DTU Electro
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Artificial pollination systems using machine learning and remote sensing

34366 - Intelligent Systems

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1 Introduction

In recent decades, global awareness regarding climate change and its profound impact on our planet has significantly increased. Phenomena such as rising global temperatures, changes in precipitation patterns and the intensification of extreme weather events are just a few visible manifestations of climate change that affect ecosystems, economies, and human societies worldwide. These changes, largely driven by human activities such as greenhouse gas emissions from fossil fuel use, deforestation, and intensive agriculture, urgently require a reassessment of how human society interacts with the environment. Climate change represents a complex challenge that requires solutions capable of simultaneously addressing multiple aspects of the current crisis. Among these, food security and stability are particularly vulnerable to climate change due to agriculture's heavy dependence on weather and climate conditions. Therefore, exploring alternative and sustainable food production methods, such as artificial pollination, becomes essential to ensure the resilience of food systems in the face of climate change.

Pollination plays a crucial role in the sustainability and productivity of agricultural ecosystems, serving as a fundamental pillar in the reproduction of plants that form the basis of global food chains. This natural reproduction process of pollen exchange between flowers, carried out by a wide range of pollinators, including bees, butterflies, birds, and even some mammal species, is essential for the formation of fruits and seeds in over 70% of food crops worldwide. Beyond its direct importance for food production, pollination also influences biological diversity, ensuring the genetic variety necessary for plants' adaptability to environmental changes and their resistance to diseases and pests. In the context of climate change, the Assessment Report 6 (AR6 – 2021) published by the Intergovernmental Panel for Climate Change (IPCC) emphasizes, with medium confidence, the negative impact of climate change on pollinators, predicting population declines in certain regions. This decline not only threatens food production but also the ecological balance of natural ecosystems, endangering the pollination of wild plants and agricultural crops, with long-term repercussions on biodiversity and food security [1].

For simplicity, and given the extensive research on honey bees, we will use *Apis mellifera* as a key representative species for pollinators. This report explores its characteristics and examines how climate change and intensive agriculture affect its role in pollination, with the aim of informing the design of an artificial pollination system. *Apis mellifera*, an efficient pollinator, perceives ultraviolet light, which plants exploit through petal pigment patterns that guide bees to pollen and nectar [2, 3]. As climate change causes flower pigment polymorphism, altering petal color and contrast due to arid conditions, these changes disrupt pollination patterns, particularly for *Apis mellifera*, as pollinators cannot adapt as quickly as plants. Consequently, affected plants may suffer declining reproduction rates, biodiversity loss, and ecological imbalance. In contrast, climate-resilient plants are less impacted [4, 5].

Furthermore, phenological asynchrony, caused by climate instability, disrupts the timing between plant reproductive cycles and pollinator foraging, reducing resources for bees and lowering crop pollination rates. Pesticides, including herbicides, insecticides, and fungicides, harm pollinators in various ways. Herbicides reduce plant attractiveness, insecticides like neonicotinoids impair bee navigation and memory, and fungicides weaken immune systems and disrupt gut microbiomes. These chemicals collectively threaten pollinator health and colony survival [6].

1.1 Motivation

Given the challenges highlighted above, ranging from climate change impacts on pollinator behaviour and phenology to the detrimental effects of intensive agriculture on their health, it is evident that natural pollination processes are increasingly at risk. The decline in pollinator populations, particularly in critical species like *Apis mellifera*, threatens not only global food security but also the stability of entire ecosystems. As climate change and agricultural practices continue to undermine the resilience of these essential organisms, there is an urgent need to explore innovative solutions to support and complement their role [7, 8, 9, 10].

Therefore, developing an artificial pollination system that can replicate or enhance natural pollination processes is becoming a necessary step. This system would not aim to replace natural pollinators but rather to support their declining populations by assisting in pollination tasks, especially in regions where bees are struggling to thrive. By utilising technology to mimic the natural behaviour of bees, particularly their unique ultraviolet vision and efficient foraging strategies, we can create a solution that helps safeguard both agricultural productivity and biodiversity in the face of ongoing environmental challenges.

1.2 Objectives

Specifically, our project aims to fulfill the following main objectives:

- Automatically cover the target area
- Detect flowers in real time
- Approach detected flowers safely
- Apply the artificial pollinator

Further, less significant objectives regarding the economic and legal requirements are discussed in chapter 4, as well as in the specific component descriptions.

1.3 System overview

We will briefly describe the main components of our artificial pollination system. The following chapters in our report will detail them.

The system is built as a compact drone, such as a modified DJI Mavic 3M, equipped with various additional components that enable its functionality. In essence, the drone features a microcontroller integrated with an convolutional neural network (CNN), trained to recognize flowers by identifying their reproductive organs for precise pollination. It is fitted with a high-resolution camera for real-time flower detection and positioning. To execute pollination, the drone employs a soap bubble pollination system, which includes a tank to store the pollen solution and a mechanism to release the solution through bubbles. A LiDAR sensor is installed to ensure accurate operation by measuring the distance between the drone and the crop below, activating the pollination system when the drone reaches the optimal height. Autonomous flight software is used to program and navigate the drone, allowing it to operate without manual intervention. Together, these components enable the system to function efficiently and effectively in various agricultural environments.

