

Bachelor Degree in Computer Science & Engineering
2025-2026

Bachelor Thesis

Advancing Plant Phenotyping in
Rangelands Through Drone-Derived
Imagery and Video Data

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Leganés, Madrid

June, 2026



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ABSTRACT

Site-specific weed control (SSWC) has been a problem since humans started to develop the field of agriculture. During the ages, existing methodologies did not change at all: they were based on manual detection and extraction. However, this changed with the appearance of modern computers.

In the last fifty years, there has been an extreme evolution in the detection of non-desired weeds. However, it was not until recently that newer computational methodologies based on Deep Learning and Artificial Neural Networks — more specifically Convolutional Neural Networks — were introduced into the field that the advances became truly efective.

This work addresses the development of a computer vision model capable of locating and counting instances of *Eryngium horridum*—commonly known as "cardilla"—a perennial, spiny weed species native to the grasslands of Uruguay, Argentina, and southern Brazil. By leveraging drone-derived imagery and video data, this thesis aims to contribute to precision agriculture and ecological monitoring, enhancing the sustainability and efficiency of rangeland management practices.

Keywords: Site-specific Weed Control, Object Counting, Object Segmentation, Computer Vision, Artificial Intelligence

DEDICATION

I would like to dedicate this work to the two fundamental pillars of my life:

To my family. You have been there for me no matter what. Even when I did not deserve it. You will always be the beacon I need when I must return to safe ports.

To my brothers. We are not blood-related, but you will always have a seat at my table. With you, I found loyalty even in the worst of the storms.

*" We will all die and the universe will carry on without care.
All that we have is that shout into the wind—how we live. How
we go. And how we stand before we fall. "*

— Pierce Brown, *Golden Son*

CONTENTS

1. INTRODUCTION AND MOTIVATION	1
1.1. Motivation	1
1.1.1. About the <i>Eryngium horridum</i>	3
1.1.2. Technical challenge	4
1.2. State of Art: An introduction to Object Detection and Segmentation	6
1.2.1. Associations Algorithms	6
1.3. Regulatory Framework	6
1.3.1. European Regulatory Framework	6
1.3.2. Regulatory Framework in Hispanic America	9
1.4. Socio-economic impact	11
2. DATASET	12
3. MODELS	13
3.1. T-Rex 2	13
3.2. YOLO	13
3.2.1. Results	14
3.3. Modified YOLO: exploring the limits of object detection	14
3.4. YOLO + SAM2: improving accuracy through masks.	14
BIBLIOGRAPHY	15

LIST OF FIGURES

1.1	Gross Domestic Product (GDP) share of agriculture, forestry, and fishing (in %) between the years 1960 and 2024. Source: <i>World Bank Data</i> [1]. . .	1
1.2	<i>Eryngium Horridum</i> : Left image: bottom part of the plant. Upper right: flower. Bottom left: inflorescence	3
1.3	Recorded aerial view from an unknown height. Sizes differ between each individual deppending on different factors, such as the dryness of the plant.	4
1.4	Visual representation of the MOT problem. The multiplexer determines the approach: either Detection-based Tracking or Detection-Free Tracking.	5

LIST OF TABLES

1.1 Comparison between DBT and DFT. Adapted from [9]	5
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1. INTRODUCTION AND MOTIVATION

The purpose of this chapter is to introduce the topic of the thesis, present the current state of the art — from both theoretical and practical perspectives — and outline the motivations behind it, as well as the regulatory framework and the associated economic impact.

1.1. Motivation

Agriculture plays a crucial role in the economy of the vast majorities of the countries in the world. Although in developed countries such as Spain it plays a less important role (near 2.3% in 2024[1]), in some developing countries such as Hispanic America it can raise up to 8%.



Fig. 1.1. Gross Domestic Product (GDP) share of agriculture, forestry, and fishing (in %) between the years 1960 and 2024. Source: *World Bank Data* [1].

