Weed management in sugar beet farms: Quo Vadis?

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Project Work

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Affidavit

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Smart farming has increased in popularity thanks to new possibilities brought by the Internet of Things(IoT). Among the benefits which IoT can bring, these new technologies allow a higher yield with a lower use of resources by real-time control of the plantation. Weeds are notorious to ruin the production of a plantation and sugar beet fields are among the most effected ones. An effective weed management system is therefore essential for sugar beet farms and smart farming seems to be the answer everybody has been looking for. In this paper we will explore how Machine Learning can help us achieve the highest efficiency possible leading to a higher production yield by introducing new technologies to traditional methods.

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1 Introduction

The seemingly unstoppable growth of global population compounded by climate change is putting an enormous pressure on the agricultural sector. As estimated by the World Resources Institutes (WRI), the number of people on our planet will reach 10 billion by [AAUS+19] and, as a result, the agricultural production must double to keep up with the demand [SGSS16]. However, the agricultural sector is facing various challenges due to plant diseases, pests and weed infestation and in these times, like never before, the switch to a more sustainable model seems inevitable. The main target of sustainable farming is to increase yield while reducing reliance on herbicides and pesticides, therefore trying to target treatments only to plants that specifically require it, by monitoring key indicators of each individual crop; a technique usually referred to as precision farming. This technique is notoriously time and energy consuming if done manually and therefore is usually discarded in favor of more traditional methodologies. [LHS+16]
In the last years there has been, however, an increased focus on integrating cutting-edge technology with precision farming systems to improve quality and quantity of agricultural production, while at the same time lowering the inputs significantly [IRP+21]. This system is also known as "smart farming" and it is based on the adoption of autonomous robots, which could be both wheeled robots and Unmanned Aerial Vehicles (UAVs), and it has been enabled by the advancements in the field of the Internet of Things (IoT).
IoT is the key technology behind smart farming and allows to add value to the data collected by automated processes by ensuring data flow between different devices. [IRP+21]. More importantly, IoT allows more cost-efficient and timely production and management practices, as showed by Glaroudis et al. in [GIC20], and helps reduce the inherent climate impact by enabling real-time reactions to infestations, such as weed, pest or diseases, and by enabling a more adequate use of resources such as water, pesticides or agro-chemicals.[IRP+21].
In other words, IoT makes precision farming not only more efficient in terms of both money and resources, but even more sustainable than other traditional farming methods

One of cultivars which will benefit immensely by the adoption of smart farming is the sugar beet.

The *Beta vulgaris L*,depicted in Fig n.1.1, commonly referred as sugar beet, is ranked as the second most cultivated sugar crop all over the world, next only to sugar-cane. [BP20]
As showed by May in [May03], being a slow-growing crop early in the season, this plant seems to be a very poor competitor against weed, a claim backed up by Schweizer's research, which reports that sugar beet root yields can be reduced by 26–100% due to uncontrolled weed growth. [SD89]
An approach based on smart farming can reduce the negative effect of weeds on sugar beet plantations and increment the yield and the sustainability of said plantation. The

Fig. 1.1: Representation of a sugar beet plant [Mas91]

purpose of this paper is to explore various approaches for weed management and detection based on machine learning technologies and to give an overview of the state of the art to help the reader implementing the most suitable solution to achieve a more sustainable and efficient sugar beet production.
In the next section, we will try to answer the question of which weed species mostly effect sugar beet plantations. Subsequently, we will make a brief rundown of the traditional techniques for weed management and how they can be automatized.
In section 4 and 5, we will focus on one of the most important steps in machine learning: data collection. We will firstly find out about available methods to collect data and create a personal dataset and then explore some publicly available datasets of weed and sugar beets images.
In section 6, we will analyze the different solutions proposed for weed detection using machine learning.

2 Most common weed in sugar beet fields

Before exploring techniques to manage weeds in sugar beets plantations it is necessary to identify which species of weed are most commonly found in the fields. This step will reduce the time and resources since it allows to develop problem domain solutions. Throughout the world approximately 250 plant species have been selected as dangerous weeds and 60 of these have been found in sugar beet farms. [CM10]
However, as described by May and Wilson in [MW06], usually fewer than 10 are to be found in a sugar beet farm. Around 10 is also the number of major weeds in the sugar beet fields around the globe, most notably *Elytrigia repens* (Fig n.2.1b)and *Convolvulus arvensis* (Fig n.2.1c).[HC77]

(a) Amaranthus retroflexus[Med]

(b) Elytrigia repens[Ras]

(c) Convolvulus arvensis[Unk]

(d) Chenopodium album [Hug]

Fig. 2.1: Picture of common weeds found in sugar beet fields

The annual broad-leaved weeds (Dicot) are:

- *Amaranthus retroflexus* Fig n.2.1a
- *Chenopodium album*
- *Matricaria recutita*
- *Polygonum aviculare*
- *Fallopia (Polygonum) convolvulus*
- *Sinapis arvensis*
- *Stellaria media*

The annual grasses (Monocot) are:

- *Echinochloa crusgalli*
- *Poa annua*
- *Setaria viridis*
- *Chenopodium album* (Fig n.2.1d)

The last one, namely the *Chenopodium album*, belongs to the same species as sugar beet and it's one of the most frequently reported weeds in the fields of this crop. [CM10]
According to Zoschke and Quadrant in [ZQ02], dicot weeds are also more destructive compared to monocots.
The most important dicot weeds of sugar beet growing areas are from the families of Chenopodiaceae, Asteraceae, Brassicaceae, and Polygonaceae. [BP20]
A more detailed list of important problem weeds is given in Fig n.2.2.

