it's vital to address limitations such as payload capacity constraints and weather sensitivity to ensure practical deployment and integration into mainstream agricultural practices. In summary, nano drone pollination represents a cutting-edge approach with the potential to significantly improve agricultural productivity and contribute to ecosystem preservation.

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