The drone autonomously navigates through agricultural fields, using its camera and CNN model to detect flowers. Upon identifying a flower, it positions itself above the target and descends. The LiDAR sensor continuously monitors the distance between the drone and the crop below. Once the drone reaches the optimal height, the bubble pollination system activates, releasing the pollen solution precisely onto the reproductive parts of the flower. After completing pollination, the drone ascends, moves to the next detected flower, and repeats the process.

The GANTT chart in appendix A.1 describes all the tasks and sub-tasks, as well as the timeline needed for completing our artificial pollination system.

We recommend to split the tasks between 3 teams (hardware, flight control, object detection) as to make the completion of tasks in parallel possible, in order to make the timeline of development of the prototype feasible within three weeks. Depending on how capable the project members are in each topic, team sizes of 1-3 people would probably be sufficient. An additional member to manage the orchestration of the teams could be helpful as well. To ensure enough time for the integration of all sub-components, we recommend to finish all tasks before the end of week two. If any project member, at some point during the project, has to wait for another task to be completed, it should go without saying that they should offer to help out the other teams.

1.4 Course-inspired technologies

The core idea for this project was developed early on in the course, meaning that in general, many technologies that were known without this course are part of this project. Nonetheless, some technologies that were taught in this course and are relevant for this project are listed below, alongside a short description as to why:

- **Machine learning** (In the form of deep learning):
  A central component of this intelligent system is the object detection for the flowers. Although admittedly the implementation of modern deep learning models does not require a deep understanding of machine learning, the theory and practical experience gained from this course are very helpful in understanding the inner workings of such models.
- **Edge computing**:
  The proposed drone system utilizes edge computing to allow real-time and reliable processing of the video data.
- **Data security**:
  As the system utilizes a camera, familiarity with data security acts are invaluable for a market oriented product.
- **Business aspects**:
  To better organize any system, it is important to consider the business side of the project as well. The course taught the basics of this factor.

Internet technologies, such as cloud systems, were not considered as relevant to this project, mostly because the latency that comes with utilizing these would impact the real-time performance of the system. For a more advanced version, these might become more interesting regarding data analysis and remote monitoring. The same goes for communication technologies: Although we do not include any form of ”special” communication technologies in the proposed prototype, a larger scaled system should include communication from the drone to the operational center, potentially even communication between different drones to allow swarm optimization techniques.

2 Software

The software for this system can be separated in four parts, each of which can be developed mostly independent to each other:

1. Object detection
2. Flight control
3. Pollination trigger
4. Telemetry / Telecommunication

The first two points are covered in section 2.1 and section 2.2.

Ideally, the pollination trigger is a simple electronic signal via a GPIO pin, that will be activated when the LIDAR sensor returns the required distance. This is a simple concept that needs no further explanation in this report.

While the drone system itself should be able to operate independently, implementing a communication system for telemetry and telecommunication is essential for scalability and monitoring. For the system's owner, a simple UI should show the status of the different drones (battery, tank, working hours, ...) and the covered area plus the recently pollinated plants/regions. A control interface for manual interference would also be helpful and likely a legal requirement. In a scaled environment, the drone could be part of a swarm, meaning that each drone has to communicate with other drones for better organization. A great basis for this communication system can be provided by utilizing the 5G network and 3GPP standards [11]. However, the prototype only aims to showcase the automated pollination in a controlled and monitored environment, so we recommend to only pursue the communication system after creating the successful prototype.

2.1 Object detection

The object detection software will cover how the system can detect flowers by using a neural network and a video stream. The network will be trained on a flower dataset and provide real-time detection of the target by utilizing a direct video stream from the drone's camera.

2.1.1 Dataset

The topic of detecting if a plant is ready for pollination is a highly complex topic of biology and engineering, that includes electromagnetic fields, plant indicators and other concepts that pollinators and flowers developed through evolution [12]. As this alone would provide too big of a challenge to do on it's own, we decided to keep the focus of this project on detecting petals and pollinating the plants periodically instead.

To reduce the workload for the prototype, we recommend using the existing Oxford 102 flower dataset [13], which contains 102 different types of flowers with varying numbers of images in the visible light spectrum. The data also includes segmentation data, that separates the flower from the background. This segmentation data should be used to generate boundary boxes for each image. This data provides a great foundation to train the model.

To harden the model, more images should be collected that were taken with the drone, thus will probably have slightly different lens distortions, as well as a wider capturing range, being a good complimentary set for the more close-capture oriented Oxford 102 dataset. For these new images, boundary boxes would have to be created manually.

For optimal detection quality, the system should emulate the vision of the honey bee more closely. The honey bee can see in the ultra-violet range of around 300-650 nanometers, which flowers utilize to make their petals more visible in that spectrum [14, 15, 16]. An example of these patterns can be seen in Figure 2.1.