Maintaining an adequate rhythm of production is vital not only for the economy, but for sustaining the quality of life of the population. Thus, innovating with new technologies in this field has always been necessary to supply the increasing demand.

Weeds have been consistently a problem; not only they reduced the quality and quantity of the crops, but detecting them was an extenuating job. Until the development of modern machinery, it was mainly done by hand — covering entire fields and removing them — or using agriculture techniques for avoiding their apparition — mainly grazing and crops rotation —, with mediocre results.

In the early years of the XX century, tractors were starting to be more and more common, reducing manual labour activities a lot. However, there was still the possibility

of developing weeds in the fields and not being able of estimating the total amount of them in the total land size.

Estimating the amount per hectare (or other desired unit of measure) is vital for understanding how weeds are influencing in the growth and quality of crops. Depending on the density of these unwanted plants, different quantities of herbicides can be used, reducing toxins and improving the condition of the batches.

Modern computation technologies were firstly used near the 70s: archaic solutions based on reflecting-based living ("green") plants with photoelectric diodes[2] were proposed. However, these methods were highly dependant on the ability of controlling the constantly in-change environment.

In the 80s, with the appearance of digital cameras, a new bunch of possibilities appeared. As the spectral-colour range cameras were more and more affordable, a totally new world for exploring this field was discovered.

The first predecessor of formal Convolutional Neural Networks — known as the neocognitron —, presented by Kunihiko Fukushima was a totally game-changer. It was a multilayer perceptron (MLP) able to extract features and predict handwritten numerals from "0" to "9"[3]. Fukushima also proposed several unsupervised training algorithms. Although they were revolutionary, after the proposal of back-propagation [4] (which is heavily used in computer vision currently) they fell into disuse.

After it, a spiral of hype and constant changes for these neural networks came into scene. In 1998, the LeNet-5[5] was the first neural network to include back-propagation end-to-end which was tested with the MNIST dataset.

In 2012, the neural network AlexNet was proposed. With nearly 22,000 categories (labels), this neural network was able to generalise a vast number of different objects with high precision. However, the most innovative thing was that it was **trained using Graphics Processing Units — GPUs** —[6], something that was never used in the field. This rapidly raised the level of training methodologies, reducing the time elapsed.

Only three years later, Microsoft engineers proposed a new method to lighten the weight of neural networks. After benchmarking and stating that "**the deeper network has higher training error, and thus test error**"[7]. This means that the more layers a network has (above a critical limit), the less precise it gets. They propose the Deep Residual Learning, based on the difference (error) between the expected value and the obtained one.

$$F(x) = H(x) - x$$

$$y = F(x) + x$$

Using this approach, the net eases the learning process compared to the standards of the moment. As a subsequent effect, they are able to reduce the weight of the networks up

to an 80% (compared with VGG nets).

It was not until 2012 that convolutional neural networks were mature enough in order to be applied in the agriculture field. However, there have been (and still are) important limitations when using these methodologies — which are by far the most effective—.

The main limitation is not computational or algorithmic, but the datasets used for training the nets. It is common to have a very limited dataset with very few instances of useful data to preprocess and work with. Restricted to the regions where they were obtained, it is complicated to make a dataset that is representative for an extensive region.

Nonetheless, the region is not the only factor, but also the seasons of the year. Generating a fine dataset that shows every phenotype of a given plant in a specific moment is expensive — economically and humanly —.

Thus, the aim of this work is not only to create a model able to segment and count instances of the cardilla, but to create a dataset competent enough to provide the sufficient information for future works about the field.

1.1.1. About the *Eryngium horridum*

Original from Hispanic America, the *Eryngium horridum* —also known as cardilla or caraguatá— is common to locate in the plain lands of Uruguay, southern Brazil and central-eastern Argentina.

The plant is a perennial forb with a highly distinctive morphology; it is a rosette with numerous spiny linear leaves that can reach up to 65 cm in length and 2 cm in width. Its inflorescence axis can grow as tall as 2 meters [8].