Scientific name	Common name(s)
Abutilon theophrasti Medic	Velvetleaf
Agropyron repens (L.) Beauv (see *Elytrigia repens*)	
Amaranthus powellii S. Wats.	Powell amaranth
Amaranthus retroflexus L.	Common amaranth, redroot pigweed
Ambrosia artemisifolia L.	Common ragweed
Avena fatua L.	Wild-oat
Bilderdykia convolvulus (see *Fallopia covolvulus*)	
Brassica napus L.	Rape, wild buckweed
Chamomilla suaveolens (L.) Rauschert (see *Matricaria discoidea*)	
Chenopodium album L.	Common lambsquarters, fat-hen
Cirsium arvense (L.) Scop.	Canada thistle, creeping thistle
Convolvulus arvensis L.	Field bindweed
Datura stramonium L.	Jimsonweed, thorn-apple
Echinochloa crus-galli (L.) Beauv.	Barnyardgrass, cockspur
Elymus repens (L.) Gould (see *Elytrigia repens*)	
Elytrigia repens (syn.) *Elymus repens; Agropyron repens*	Common couch, quackgrass, twitch
Fallopia convolvulus (L.) A. Löve (syn) *Bilderdykia convolvulus; Polygonum convolvulus*	Black bindweed, wild buckwheat
Galium aparine L.	Common clave, goosegrass
Helianthus annuus L.	Common sunflower
Kochia scoparia (L.) Schrad.	Kochia
Matricaria chamomilla L. (see *Matricaria recutita*)	
Matricaria discoidea (syn.) *Chamomilla suaveolens*	Pineappleweed
Matricaria recutita (syn.) *Matricaria camomilla*	False chamomile, mayweed
Persicaria lapathifolia (syn.) *Polygonum lapathifolium*	Pale persicaria
Persicaria maculosa (syn.) *Polygonum persicaria*	Ladysthumb, redshank
Physalis spp.	Groundcherries
Poa annua L.	Annual meadow-grass
Polygonum aviculare L.	Knotgrass, prostrate knotweed
Polygonum convolvulus L. (see *Fallopia convolvulus*)	
Polygonum lapathifolium L. (see *Persicaria lapathifolia*)	
Polygonum persicaria L. (see *Persicaria maculosa*)	
Polygonum spp.	Smartweeds, polygonum
Portulaca oleracea L.	Common purslane
Setaria faberi Herrm.	Giant foxtail
Setaria glauca (L.) Beauv.	Yellow foxtail
Setaria spp.	Foxtail, bristle-grass
Setaria viridis (L.) Beauv.	Green foxtail, green bristle-grass
Sinapis arvensis L.	Charlock, wild mustard
Solanum sarachoides Sendtner	Hairy nightshade
Solanum tuberosum L.	Potato
Sonchus arvensis L.	Perennial sow-thistle
Sorghum halepense (L.) Pers.	Johnsongrass
Stellaria media (L.) Vill.	Common chickweed
Viola arvensis Murr.	Field pansy, field violet

Fig. 2.2: The list of the most reported weeds in sugar beet plantations [CM10]

3 Weed Management Techniques

There is already a plethora of weed management systems which involve the use of different kind of techniques. We will discuss briefly the most utilized ones, since choosing among them is tricky and finding the one which fits the requirements of an application is not trivial. In most cases, multiple approaches are put in place to achieve the most optimal result: for instance, even though tractors and hand labour are still vastly used, since the 50s, herbicides have been the most used method of weed management in sugar beets farms. [CM10]
Modern recommendations derive from the observations that sugar beet plants must overcome weeds early in the season; hence it is essential to design programs which limit the regrowth of reservoirs of weed seeds. Programs incorporating the most suitable crop rotations, herbicides and tillage practices limit the number and diversity of seeds in the seed bank. Weed management systems must be put in place for between 2 to 4 years to reduce weed seed banks and then kept under control for the duration of the field. [CM10]
We will go through the already mentioned methods and how they are used, to understand the benefits they bring.

3.1 Crop Rotation

The first management technique we are going to analyze is called crop rotation. Crop rotation is the practice of planting different crops sequentially on the same plot of land to improve soil health and optimise nutrients within it. This practice should be considered over the whole field, not on a single-crop basis, to ensure the protection of one weed species in the field. [BP20]
Due to its own nature, this sort of weed management technique is very environmentally sustainable and very effective with a very low use of resources. Another advantage of this technique is the ability to utilize plants to control different weed species. This is an advantage because certain crops makes the management of some weeds easier, for example it is easier to control equisetum in sorghum, in maize or wheat stubbles than in sugar beet. [BP20] Furthermore, crop rotation influences the stability of beet yield and quality as reported by Götze in [Gö17].