Figure 2.1: UV patterns in flowers. (A and B) Ludwigia peruviana. (C and D) Chrysopsis villosa (Left), Helianthella quinqueneris (Top), and Viguiera multiflora (Right). Excerpt from [16]

However, the task of collecting a sufficient amount of UV images, as well as equipping the camera with an UV filter, would add too much work to this prototype and should only be added to improve the model for a market-ready product.

2.1.2 Neural network

The state of the art for real-time object detection are one-stage detectors. The most popular one-stage detectors include YOLO, SSD and RetinaNet. YOLO experiences the most frequent updates and offers many different ratios of quality versus speed, making it, in our opinion, the best option for this project.

To put it simple, YOLO divides the given image into a grid and classifies each element of the grid using a convolutional neural network. It creates boundary boxes and a map of classifications, which is then used to construct the target boxes, as can be seen in Figure 2.2 [17].

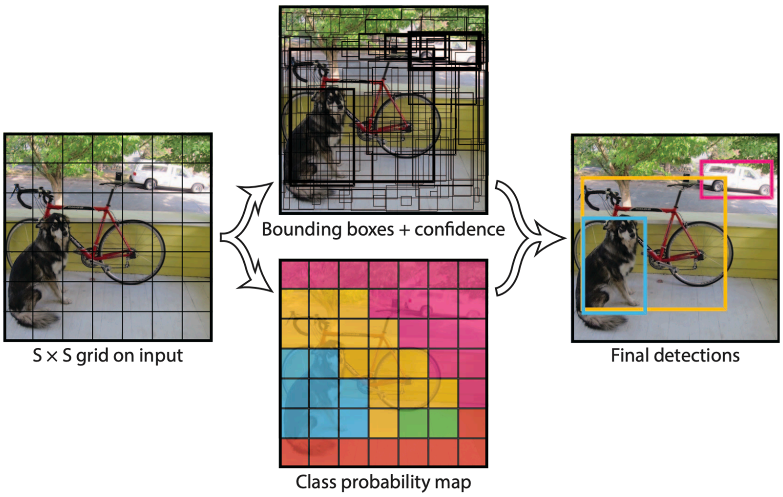

*Figure 2.2: Example of the YOLO object detection. It divides the image into an S × S grid and for each grid cell predicts B bounding boxes, confidence for those boxes, and C class probabilities. These predictions are encoded as an S×S×(B*5+C) tensor. Excerpt from [17]*

According to a comparison of different YOLO versions on a dataset of common weeds

[18], which is fairly comparable to flower detection, the most recent version (v11) is the fastest and among the most precise versions, thus being the recommended version for this project. It has to be taken into account that YOLO undergoes constant development and at the time of the project implementation, a newer model might be available.

2.1.3 Computing

Two possible options to power the object detection would be to utilize Edge AI or to process centralized. Edge AI processes everything on-board, whereas centralized processing would send the data to a server, which processes it and sends commands back. For optimal real-time detection, Edge AI is the only vible option. A microcontroller is recommended in section 3.4. For usage of the model on a microcontroller, it has to be converted to a tensorflow lite file. Ultralytics provides a library to convert the trained model to tensorflow lite, so this does not imply a problem.

2.2 Flight control

The flight control is responsible for two things: Basic field coverage and approaching the flower. To cover the complete field, this prototype will focus on a very basic one dimensional path. To approach a flower, the drone has to use control elements like PID controllers to position the boundary box of the detected flower at the correct position and approach the flower by using the LIDAR sensor as a reference. The whole approach has to be ”reverted” after the pollination process so that the field coverage can be continued. The drone should account for wind influence.

2.2.1 Covering the area

The drone has to provide a basic algorithm to decide where to fly. In a more complex environment, this could implement popular efficient coverage methods as seen in many UV’s like Boustrophedon Decomposition [19] or a spiral pattern, or to go further in the case of deploying multiple drones in one area, algorithms based on ant colony or particle swarm optimization might provide more efficient and dynamic coverage methods [20, 21].

To simplify this prototype, we recommend just implementing a basic one dimensional movement, that moves into a specific direction and returns on the same path. The drone will have a predefined path, expressed as a start and end position in vectors. After it approached a flower, it should return to this line in the most direct way.

2.2.2 Approaching the plant

The neural network will return a boundary box for our target. By using PID control mechanisms, the drone can adjust its jaw angle and height to adjust the aim to the center of the boundary box. When the box is aligned, the LIDAR sensor should be used in combination with PID control to approach the flower until the required distance is achieved.

2.2.3 Safety

To ensure safe operation, the drone should have a ”manual interference” mode. This has to block all software operations and allow movement of the drone via RC. In a scaled environment, this control should be extended to allow simplified control via a network interface as explained in the beginning of this chapter.