Fig. 1.2. *Eryngium Horridum*: Left image: bottom part of the plant. Upper right: flower. Bottom left: inflorescence

One peculiarity of this plant is its resilience in adverse conditions. After experiencing fires or frosts, it has been mentioned to see the floral part of the stem to grow quicker and bigger than before.

Although there are no common uses for this plant, it is known that it helps in the scarring process. However, here ends its applications. It is not harvested, at the contrary, it is heavily prosecuted because of the rapid growing through fields, destroying useful terrain for cropping in a few months. Not even the livestock desires to eat it, unless excessive hunger.

A quickly identification of the plant is needed to solve the issue before it ruins the field and the crops already planted.

1.1.2. Technical challenge

Although it is clearly obvious the distinctive shape of the plant, trying to observe them from an aerial perspective gets much more complicated. Depending on the height of the UAV (Unmanned Aerial Vehicle) and the quality and resolution of the camera, the difficulty can increase exponentially.



Fig. 1.3. Recorded aerial view from an unknown height. Sizes differ between each individual deppending on different factors, such as the dryness of the plant.

Estimating the possibles individuals per hectare by hand, even with the help of UAVs, is complex enough. In the last ten years, the trend of computer vision has also arrived to this field.

Computer vision, which a field of artificial intelligence — more specifically from machine learning —, is a discipline that allows computers to process images (frames) and to extract meaningfully data and make decisions.

This challenge is based on the Multiple Object Tracking (MOT); which aims for identifying an arbitrary number of n individuals with the maximum precision possible.

In the literature, there are currently two approaches for solving the MOT problem: **Detection-based Tracking (DBT)** and **Detection-Free Tracking (DFT)**. Whereas the DBT is used an external and automatic detector for localising the objects in the frame, the DFT needs some manual input at first glance in order to keep up with the trajectory of the item.

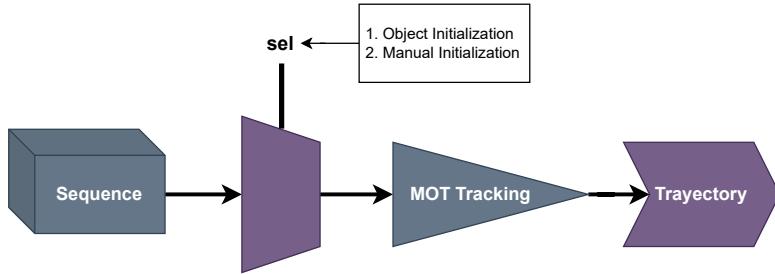


Fig. 1.4. Visual representation of the MOT problem. The multiplexer determines the approach: either Detection-based Tracking or Detection-Free Tracking.

These approaches, although similar, are not used in the same use cases. The applications differ, as well as the advantages and disadvantages depending on the scenarios where they are used.

Variables	DBT	DFT
Initialization	automatic, possibly imperfect	manual, perfect
# of objects	varying	fixed
Applications	specific type of objects	any types of objects
Advantages	ability to handle varying number of objects	free of object detector
Disadvantages	performance depends on object detection	manual initialization

TABLE 1.1. Comparison between DBT and DFT. Adapted from [9]

Whereas the DBT is made up from a pipeline: the **detector** (in charge of predicting the boxes of the items) and the **associator** (in charge of associating each box with a label or class) and then uses associations algorithms (see 1.2.1) for identifying the movement of an object, the DFT is much more complex. The net itself learns how to predict the trajectory of the individual, using transformers and tokens for maintaining the individual identity of the model.

At first, DFT may seem like a reasonable option to choose. However, its complexity is not trivial. It is important to mention that usually is required to have big datasets for these types of models. In this work, the quantity and quality of the frames are not as large and precise as it would be preferable. Thus, Detection-Based Tracking is a better option.