3.2 Tillage

Tillage system (conventional tillage, minimum tillage and direct drilling) during land preparation can vary the weed flora in the field. The impact of tillage on weed has not been detected for annual weeds, which tend to be considerably more problematic than the others, while Polygonaceae, Gramineae and perennials were preferred by minimum tillage (Fig n. 3.1). The minimum tillage could lead to increase in not only perennials and gramineae but also the Compositeae weed species (Fig n. 3.2).

Soil cultivation	Preceding crop	Weeds
Conventional tillage (>20–25 cm)	Sunflower, maize, soybean	*Abutilon theophrasti*, *Amaranthus* spp., *Ammi majus*, *Chenopodium album*, *Cyperus rotundus*, *Cyrsium arvense*, *Cynodon dactylon*, *Datura stramonium*, *Echinocloa crus-galli*, regrowth of sunflower, *Polygonum* spp., *Salsola Kali*, *Sorghum halepense*, *Xanthium strumarium*
Minimum tillage (15–20 cm)	Wheat, sunflower, soybean	*Alopecurus myosuroides*, *Amaranthus* spp., *Ammi majus*, *Chenopodium* spp., *Cirsium arvense*, *Cynodon dactylon*, *Fallopia convolvulus*, *Lolium* spp., *Phalaris* spp., *Polygonum aviculare*, *Sinapis* spp.
Direct drilling	Wheat, sunflower, maize, soybean	*Agropyron repens*, *Alopecurus myosuroides*, *Cirsium arvense*, *Convolvulus* spp., *Equisetum* spp., *Fallopia convolvulus*, *Phalaris* spp., *Picris echioides*, *Poa* spp., *Sorghum halepense*

Fig. 3.1: Effect of tillage in the preceding crops on the weed species occurrence in sugar beet plantations[BP20]

Biological group	Species	Years of minimum tillage§		
		1st	2nd	3rd
Geophyte	*Agropyron repens*	0	0	++
	Cirsium arvense	+	0	+++
Hemicryptophyte	*Picris echioides*	+	0	+++
	Taraxacum officinale	0	0	++
Therophyte	*Alopecurus myosuroides*	++	++	+++
	Conyza canadensis	0	0	++
	Daucus carota	0	0	+
	Lolium multiflorum	0	0	++
	Poa annua	+	++	++
	Senecio vulgaris	+	0	++
	Sonchus spp.	+	+	++++
	Veronica persica	+	+	++

Fig. 3.2: Spreading of weed species related to the time duration of minimum tillage[BP20]

3.3 Mechanical Control

Mechanical control implies removing the weed by simply uprooting, or chopping the whole plant from its root. In sugar beet farms, mechanical control is often achieved through the use of tractor-mounted hoes, since in many European countries hand hoeing a big field is an extremely expensive practice. As a matter of fact, hand hoeing is only diffused on smaller holdings or in extreme cases where the activity of herbicides is reduced so that they are not completely effective, then manual weed control is often required. [CM10]
Tractor-mounted hoes are still the preferred tool for weed management in most sugar beet producing countries to kill weeds between rows. They can be used as an alternative to herbicide, since they can eradicate weeds when the infestation is low or some weeds are too far advanced to be properly controlled by the herbicide. [CM10]
Furthermore this tool can be used in addition to herbicide, in case those have been sprayed over the rows and weed still needs to be controlled in between.
One of the drawbacks of this approach is that it brings dormant weed seeds to the soil's surface, leading them to germinate once again. Furthermore it could unintentionally allow perennial weeds to propagate, by chopping up and spreading segments roots, rhizomes, stolons and tubers that will each grow into a new weed plant. [CM10]
The peak performance of tractor hoes is achieved in dry condition with friable soil, as rerooting of weeds is unlikely to reoccur. On the one hand, it is true that under moist conditions weeds are easier to remove from the soil, but some species, like for i.g. monocots, can easily reroot in wet conditions.
The main drawback of tractor-mounted hoes is however related to its nature. First of all,

these tools tend to be very bulky and, therefore, require much greater distance between the crop rows, leading to a much more inefficient use of the field. Moreover, these tools tend to be inaccurate and could ruin the sugar beet plants, if not eradicate them entirely. Finally, timing is an essential factor as well. For example, damp soil conditions never permit the use of hoeing machines ([BP20]) and even the effectiveness is reduced due to regrowth of the weeds in this condition, as we discussed previously.
The solution for all of those problems is to use precision farmings approaches, which, however, like we pointed out in previous sections, tend to be extremely expensive. It is therefore evident how mechanical control techniques are not only very suitable candidates for the integration with smart farming techniques, but could also vastly benefit from them. In other words, traditional techniques could be enhanced by modern, smarter, technologies, which can integrate the accuracy of precision farming with the efficiency of said traditional techniques.

3.4 Herbicides

Herbicides are still the main protagonist of weed management in sugar beet plantation due to their cost and availability. However, in recent times, herbicides have become a controversial topic in the research field. We will try to identify which ones are used, when are they used and what benefits, and drawbacks, they bring along.
Herbicides can be divided into 2 macro categories: Pre- and Post-Emergency herbicides.