3 Hardware

3.1 Pollination system itself

Since the natural and artificial flower pollination is a critical process in the life cycle of flowering plants and the rising cost of pollen grains are considered to be significant worldwide problems, it is important to find a good and efficient pollination system, which are working during asynchronous weather events and without relying on available insect pollinators [22][23]. This section discusses various plant pollination methods, including brush, spray and soap bubble pollination.

3.1.1 Brush pollination

The brush pollination uses a small, mechanised brush to bring pollen directly to the flower pistils. This enables an precise placement of the pollen on individual flowers, which ensures controlled pollination. Together with drones the brush pollination is a efficient and accurate method to bring pollen to flowers at high altitudes or in hard to reach areas. Since this technique brings pollen directly to the pistils, the efficency is maximized and supports a high druit set rate [24].

3.1.2 Spray pollination

Spray pollination is a technique that mechanically disperses pollen onto plants through spray devices (e.g., 3.2 mg of pollen grains by one-push spraying). While it can cover large areas efficiently, it often results in significant pollen waste because the pollen is not precisely targeted to individual flowers. Using automated systems like drones can improve the precision, however, this method still presents challenges, including uneven pollen distribution and reduced overall effectiveness. Despite these improvements, spray pollination requires further optimization to maximize efficiency and sustainability [22].

3.1.3 Soap bubble pollination

Compared to a brush and spray pollination offers the soap bubble pollination several advantages. One major advantage is that soap bubbles allow precise, targeted and gentle pollen release, which significantly increases the efficiency of pollination. The light and flexible structure of soap bubbles enables them to attach specifically to the flowers without causing damage of the flower structure. This is important for sensitive plant species that could damaged by methods such as brushes or sprayers.
With each application requiring only 0.06 - 0.08 mg of pollen for 2-3 bubbles, this method reduces the usage of pollen by up to 99% compared to other techniques, which means a high efficiency and low pollen consumption. This reduces the material costs and is for plant species with high pollen requirements a good sustainable solution. The tests of the study showed that the combination of drones and soap bubbles achieved a pollen transfer rate of over 90%, which is at least as effective as the brush method. In experiments with pear blossoms, 2 to 10 soap bubbles per blossom resulted after 16 days in a comparable fruit yield to conventional brush pollination. There are also some critical points that need to be considered to ensure the effectiveness of soap bubbles. Soap bubbles are sensitive to winds, temperature and humidity, which can affect their stability and direction of flight. To get the bubbles stable under changing conditions, the bubbles can be treated with stabilizers such as hydroxypropyl methylcellulose (HPMC). In addition, applications should be adjusted to windless time windows, as the drone air vortices could caus the bubbles to burst early. To ensure an effective pollination, drones need to target the flowers with

precision. Therefore a good navigation system and sensors are required to recognise individual flowers and release targeted bubbles.

To sum up, soap bubble pollination together with autonomous drone technology has the potential to change agricultural pollination in the long run by reducing pollen consumption, protecting the flowers and enabling targeted application over large areas [22].

Table 3.1: Consumption of pollen grains used in different types of pollination methods with a single trigger[22]

Methods	**Weight of pollen grains (mg)**
Soap-bubble-mediated pollination (bubble gun)	0.06 $\pm 0.00 - 0.08 \pm 0.01 (2-3$bubbles$)$ 0.14 $\pm 0.01 - 0.28 \pm 0.02 (5-10$bubbles$)$
Hand pollination (spherical feather brush)	1,747.29 ± 436.61
Machine pollination (machine tool)	165.31 ± 36.30
Solultion pollination (hand spray)	3.24 ± 0.43

3.2 Drone selection for pollination

A drone-based pollination system is a promising alternative to conventional pollination by insects. Since drones are airborne pollinators like bees, they have the potential to perform pollination tasks and reduce the dependence on natural pollinators. Currently there is a high research on various types and configurations of drones, including drones specifically designed for pollination as well as commercially available drones adapted for pollen spreading. Some concepts focus on the propagation of pollen by air vortices or direct contact delivery. However, each approach has specific advantages and limitations, in our case we focus on soap bubble pollination. For the usage in an AI-controlled soap bubble pollination system, it is important to compare diffrent drone types and their technology to find the best solution for a precise and scalable pollination [23].

This section will focus on finding the optimal drone for this surpose.

The drone system comprises multiple elements and requires certain features to ensure a good compatibility with the neural network, the database, and the artificial pollination system itself. Thus, the first element required in the drone system is the camera with which it orients itself in the environment and analyzes the crops. Conceptually, the camera has multispectral vision. It is imperative that the vision spectrum of the camera corresponds to the wavelengths in which the images in the database are captured.

The dimensions of the drone are an important aspect for several reasons. Thus, there is a proportional relationship between the size of the deployed drone and the size of the propeller required to carry its weight in flight. Ideally, the artificial pollination system would be compact in size, because it is desired to avoid the turbulence effect caused by the movement of the propellers over crops. However, the size of the drone and the propellers should be capable of adding the necessary additional sensors and the pollination system itself. Thus, it is essential that the drone has the ability to take off and fly properly with both its own weight and the weight of the added components.