- Freedom for controlling the detector (YOLO, Faster R-CNN...)

- Atomic: is easier to modify local features.
- Different methods of association can be used for experimenting with them.

In summary, while both DBT and DFT approaches seems to be good enough results, the **Detection Based Tracking** method can give us more interpretability and control while developing the framework, specially with the data limitations of this study.

Therefore, the main focus of this study will be on the DBT pipeline, combining different classification models with associations algorithms. However, to evaluate the potential of more recent and capable technologies, the **T-Rex 2** model [10] — a representative of the DFT family — will be also tested as a comparative benchmark.

From this technical review, several questions arise:

1. How effectively can a detection-based model identify, localize and track the *Eryngium horridum*?
2. How do supervised models performed (DBT) compared to end-to-end transformers-based arquitectures such as T-Rex 2 (DFT)?
3. What are the limitations and generalization capabilities of these models when faced across different plant densities, flight altitudes, and observation perspectives?

1.2. State of Art: An introduction to Object Detection and Segmentation

1.2.1. Associations Algorithms

1.3. Regulatory Framework

1.3.1. European Regulatory Framework

The regulatory framework about these emerging technologies — such as AI and UAVs — are still being defined worldwide. In the European Union, several laws about the usage of AI and UAVs have been already defined for the correct usage of both technologies.

European Regulatory Framework of UAVs

Unmanned Aerial Vehicles regulatory framework started to develop in the early 2020s, with the approval of the Implementing Regulation (UE) 2019/947, which defines the rules and procedures for the usage of drones in european aerial space and the Implementing Regulation (UE) 2018/1139, which integrated the drone normative with the European Union Aviation safety Agency (EASA).

One of the most important points of this regulation is the classification of the drones: *open*, *specific* or *certified*, which depends on several factors such as the danger of the mission and the capabilities of the vehicle. Depending on the category of the vehicle, different requirements may be needed (for the pilot and the plane) to fly in european space.

1. **Open:** *low danger operations*. Most are recreational or simple comercial flights. No previous authorization is required if the drone follows several requirements: weight does not surpass 25 kg, maximum flight altitude is 125 meters high and the vehicle will not approach any vital infraestructure (such as airports). The pilot must have constantly visual sight of the vehicle.
2. **Specific:** *medium danger operations*. In this category, flights required to have a previous authorization of the corresponding authorities (AESA in Spain). However, the limitations of these flights are less restricted than in the open category: night operations, increase size and weight of the vehicle and the possibility of flying in urban zones.
3. **Certified:** *high danger operations*. Compared to traditional aviation operations. This category includes vehicles that transports passengers or dangerous commodities or that used autonomous flights without any possible human interaction. Currently, there are very few operations that are currently in the need of this category; it is aimed for future projects.

In addition, the law in Spain (and thus in the entire European Union) requires that every drone pilot must be certified with a license, obtaining an unique identity number valid in the entire European Union.

This work aims to contribute to the open and specific categories. Here, individual such as farmers or researchers may be in the need of using drones for recognising and identifying weeds in their fields.

However, these services can be also done through a company specialized in this. The pilots the company must be certified pilots as well. And because of the high amount of flights per week that these pilots may need to do, exists the **Light UAS Operator Certificate** (LUC) for frequent operators. These operators do not need to ask for previous authorization to AESA, reducing the bureaucracy and speeding up the process of asking for authorization, which can last up to ten working days.

European Regulatory Framework of Artificial Intelligence

In 2024 the European Union adopted the first worldwide normative with respect to artificial intelligence: the reglament (UE) 2024/1689, also known as the Law of Artificial Intelligence or AI Act. It is defined as a machine-based system designed to operate between different levels of autonomy.

The AI Act introduces a well-defined categorization of risk for AI systems. Depending on the risk category, some systems are forbidden, whereas others may require and extensive assessment before market entry.