Pre-emergency Herbicides comprise the residual soil-applied herbicides, which are applied before or after sowing.[CM10] Soil applied residual herbicides have the advantage of reducing the number of weeds emerging with the crop and can also sensitize survivors to subsequent post-emergence sprays ([CM10] , [DMP82], [ZVG12]).
This type of herbicides can be applied to the field prior to sowing, they will be incorporated into the soil, process which has the result of decreasing the performance variability of residual herbicides by reducing the effect of weather on their activity (incorporation is used mainly in semi-arid production areas, therefore not widely used). Those herbicides can also be used after sowing, before sugar beet seedlings emerge or crop damage may results.
Such herbicides are of the highest importance because they are able to reduce weed density and provide flexibility with timing and selection of post- emergence treatments. [MH85]
Pre-emergency Herbicides, however, constitute a harm for the environment, as demonstrated by Meyer et al. in [MWA86], and therefore should not be used due to ecological reasons.
New adoption methodologies for post-emergency herbicides led to changes in the doses of Pre-Emergence herbicides used. As pointed out by Cioni and Maines in [CM10], the increased reliability and earlier use of post-emergency herbicides allowed the use at a lower amount of pre-emergence herbicides, making them cheaper, and they are now seen by growers as an aid to Post-Emergence spraying.
The main pre-emergence residual broad-leaved weed control herbicides for sugar beet production are: Chloridazon, Clomazone, Cycloate, Ethofumesate, Quinmerac, Lenacil, Metamitron and Metolachlor.
Herbicides that may be used before sowing to control grass weeds are Cycloate, Dalapon,

EPTC, Metolachlor, TCA and Triallate. However, these graminicides, especially Dalapon and TCA, have been replaced by selective post-emergence graminicides which are much less likely to cause crop damage. [CM10] [MW06] The major factors to consider when choosing among the big variety of herbicides are the weed spectrum, the soil type and the soil organic matter.

The aforementioned Post-Emergency herbicides are used mainly for controlling weeds for broad-leaved and grasses. There is a large amount of tank mixes and products, the main ones being: Chloridazon, Clopyralid, Ethofumesate, Lenacil, Metamitron, Desmedipham, Endothal Phenmedipham and Triflusulfuron-methyl. Tank mixes are usually used because those herbicides seldom have a wide enough control spectrum to cope with all weeds and therefore mixing them is necessary to provide a broader spectrum of weed control. [CM10] Most of the post-emergence graminicide should be applied at a comparatively later phase of crop growth to offer adequate time to grow. [CM10] and are applied in a low- volume and low-dose for controlling of broad-leaved weeds. [Can88]

Apart from the well known environmental damage, which the use herbicides leads to, another implication is the effect that they have on the sugar beet crops. Most of the selective herbicides have influence on sugar beet growth, with early symptoms showing on the leaves, and this can reduce the yield. [Pet04]
To overcome such limitation, genetic modification technology has been used on both the crop and the herbicides, so that either the plants are resistant or the herbicides have no effect on them. However, the intense use of more than one herbicide resilient crop as shown to cause problems regarding outcrossing of resistance, choice of herbicide tolerant weeds and volunteer crops, surface water contamination, a move in weed flora, and injury to non-target plants by application herbicide drift. [BP20]

3.5 Automatic Weed Management Techniques

Automatic weed management techniques has been the focus of many studies in the last years. Some of these focus on automation of herbicides spraying, like for example [GO06], [KS13]. In this paper, however, due to their environmental impact and the effects they have on the plants themselves, we are not going to focus on them. Moreover, we will neglect solutions which still implies the use of manual labor, like the one in [PRSF+14] ,which still requires around 45% of manual labor. Instead, we will concentrate ourselves on the solutions which try to fully automize the mechanical control of weeds.
This field presents numerous difficulties related to the ever-changing environment of agricultural fields and fully automated systems are not yet available and may not exist for many years. As for the moment, camera-steered hoes with a hydraulic side shifting control for row crops are widely available. [MPK+20]
The first solution we are going to analyze is the one proposed by Raja et al. in [RNSF20]. Even though the authors did not focus their attention on sugar beets, but on lettuce and tomato plants, with their novel robotic weed knife control approach, they managed to reduce the number of weed plants by 83%.
Frasconi et al. in [FMF+14] proposed an approach which made use of burners to perform

site-specific flame weeding in maize. Even though the machine is still in an early stage, the results were promising but not completely satisfying, according to the authors.
One approach that achieved great success in sugar beet plantations is the one proposed by Machleb et al in [MPSG21]. In their study, they proposed a modified version of a conventional finger weeder and a red-infrared camera was used for individual crop plant recognition. They concluded that this combination achieved similar or even higher yields than the multiple herbicide application treatments. [MPSG21]
To compensate the slow working speed of their system, the authors of this work suggest the use more robots simultaneously.

4 Data Acquisition Techniques

Once we understood the most common weed in sugar beet plantations and the main methods traditionally used for managing them, we can start exploring the proposed solution to optimize them with the help of Deep Learning. Deep learning based weed management and classification techniques require an incredible amount of data in order to be reliable, therefore the first step to take is identifying which one suits the application. Numerous methodologies have been proposed in academia for the collection of said data. The first topic we must explore is the platforms on top of which sensors and cameras are mounted. Typically such platforms are either Field Robots (FRs) or Unmanned Aerial Vehicles (UAVs), but they could be of completely different nature.