Another relevant factor in choosing a drone is the ability it can be programmed for autonomous flight through various planning applications and execution of autonomous flight missions. Furthermore, the compatibility with other software packages is important to integrate flower recognition algorithms and machine learning models. Given these technical considerations, two types of drones with promising potential will be mentioned whose potential is worth exploring at a theoretical level.

The considered drone is the DJI Mavic 3, shown in Figure 3.1. The DJI Mavic 3 is a compact and foldable drone, designed for precision agriculture and multispectral visualization and monitoring of the environment. Weighing only 951 grams, this drone combines portability with advanced functionality, allowing collect detailed data about crops and the environment without generating significant turbulence during flight, which minimizes the impact of propeller airflow on the crops that are intended for pollination [25].

Equipped with a imaging system, that includes an RGB (Red-Green-Blue) camera with a CMOS (Complementary Metal-Oxide-Semiconductor) sensor, which captures images by converting light into electrical signals as well as a multispectral camera with four lenses that capture images in green, red, red edge and near-infrared spectrums [25].

Using DJI Pilot and DJI Terra applications, the DJI Mavic 3M can be programmed for automated flight missions. DJI Pilot allows planning of flight missions by setting waypoints, adjusting altitude, speed, and camera actions for each waypoint. DJI Terra is used for planning and processing high-precision mapping missions. Once the mission is planned, the data is transferred to the drone, the automated flight can be initiated to enabling autonomous collection of images and multispectral data [25].

To connect the drone to a flower database and enable flower recognition, advanced software platforms and DJI Software Development Kits (SDKs) are used. The data collection is processed in DJI Terra to create orthomosaic maps and 3D models, which are then exported to third-party platforms such as Pix4D or DroneDeploy. These platforms use machine learning algorithms to analyze the images with the ability to identify various types of flowers. The integration of a flower database can be achieved by developing customized applications using the DJI Mobile SDK or DJI Onboard SDK, which allow real-time or post-flight data analysis, comparing the captured images to determine the flower species [25].

We are planning to install a payload system that can be used to transport the pollination system. This system is designed for a payload capacity of up to 500 grams and ensures efficient transport. DJI's integration is designed to maintain optimal flight performance while carrying the additional load.

Figure 3.1: DJI Mavic 3M [26]

Figure 3.2: Payload system [27]

3.3 Sensors for navigation

An additional sensor can increase the effectiveness of the process, therefore in this continuation of the presentation on the hardware of the autonomous artificial pollination system, the presence of additional sensors is determined. For example, Lidar (Light Detection and Ranging) sensors, which use laser pulses to measure distances between the drone and other objects, could prove beneficial when integrated in the pollination system. In other words, proximity sensors like Lidar can measure the distance between the drone and the crop, and when reaching the optimal height relative to it, can trigger the operation of the pollination system. This distance vary depending on the chosen pollination system.

An example of such a sensor is the RPLIDAR S3. The RPLIDAR S3 operates on the principle of measuring the time of flight (TOF) of the laser. The sensor emits a modulated infrared laser beam, which is reflected by objects in the surrounding environment. The reflected signal is captured by the acquisition system of the sensor and the internal processor calculates the distance and angle to the object. This data is transmitted through the sensor's communication interface. The system is extremely sensitive, detecting very small variations in the time required for the signal to return. The core of the scanner rotates continuously, allowing the sensor to perform a complete 360-degree scan and updated in real time. The data is transmitted to the host system via the TTL UART interface, where it is used for navigation, obstacle avoidance or mapping. The RPLIDAR S3 has a rotation speed detection system and automatic angular resolution adaptation, ensuring high performance under various conditions. Finally, it uses modulated laser pulses to reduce interference from ambient light, ensuring accurate measurements even under direct sunlight conditions [28].

Regarding the reliability of this sensor in its integration into the artificial pollination system, the RPLIDAR S3 can be mounted and calibrated to accurately measure the height of the drone above the crops. The collected data can be processed to automatically trigger the pollination system when the drone is at the optimal height, ensuring an even distribution of pollen on the reproductive organs of the flowers. The use of this sensor can have a positive impact on the success rate of the pollination process of this system [28].

3.4 Microcontroller

A suitable microcontroller development board to implement that balances price, power and efficiency, would be the Coral Dev Board. It is compatible with TensorFlow Lite and has common interface options like GPIO pins, USB ports, HDMI and WiFi.

3.5 Additional hardware

To make the pollination system operational, we need an additional tank and a servo motor to run the developed pollination generator. The tank can also be 3D printed. The servo motor should be controlled by the Coral Dev Board. To drive a servo motor with the Coral Dev Board, an choice would need to be compatible with its 3.3V GPIO output and be controllable through PWM signals. A good option would be a servo motor like the TowerPro SG90 or MG90S, which are commonly used for projects involving microcontrollers and development boards. These models require only basic PWM control, making them suitable for the Coral GPIO capabilities.