- **Unacceptable risk:** applications such as social scoring systems and manipulative technologies are absolutely banned in the EU.
- **High risk:** applications based on risk evaluation (such as risk or infrastructure) must pass strict compliance reviews.
- **Limited risk:** limited applications such as recommender systems, image or video processing and more need to clarify to the user its usage and the usage of AI for generating the output. Data quality, transparency and fairness standards are required even for these types of applications
- **Minimal risk:** spam filters or AI in video games fall in this category. They are not subjected to any regulatory framework.

The work proposed in this document clearly falls into the *limited risk* category. Thus, it is important to remark that transparency and fairness are vital. This is because the output of an AI model could cause confusion or influence decision-making capabilities of the user.

Several minimal obligations are required to these systems for the sake of the protection of the user:

- User must always know that is using AI.
- Artificially generated contents must be labeled as "AI Generated" in order to avoid confusion or wiles.
- A transparent design means a less biased model.
- It is recommended to include ethics by design. This can be done by evaluating biases during training or applying *algorithmical justice*

The AI Act also mentions that the systems must be explainable (XAI). The goal of XAI is quite ambitious: surpassing the black box issue and integrating algorithms with human values, empowering and enhancing the individual in the decision-making process [11].

European Regulatory Framework of Personal Data and Privacy

In Europe, every use of personal data needs to follow the privacy policy established by the European Union; more specifically the GDPR — General Data Protection Regulation — which its effective date was 2018.

The GDPR imposes some fundamental principles about the usage of data, which can be used in AI projects. These principles are based on transparency, loyalty and legality. Moreover, a limitation must be set for the usage of the data in order to prevent a misuse of it.

Furthermore, the data must be stored following the principles of integrity and confidentiality up to an arbitrary number of years defined during the process of collection.

One relevant change of the GDPR is that the population has rights about its own data: they have the right to access, change, remove or oppose to their usage in some applications. This means that every institution that automates processes using AI must be transparent about their usage and how it arrives to the conclusion given, which again brings us to XAI (eXplainable AI).

It is important to mention that the GDPR and AI Act were created to coexist: if an institution wants to apply a service using AI, it must be subjected to both the AI Act and the GDPR.

1.3.2. Regulatory Framework in Hispanic America

In contrast to the European Union's harmonized legal ecosystem, Hispanoamerica presents a more fragmented regulatory landscape regarding artificial intelligence, data privacy, and UAV (drone) operations. However, several countries have made considerable advances toward regulating these technologies, particularly in the areas of **data protection** and **civil aviation**.

Data Protection and Privacy Laws

Many Hispanoamerican countries have enacted specific laws to regulate the collection, processing, and use of personal data, largely inspired by international frameworks such as the EU's GDPR.

- **Brazil** enacted the *Lei Geral de Proteção de Dados* (LGPD - Law No. 13.709/2018), a comprehensive data protection law closely modeled after the GDPR, which applies to both public and private sector data handling. It includes principles such as consent, purpose limitation, data minimization, and accountability, and is enforced by the national authority ANPD.
- **Argentina** was a pioneer with its Data Protection Law 25.326, which regulates personal data processing and guarantees data subject rights. The law also prohibits the dissemination of image or video data containing identifiable individuals without prior consent.
- **Chile, Mexico, and Uruguay** have similar legislative frameworks, each including provisions that require informed consent, secure data processing, and individuals'

right to access or correct their data. In Uruguay, the Law 18.331 governs personal data protection and is overseen by the Unidad Reguladora y de Control de Datos Personales (URCDP).

These national frameworks establish that any AI or drone-based system capturing or processing images, biometrics, or location data must comply with consent and purpose principles. This significantly affects agricultural or surveillance applications involving UAVs or computer vision.

AI-Specific Legislative Developments

Unlike the EU's AI Act, Hispanoamerica does not yet have unified legislation targeting artificial intelligence. Nevertheless, several countries have launched national AI strategies and draft bills focused on ethical guidelines, transparency, and fostering innovation.