4.1 Unmanned Aerial Vehicles (UAVs)

UAVs are often used in data acquisition because of their great flexibility. Generally, they are used for mapping weed density across a field by collecting RGB images ([HSD+21], [HDL+18]) or multispectral images [HSD+21]. UAVs can identify the crop rows and map weeds within them ([BHC18], [KAY+21]) since UAVs can fly over the field at a constant height and capture a very large area. Their flexibility is also augmented by the fact that UAVs can also fly at a low high, e.g. 2 meters, so that each plant can be labelled and further inspected. [ZWH+18]. Lam et al. in [LDP+21] even propose a workflow where images are taken at an altitude of 10 and 20 m for better accuracy.
Finally, UAVs tend also to be inexpensive. For instance, authors of [KAY+21] utilize a small consumer UAV, the DJI Phantom 4(DJI, Shenzhen, China) following an autonomous flight plan using the ‘double grid’ mission in Pix4Dcapture[1]. Other studies use the same brand, but a different model. For examples, Islam et al. of [IRW+21] preferred a a Phantom 3 Advanced drone, on which a camera with the 1/2.3” CMOS sensor was mounted.

4.2 Field Robots (FRs)

Another method for collecting data in a farm is to use the so called Field Robots (FRs). FRs are not as flexible as drones because the height can not be changed, however they are able to carry different cameras or sensors. Similarly to UAVs, they can be used to collect RGB images with the help of digital cameras ([MAD+19], [LHS+16]). Authors of [LHS+16] utilize different versions of the BOSCH’s Bonirob system with a single 4-channel JAI camera, thanks to which they are able to collect multi-spectral images.

[1] `https://support.pix4d.com/hc/en-us/articles/115002496206`

The same system has been used by the authors of [LY20], however with some inclusions. In addition to the camera, they used a Kinect One for RGB and depth information of the scene; Velodyne VLP16 Puck, a 3D lidar sensor which provides distance and reflectance measurements; Nippon Signal FX8, a 3D laser range sensor that provides distance measurements up to a maximum range of 15 m; Leica RTK GPS and Ublox GPS (this one being cheaper than the Leica system), in order to track the robot's position.

4.3 Collect Data Without Camera Mounting Devices

Weed data can also be collected by cameras without the use of a vehicle, e.g. by using handheld cameras. For instance, in [GFP+20] part of the datasets contains images taken on site by the authors with a reflex camera (Nikon D7200).
In other cases, cameras were mounted directly on specific devices. For example, in [DAGMG+20], the authors have attached their Fujifilm FinePix Real 3D-W3 digital camera on conveyor at a height of 70 cm from soil surface.
Another ad-hoc solution for collecting data is the one described in [OKP+19]. They developed a specific solution, namely the *WeedLogger*, to collect GPS stamped images of the plants.
Un-mounted cameras allow to take pictures of the plants in grater details, as demonstrated by the authors in [TYDJY20]. They focus the camera on many parts of weeds, such as flowers, leaf, fruits, or the full weeds structure. [HSD+21]

5 Datasets

In the previous section we explored different approaches to collect data for training the machine learning model. The data we feed to the model is going to determine whether the model is going to fulfill our requirements and solve the problem or not. Usually the rule of thumb in machine learning problems is to input as much data as possible to the model for a better, more efficient solution and, in some cases, the collected data is not enough, requiring the engineers to resort to publicly available datasets. Those datasets, however, might might focus on different requirements, hence may not be suitable for a specific condition. In other words, the datasets must be carefully selected and evaluated following certain criteria which are specific to the application. We will explore the most complete, publicly available, datasets around, which have a strong focus on sugar beet and weed recognition, and we will try to choose one amongst them which better suits our application.

5.1 Public Datasets

Chebrolu in [CLS+17] proposes a 5TB publicly available datasets containing not only images of the plants, but also data from vision, laser, GPS, and odometry sensor. Such dataset contains pictures of both sugar beets and weeds, in various stages of the crops growth, under controlled lighting, taken during one crop season by a JAI AD-130GE camera mounted on a mobile robot which would scout the whole field regularly. In addition to the data for navigation, this dataset comprises 283 multi-class (i.e., sugar beet and nine different types of weeds) annotated images at a pixel level, and an even larger set of about 12,340 images with three-class. [LY20]
Because of the quantity and quality of the pictures, including also the other sensor data, the author claims that "no comparable, publicly available dataset exists."[CLS+17]
Cheroblu proposes also an additional dataset containing images taken by UAVs in [LCLS19]. The dataset is divided into two fields, namely field A and field B. For the field A they used a DJI MATRICE 100 UAV with a Zenmuse X3 camera to collect the images; while for the other field, i.e. field B, they used a DJI PHANTOM 4 UAV with a GoPro. They collected the images during multiple sessions and the amount of pictures is around 3 GBs.
Another publicly available dataset for sugar beets detection is the one proposed by the authors in [GFP+20]. This dataset has a peculiarity compared to the one mentioned previously. As a matter of fact, the dataset contains also synthetical images, i.e. images artificially created starting from original images. According to the authors, the reason behind this approach was to optimize the training process by feeding more images. The number of synthetically generated images is around two thousand obtained from around a thousand real images. Said images has been manually collected from two sugar beet fields under different lightening conditions using a digital single-lens reflex (DSLR) camera