3.6 Hardware system overview

The table 3.2 provides an overview of the hardware components used in the drone-based pollination system. It contains details about the drone model, the control and sensor devices as well as the customized parts such as the 3D-printed tank and the pollination mechanism.

Component	Description
Drone	DJI Mavic 3M
Coral Dev Board	Development board for ML and control
LiDAR Sensor	Sensor for distance measurement and navigation
Pollination System	Custom attachment for pollination
TowerPro SG90/MG90S Servo Motor	Motor for actuating mechanisms
3D-Printed Tank	Customized tank for the pollination system

Table 3.2: List of hardware used for the drone-based pollination system

The figure 3.3 shows a drone equipped with our developed pollination system. Under the drone, in the grey housing, are the components that are essential for operation: a microcontroller, a tank for storing the pollinating fluid and a motor that drives the pollination mechanism. The black area below houses the LiDAR sensor. Below is the blue arm of the pollination bubble machine, which releases bubbles of pollen to mimic the natural pollination process.

Figure 3.3: Drone with pollination system [29], and self edited

4 Economic and engineering viability

In general, the proposed system combines many state-of-the-art technologies. But as can be seen throughout the report, it is very easy to split this project into smaller tasks, allowing for developing rather trivial solutions to each subtask. This reduces the project complexity a lot and allows for high specializations in the team, as everyone only has to be familiar with one specific topic.

However, aside from engineering, there are some other things to consider.

4.1 Legal restrictions

The system involves autonomous drones, agricultural chemicals, and video capturing, each with its own legal considerations that vary by country. Autonomous drones are typically regulated by local aviation authorities, requiring licenses, certifications, and risk assessments. Unlike regular drones, autonomous drones are considered higher risk and may face stricter operational limitations [30]. When drones apply chemicals like pesticides, the chemicals themselves must be certified, and aerial pesticide use is often restricted due to the risk of environmental harm from drift, potentially requiring special permits [30]. While the software does not store video data, privacy regulations, such as GDPR, must be respected, including minimizing data collection and ensuring transparency about its use. As drone regulations regarding privacy are still developing [31], it's important to stay updated on current laws. For the prototype, it's recommended to ignore these restrictions and use the system in a controlled, private environment, such as indoors.

4.2 Commercialization

The commercialization of the drone-based artificial pollination system involves finding ways to make the technology practical and marketable while addressing licensing issues. One challenge is that YOLOv11, the object detection system we use for flower recognition, is licensed under the Affero General Public License (AGPL). This license requires that any software using YOLOv11 must also be open-sourced under the same license if it is shared or distributed. There are several solutions to avoid this and protect our innovations:

1. **Using a different framework:** Instead of using YOLOv11 in the final product, we could replace it with another object detection system that has a more flexible license, such as Apache or MIT, which would allow us to keep our work proprietary.
2. **Cloud-based approach:** We could run the flower recognition software on cloud servers and not on the drone itself. In this way, we do not distribute the software directly, which means that the AGPL restrictions for product users would not apply.
3. **System as a Service:** Similar to the cloud-based approach, the AGPL restrictions would not apply if we ”rent out” the whole system as a service instead of a product.

The system has strong market potential because it saves a lot of pollen, works with different crops, and offers a sustainable solution to pollination challenges. To reach customers, we could partner with agricultural equipment companies to help distribute the product more effectively. In terms of pricing, we could sell the drones and hardware upfront and charge a subscription fee for software updates and maintenance. This approach would make the system affordable to a wider range of farmers while providing a regular income to support ongoing improvements.

4.3 Business analysis

Our drone-based artificial pollination system offers an innovative solution to some of the biggest challenges in agriculture today, such as the decline of natural pollinators, rising labor costs and the need for more sustainable farming methods. To better understand how this system can succeed in the real world, we created a Business Model Canvas. This model highlights the key parts of the project, like the technology needed, potential customers, costs and how we plan to generate revenue.

The Business Model Canvas focuses on partnerships with drone manufacturers and farming distributors, the use of advanced AI for precision pollination and flexible options to meet the needs of both large farms and smaller operations. It shows how we want to offer a system that is not only effective and scalable, but also environmentally friendly and affordable.

In the appendix A.2 you will find the Business Model Canvas, which shows the main components that make our solution practicable and ready for the market.

5 Environmental and societal impacts

As our intelligent system is meant to be implemented over a large scale, we must discuss the impacts it might have on the environment and human society, whether it is positive or negative.

We will firstly address the positive environmental and societal impacts made by our artificial pollination system. To begin, it is clear that our system will provide aid to natural pollinators, creating a solution to their decline by supplementing their efforts with artificial pollination. From this, a number of effects will cascade, as follows. Firstly, there will be a reduced risk of food shortages, as our system will ensure a reliable and efficient pollination of crops, actively contributing to higher crop yields. Secondly, unlike natural pollination, our system will be suited to indoor and vertical farming, eliminating the need to grow crops in the outdoors, which can prove to be more and more challenging with our changing climate. While manual pollination is still an option for this scenario, our system provides a less time-consuming solution if we were to look at actual pollination time alone. Lastly, our system can open a new industry sector, creating work opportunity for many.