- **Brazil** released its *Estratégia Brasileira de IA* (2021), outlining policy objectives including responsible AI, scientific research, and AI in public services. A federal AI Bill was proposed in 2022 and is under parliamentary discussion.
- **Chile** introduced its National AI Policy in 2021, emphasizing development based on human rights, inclusion, and explainability.
- **Argentina, Colombia, and Uruguay** are also developing their national frameworks, supported by regional cooperation through organizations like CEPAL and the IADB.

Though still in progress, these initiatives aim to provide a regulatory basis for ethical AI deployment in agriculture, education, and digital public infrastructure.

UAV and Drone Legislation

Drone regulations in Hispanoamerica vary considerably by country. However, civil aviation authorities generally restrict operational parameters such as maximum altitude, speed, and flight over populated areas.

- In **Brazil**, the National Civil Aviation Agency (ANAC) regulates UAVs through RBAC-E94, which establishes over 70 provisions for certification, weight categories, and operation types. Drones used for commercial, agricultural, or research purposes require operator registration, flight authorization, and in some cases, insurance.
- **Argentina** maintains similar strict controls, requiring UAV registration, operator licenses, and compliance with maximum altitude (120 m) and speed (161 km/h) limits [12].

- In contrast, **Uruguay** has a more permissive regime for recreational drones: no formal permit is required for sport or leisure flights, provided that basic safety measures are followed and no sensitive areas are overflown.
- Countries such as **Colombia, Peru, and Mexico** follow hybrid approaches based on international aviation safety standards, including pilot certification and risk assessment for advanced operations (e.g., BVLOS, agricultural spraying).

Overall, while regulation is less standardized than in Europe, most Hispanoamerican countries are actively updating their frameworks to address UAV usage, particularly as drone-based AI systems become more prevalent in agriculture, infrastructure monitoring, and environmental surveillance.

1.4. Socio-economic impact

2. DATASET

Explicar características, fuentes de obtención, limitaciones y más.

3. MODELS

3.1. T-Rex 2

- DFT
- Tiene una alta precisión para identificar las cardillas, pero no alcanza a capturar el tamaño total de dicha planta con una sola imagen como muestreo. Si se añadiesen más imágenes, se podría tener una mayor precisión.
- De nuevo, dependiendo de la imagen del muestreo el resultado cambia mucho. Cuando el muestreo es una imagen clara de las cardillas — en perpendicular con el suelo — la precisión mejora mucho para ese tipo de imágenes, pero no mejora (incluso empeora) en las imágenes que no son de ese tipo.
- De nuevo, por el tamaño de muestreo, no es capaz de generalizar correctamente si nos encontramos con unidades secas o no.
- En fotos con mucha maleza, la generalización no funciona como se esperaba (importante mencionar que ninguna foto de muestreo incluía este tipo de fotos).

A pesar de todo esto, tenemos un IoU relativamente alto para algunas imágenes. La media de IoU está en 0.697

Se debería de probar con más tipos de imágenes de muestreo. No tengo tokens suficientes. -> T-Rex no permite esto. Por ello, no lo hace un buen modelo para este tipo de situaciones.

Hipótesis: el modelo es muy bueno, pero se debe de ejecutar con un dataset relativamente grande y bueno para que sea capaz de servir como un muestreo amplio para muchos casos genéricos.

3.2. YOLO

- Obtenemos muy buenas precisiones: YOLOv8s + YOLOv8l + YOLOv11s + YOLOv11l (mejor precisión con YOLOv11, pero resultados muy aceptables con YOLOv8).
- Falla cuando hay densidad muy alta de cardilla, lo que reduce la precisión enormemente creando boxes demasiado grandes
- Limitado por el hardware actual. Modelos con confianza relativamente media-alta. Limitados por dataset.

3.2.1. Results

3.3. Modified YOLO: exploring the limits of object detection

3.4. YOLO + SAM2: improving accuracy through masks

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