(Nikon D7200).
Authors of [DCPGP17] propose a dataset composed entirely by artificially created pictures of sugar beets. Those images are artificially generated using a procedure called procedural content generation (PCG), by modeling targeted plants and agricultural scenes with a few real-world textures. [DCPGP17] The dataset is divided into four image sets composed of the mixture of sugar beet instances and different species of weeds. Each synthetic image is pixel-wise annotated for the crop, weed and soil background. This dataset enables a reduction of human efforts required for data collection and labeling. [LY20]
Another technique used to generate a dataset is the one used by the authors of the Weednet database[SCP+17].
The images for this dataset have been collected in a sugar beet field, which was divided into three field parts for crops, crops and weed and weed alone. The images have been taken at a height of 2 meters from ground level with a UAV. The images are annotated, at pixel level for the crop, weed and background.[LY20]
The same authors also developed the Weedmap datasets, and it is to date the largest multispectral aerial dataset for sugar beet mapping. [LY20]
To collect 10,196 images 2 UAVs have been flown at 10m from the field. It comprises eight sets of high-resolution orthomosaic maps with pixel-level anno- tations for the crop, weed and background. [SPK+18][LY20]
This dataset provides a new benchmark of machine learning algorithms for generating large-scale orthomosaic map based weed mapping. [LY20]

5.2 Dataset Evaluation

The core of a dataset is the data contained in it and also the methods used to collect said data; in other words, what kind of data is in there and if it fits the requirements of our application. The Sugar Beets 2016 [CLS+17] is probably the one which stands out. With its 5TB of information of various nature, i.e. not only images of both sugar beets crops and weed, but also telemetry and others, this dataset allows to train a model very effectively for a plethora of applications. A very important feature of this dataset which makes it unique, is that the pictures are taken of crops in different stages of growth, even though it does not contain pictures of the field from the above.The dataset proposed in [LCLS19], on the other hand, specifically contains images taken from above with a UAV which helps in training a model for mapping the crops in the field. The amount of images is, however, not as substantial as the one in the dataset previously discussed and the images might need some further processing before use. A more unhortodox approach is the one found in the Synthetic SugarBeet Weeds [DCPGP17]. The images are artificially generated, and this increases flexibility exponentially in terms of quantity and quality. As a matter of fact, the number of images can vary and the images themselves can be created ad-hoc for the specific situation and therefore allowing to cover more cases.

Tabelle 5.1: Overview of the datasets

Dataset	# Imges	Platform	Modality	Stages
Sugar Beets 2016 [CLS+17]	> 10000	Ground vehicle	Multimodal	Yes
Weed net [SCP+17]	465	UAV	Multispectral	No
Synthetic SugarBeet Weeds [DCPGP17]	8518	Synthetic images	RGB	No
Weedmap [SPK+18]	> 10000	UAV	Multispectral	No
Joint stem detection dataset[LBC+18]	1321	UAV+ Ground vehicle	Multispectral+RGB	No
UAV-based Field Monitoring [LCLS19]	675	UAV	RGB	Yes

5.3 Dataset Preparation

After acquiring or selecting data from the different sources, the next step is to prepare said data for the next steps (training, testing and validating). As we saw in the previous sections, the images in the different datasets are very high quality, therefore very heavy and processing them might take time. Moreover, raw data is usually not the best option, since it contains information that is not needed.
The most common techniques are background removal, image resizing, green component segmentation, motion blur removal, de-noising, changing color model and extraction of colour vegetation indices.
Image resizing is the first approach to take. By adapting the image resolution based on the DL network requirements the process becomes faster and the complexity can be reduced. As a matter of fact, most of the studies performed image resizing operations on the datasets before injecting it to the dataset. [HSD+21]
A further optimization that can be taken and that is almost free is background removal. This approach allows the DL to process only the necessary information, i.e. to focus on the plants to recognize, which means saving time and costs. There are multiple roads to take to reach a fully removed background: the authors of [BHC18], for example, used Hough-transform to highlight the aligned pixels and used Otsu-adaptive-thresholding method to distinguish between the plants and the background; while the authors of [MLS17] applied Normalised Difference Vegetation Index (NDVI) to remove traces of the soil in the background. This approach is beneficial for UAV images taken from a high distance from the field.

6 Machine Learning Techniques For Weed Detection

6.1 Detection Approaches

Before exploring the architectures used for defining a model, we need to decide which approach suits our requirements the most.
There are two main school of thoughts regarding detection approaches, i.e. Plant-based Classification and Weed Mapping, which are followed in most of the studies. In this section, we will discuss both of them and we will explore the most relevant studies for the two approaches.
Hasan et al. in [HSD+21] provide the definition for plant-based classification: *"localise every plant in an image and classify that image either as a crop or as a weed"*. This approach requires 3 main steps, which are detection, localisation and classification, and it is very suitable for real-time weed management techniques.[HSD+21]
Such approach works in combination with mechanical management techniques, as demonstrated by [RNSF20], where an automatic robot would detect and classify the weeds, which will be lately removed with a knife. Furthermore, such approach can also be taken to reduce the amount of herbicides, as shown by Lottes et al. in [LBC+20]. In this study, a robot is used to identify the weeds which will then receive a specific treatment in order to be removed, allowing precision farming.
Hasan et al. in [HSD+21] also provide the definition for weed mapping. According to the authors, such approach can be defined as the process of mapping *the density of weeds in the field.*
Weed mapping is useful for site-specific weed management and it's mainly used to reduce the amount of herbicides utilized. [HSD+21]
This approach can be used to map the density of the weed in the field, a solution proposed by Huang et al. in [HLY+20], or to monitor the conditions of the field automatically by checking the distribution and spread of weeds and act accordingly. [SPK+18]