On the other side, we must address potential negative environmental and societal impacts our system might cause. Firstly, energy demand in terms of the construction and operation of drones might pose an issue, as many drones utilize lithium-based batteries, resulting in a negative environmental impact due to excessive mining and the sheer difficulty to recycle such materials (requires specialized facilities and it is quite complex and expensive). In that sense, our system could make the agricultural sector to be dependent on this technology, making it sensitive to technical difficulties and software malfunctions, which can pose a threat to food security in vulnerable times such as food shortages. Lastly, our system might actually negatively impact natural pollinators of all kinds, disrupting the already fragile equilibrium of this vital ecological process.

Considering the multifaceted challenges associated with integrating such an advanced artificial system, we acknowledge the complexity of its implementation across various dimensions. However, we firmly believe that the potential benefits substantially outweigh the anticipated drawbacks.

6 Conclusion

This project has presented the development of an artificial pollination system designed to address the pressing challenge of declining natural pollinator populations. The system combines drone technology with machine learning and remote sensing to offer a precise and efficient alternative to natural pollination. By employing a convolutional neural network for flower detection, a LiDAR sensor for distance measurement, and a bubble-based pollination mechanism, the system ensures targeted application of pollen to the reproductive structures of flowers. The drone operates autonomously, using pre-programmed flight paths and real-time data processing to navigate and perform pollination tasks.

The potential benefits of this system are substantial. It offers a reliable solution for enhancing crop yields, reducing the risks associated with food shortages, and supporting agriculture in environments where natural pollinators are absent or ineffective. Furthermore, the system's adaptability to modern farming methods, such as vertical and indoor farming, expands its application beyond traditional agricultural settings.

We believe this artificial pollination system has the potential to revolutionize agriculture by introducing a new era of precision and sustainability in crop production. Unlike traditional methods, this technology minimizes resource waste, reduces reliance on manual labor, and enables consistent pollination even in challenging environments. The integration of such intelligent systems into agricultural practices could foster greater resilience against the impacts of climate change, enhance food security on a global scale, and open up new opportunities for technological advancements in farming.

However, the integration of this technology comes with challenges, including its energy demands, potential costs for small-scale farmers, and the environmental implications of drone manufacturing and operation. Despite these concerns, the system is designed to complement natural pollination rather than replace it, helping to relieve pressure on ecosystems while providing a sustainable alternative in areas facing severe pollination deficits.

With continued refinement and careful consideration of its societal and environmental impacts, this system has the potential to play a transformative role in modern agriculture. It represents a step toward balancing technological innovation with ecological preservation and food security in the face of global environmental challenges.