6.2 Practical Considerations

For weed control it is critical to have not only the highest possible number of True Positives (TPs) and True Negatives (TNs), but it is also important to consider the number of False Negatives (FNs) and False Positive (FPs). A FN will lead to a removal of a crop, hence reducing the yield of the plantation; on the other hand, a FP means leaving over weed in the field. It is therefore evident that the number of FNs and FPs should be kept as low as possible.[SIHvH18]
Furthermore, training neural network is an expensive task and sometimes could limit their

practical application. To avoid such problem, cloud services can be used, as they provide a simple and relatively cheap way of using high-performance computing hardware without having to acquire and maintain the hardware on site.[SIHvH18]

6.3 Solutions For Weed Detection

Similarly to the management techniques for weed, choosing the deep learning architecture for recognizing them is no trivial task. Most related studies utilize different techniques, and sometimes even a mixture of them, in order to achieve the highest accuracy possible, with a relatively fast training process. In this section, we will analyze some of these studies, i.e. the ones relative to sugar beets, analyzing the techniques the authors use from collecting the images until the evaluation of their model.
The first piece of work we are going to explore is the one developed by Gao et al. in [GFP+20]. They developed a very fast and efficient image-based deep convolutional neural network (CNN) for weed (specifically the C. sepium) and sugar beet detection. Such CNN is based on the popular tiny YOLOv3 (You only look once) framework, but with modifications for increased performance. First of all, they reduced the number of detection scales to two instead of the default three in YOLOv3 since sugar beets are generally similar in size when they collected the pictures. Moreover, they added two more convolutional layers for better feature fusion and modified the route for feature concatenation. What makes this solution peculiar is the dataset they used for training the model. They used a relatively small dataset of around 3000 pictures, however only 452 were field images. As a matter of fact, they took 452 pictures of sugar beets under different light condition and synthetically generated over 2000 images. According to the authors, this allowed them to save time and resources avoiding to take on-field pictures of the plants. What also allowed them to save time was the use of a pre-trained model; more specifically, they took weights from the pre-trained model (darknet53), trained on the ImageNet dataset. Such process is called is called transfer learning and allows to "*overcome any potential overfit- ting due to the lack of sufficient training data*". [GFP+20]
Compared to the classic YOLOv3 and tiny YOLOv3, their model performs very efficiently, allowing a mean average precision (mAP) of 0.829, slightly lower than YOLOv3 (0.832), with an average inference time of 6,48 ms. This trade-off between speed and accuracy, brings the author to think that this model, once trained, could be deployed in a mobile platform (e.g., unmanned aerial vehicles and autonomous field robots) for weed detection and management.
Another different CNN architecture, namely Alexnet, was studied by Suh et al. in [SIHvH18]. In the study, three approaches actually have been considered: AlexNet as a fixed feature extractor, Modified and fine-tuned AlexNet as a binary classifier, Modified and fine-tuned AlexNet as a fixed feature extractor. In all three approaches, they used a dataset of 1100 images acquired by an automatic FR under a wide range of illumination and weather conditions for several days in June, August and October of 2013, in May, June, July and September of 2014 and in May, June, July and October of 2015.
In the first Scenario, three classifiers (SVM, Random Forests and LDA) were trained using supervised learning based on the 4096 feature values that were extracted from each of AlexNet's two FC layers FC6 and FC7. The highest accuracy of 97.0% was achieved

through quadratic SVM with a training time of 13.3s, however for all classifiers an average time of 0.016s was needed , therefore making the authors believe that they are all suitable real-time application in the field (classification time < 0.1 s).
In the second scenario, the architecture of AlexNet was modified by adding 2 FC layers at the end to produce binary classification output (i.e. sugar beet or volunteer potato). They studied the performance of this approach with a number of images that varied linearly from 200 to 900 and, as expected, the performance increased from 89.1% to 98.0%. Although this approach resulted more accurate than the first one, a similar accuracy is only achievable with more than 700 images, hence making it slower training-wise (for 900 images 656.4s). This approach resulted also faster in classification time (0.012), being it the fastest among all scenarios.
The third and final scenario was a mixture between the previous two, hence a fine-tuned AlexNet whose extracted features were added to three classifiers, namely SVM, Random Forests and LDA. AlexNet was fine-tuned using 300 images and the highest accuracy of 96.7% was obtained with an SVM and linear kernel. It required 195.8s for training and has a classification time of 0.0130s per image. By increasing the number of pictures from 300 to 800, the highest accuracy was achieved (97.3%)once again by linear SVM with a substantial increase in learning time (581.4s).
A summary of the performances of the 3 approaches can be found in Table n. 6.1.