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A Appendix

A.1 GANTT chart

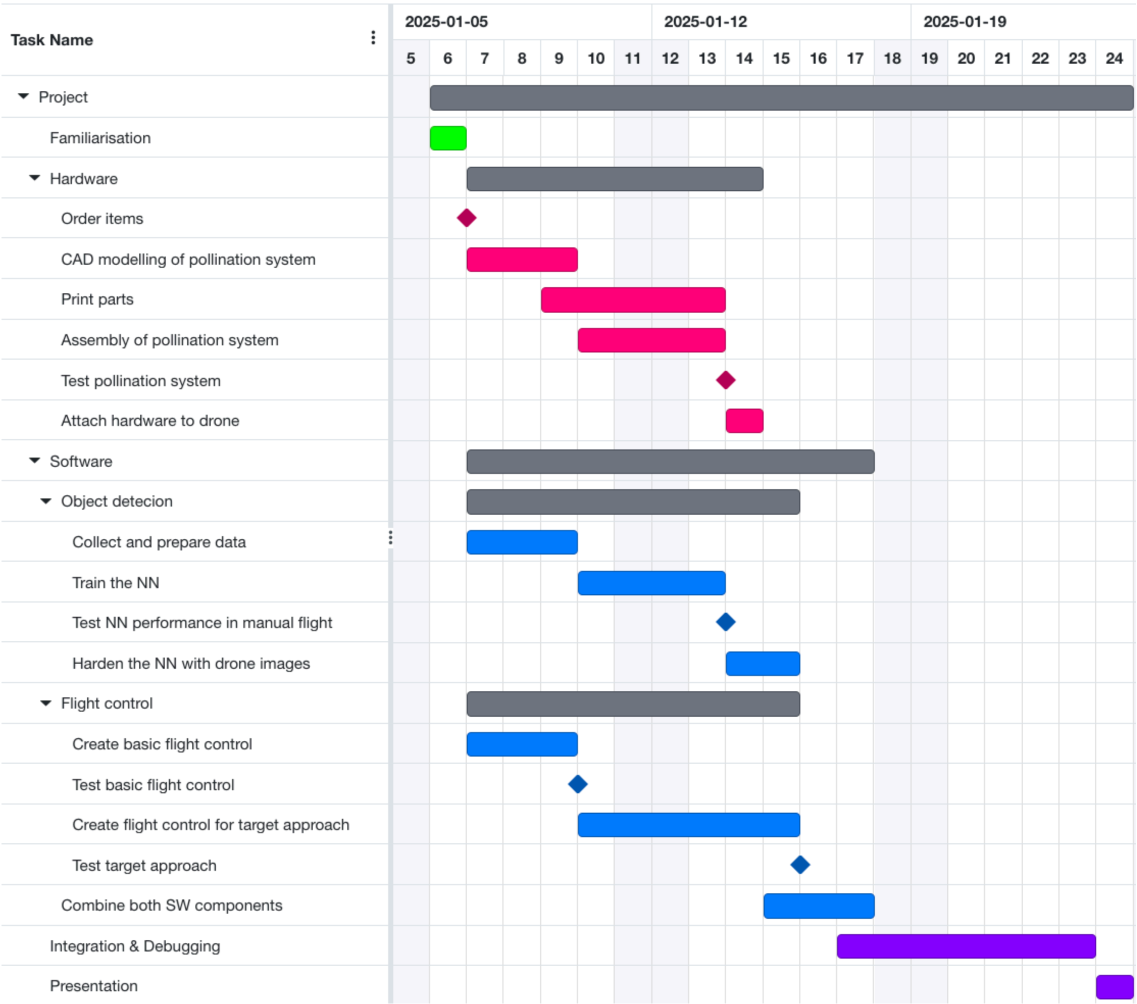

Figure A.1: Proposed GANTT chart to complete the project during the 3-week period in January

A.2 Business Model Canvas

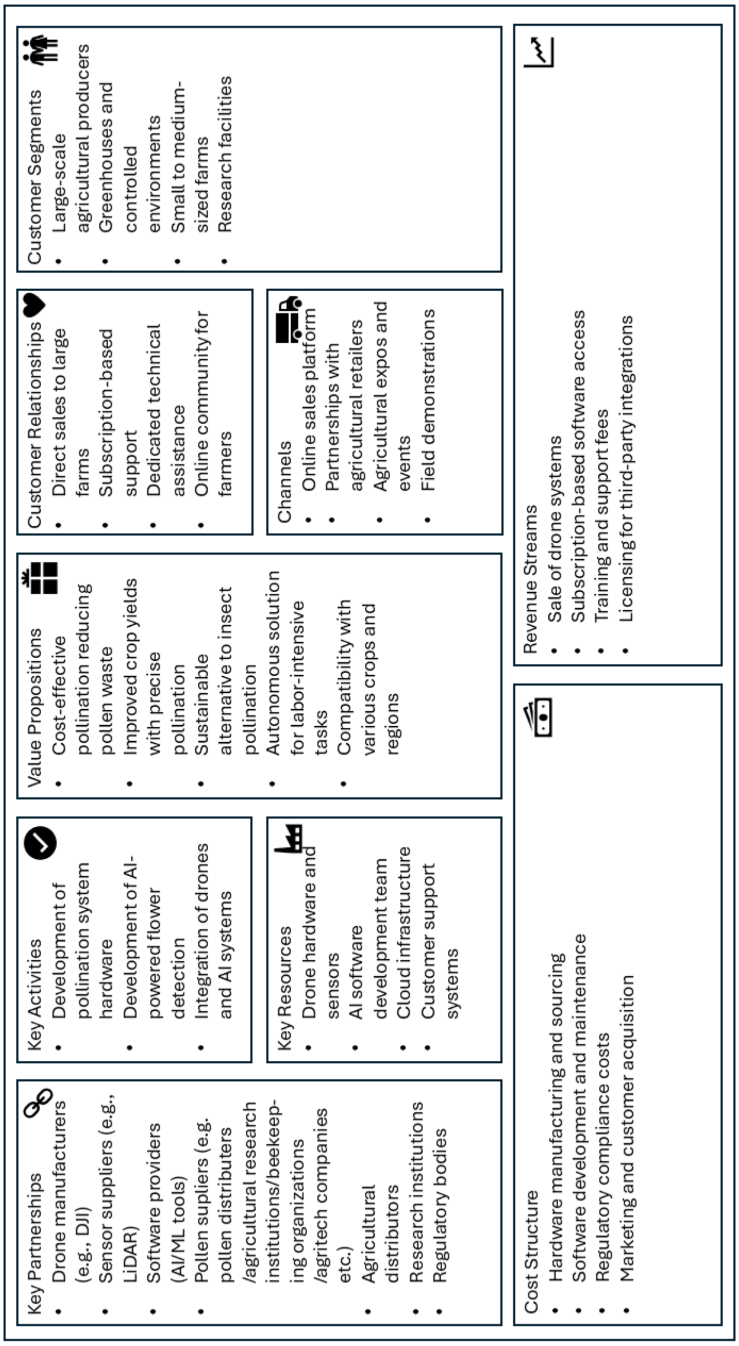

Figure A.2: Business Model Canvas

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