Approach	Highest accuracy	Training time (s)	Classification time (s)	# of Images
1	97%	13.3	0.016	1100
2	98.0%	656.4	0.012	900
3	96.7%	195.8	0.0130s	300
3	97.3%	581.4	0.0130s	800

Tabelle 6.1: Comparison between the 3 different approaches using AlexNet[SIHvH18]

Authors of [SIHvH18] also provide a very useful comparison between 6 fine-tuned deep networks, namely AlexNet, VGG-19, GoogLeNet, ResNet-50, ResNet-101 and Inception-v3, summarized in the Table n. 6.2. Such comparison outputs very useful results, as it shows how the different pre-trained networks performs in classification tasks.

To obtain such comparison, the authors trained the networks with randomly selected 500 images and pre-trained with ImageNet Dataset which contained object images commonly found in ordinary life such as desk, computer, animals, etc. Being those images distinctly different from sugar beets, performances can be further increased with a crop/weed field image dataset for pre-training.
Even though the highest accuracy has been achieved by the VGG-19 model with 30 epochs, AlexNet achieved the highest accuracy in proportion to the training time (97.9% accuracy with 9 minutes of training). Alexnet is also the model with the quickest classification time (0.0038s).

A completely different approach was instead taken by Ramirez and al. in [RAMP20]. They used the Weedmap dataset ([SPK$^+$18]), consisting of aerial images, and trained 3 different CNN architectures, namely DeepLab-v3, SegNet and U-Net.

Network	Accuracy	Training time	Classification time	Accuracy	Training time	Classification time
	20 Epoch			30 Epoch		
AlexNet	97.9%	9.0min	0.0038s	97.7%	15.6min	0.0040s
VGG-19	98.4%	37.4min	0.0130s	98.7%	71.4min	0.0124s
GoogLeNet	97.0%	23.8min	0.0033s	97.3%	36.9min	0.0035s
ResNet-50	96.2%	40.3min	0.0072s	97.2%	69.8min	0.0075s
ResNet-101	97.5%	106.6min	0.0118s	98.5%	162.0min	0.0111s
Inception-v3	90.8%	88.7min	0.0088s	94.8%	133.0min	0.0086s

Tabelle 6.2: Comparison between the different networks [SIHvH18]

Since the images are too big in size, for both training and testing, the authors of this piece of work extracted patches of 480 x 360 (for DeepLab-v3 of 512 x 512) from each image and its reference with certain overlapping, also known as *stride*. The semantic segmentation model is then trained upon tuples of patches and their references multiple times to improve accuracy.
They used 2 approaches. In the first one, they extracted references and patches from images {000, 001, 002, 004 } and performed inference over patches extracted from image {003}.
In the second approach they used less labeled samples, only images {000, 001, 002 }, and remainder ones, {003, 004} for inference. With these approaches, they concluded that DeepLabv3 is accurate up to 0.89 and 0.81 in terms of AUC and F1-score respectively. They also observed that bigger patches are more computationally demanding, therefore an optimal value should be considered. DeepLabv3 is the one which generally required more resources to obtain such high efficiency. U-Net, on the other hand, is the one that fits the most relatively to resources over accuracy ration. Finally, they also concluded that the more samples in training there are, the hight accuracy is achieved.

Fully convolutional neural networks is instead the architecture chosen by Lottes et al. in [LBC+20]. They used DenseNet as a baseline model and tested it with data gathered from different fields located in different cities in different countries such as Bonn and Stuttgart inGermany, Ancona in Italy and Eschikon in Switzerland. Their novel approach utilizes also the spatial arrangement of the plants, which, combined with the visual features, allows to localize and classify the plants, reaching an accuracy as high as 90.2%.

To reach an even higher level of accuracy, FCN are also used in the solution developed by Farooq et al. described in [FJHZ19].
They developed a FCNN-SPLBP framework for weed-crop detection composed of several layers of feature extraction method: high-level and mid-level features from a CNN-based feature learning method and low-level features are extracted using the SP based Local Binary Pattern (LBP) coding. The framework FCNN-SPLBP has been trained and tested against two datasets, i.e. UNSW hyperspectral weed dataset and Multispectral weed dataset, both of which are multisensor datasets, and proved the superiority of this framework over CNN, LBP, and SPLBP reaching an overall accuracy of 96.35%. An overview of the

whole accuracy can be seen in Table n 6.3.
Even though this framework was not specifically trained for sugar beet crops and weeds, it is very likely that this solution will work for such plantations as it is not only possible to retrain an already trained network with a new crop type, but that nearly optimal performance levels can be achieved. [BADC20]

Framework	Accuracy	Accuracy
	Dataset A	Dataset B
CNN	79.30(22) %	89.75(74) %
LBP	75.80(30) %	83.64(90) %
FCNN	85.70(18) %	92.50(55) %
SPLBP	80.25(25) %	91.67(65) %
FCNN-SPLBP	89.70(35) %	96.35(77) %

Tabelle 6.3: Overall accuracy using CNN, LBP, FCNN, SPLBP and FCNN-SPLBP for both datasets [BADC20] .

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