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A Survey on Image Processing Methodologies for Crop and Weed Detection

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Abstract: Artificial intelligence is nowadays a fast-growing area of study, in particular deep learning. One of its different uses is object recognition and computer vision. This work is intended by the integration of the two technologies. This work created a system to identify various plants and weeds as an alternative to the system on FarmBot robots. This is achieved via access to the images through the FarmBot API, computer vision for the processing of the image, and artificial intelligence for transmission learning through an RCNN that autonomously carries out plants. In addition, weeds coordinates are given as results. The machine output is compared to related research study as well as the latest version of the FarmBot weed-detector. This study forms a technical viewpoint and offers an alternative to conventional agricultural weed detectors, opening doors to intelligent and sophisticated systems.

1. Introduction

Robotics and automation have become an emerging subject nowadays; substituting and aiding humans in manual tasks that can become not only tedious and repetitive, but also difficult due to different factors such as precision. In order to go in depth on this technology deep learning has been implemented with the purpose of giving these systems intelligence, making them capable of learning. Examples can be found everywhere, from industries to humankind's daily life.

One of these examples is agriculture, where automation has found solution to some of the challenges faced by farmers on a daily basis such as crop diseases infestations, pesticide control, weed management, lack of irrigation and drainage facilities and lack of storage management (Jha, et al., 2019). As a way to bring this new technology to urban orchards, FarmBot Inc. was created. It is a local start-up that is working within advanced precision agriculture through automation and open source technology (Brown, et al., 2017). FarmBot Inc. has developed a series of robots, called FarmBots, to take care of these orchards in an autonomous way while respecting the environment.

This work aims to teach its students how to combine agriculture and technology. To do so, they intend to introduce a FarmBot into their studies and go a step further, not only programming it to do the basic agricultural tasks, but also by including deep learning to make the system capable of differencing on its own whether there are weeds on the orchard or not.

Problem statement

These last years the combination of automation and computer vision has been introduced into agriculture to reduce human workload. The FarmBot used in this work is one example of that combination. Its functions range from the automation of basic agricultural activities such as watering or seeding, to more advanced and complex tasks such as differencing between crops and weeds. This weed detection system is the focus of this paper. It is programmed to take pictures of the crop and process them by a manually activated weed-detection software application from FarmBot where the processing is done based on the colours and location of the elements of the picture. This weed detector is the starting point of this study.

Why does the weed detector have to be improved? Even if this system seems to be failproof, it is not. There are three main issues that can be considered: firstly, having to manually activate the weed detector application does not reduce the amount of human labour as much as intended. Secondly, basing the detection on colours is not accurate due to the possibility of a change of lighting or the similarity of colours between weed and plants, among other things. Finally, basing the existence of a weed on the location where the FarmBot has previously planted a seed, does not consider a situation where the FarmBot does not necessarily know where all the seeds are located.

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2. Literature survey

The field this paper is based on has been researched many times before; in order to get an overview of the previously done work, this chapter analyses some of those documents for each part of the work.

A. Weed detection

Agriculture has always been an essential activity for survival. Over the last century, and more specific, over the last 15 years, agriculture has started to mechanise and digitise; due to this evolution and automation, labour flow was almost totally standardised. Nowadays, after introducing robotics and artificial intelligence into agriculture there is no need of standardization, robots are working collaboratively with humans and learning from them how to realize the basic agriculture tasks such as weed detection, watering or seeding (Marinoudi, et al., 2019).

Weed detection is one of those basic agriculture tasks that are being automatized and digitised, in this case, because of toxicity related to herbicides; so, reducing human intervention will make possible a decrease in the use of herbicides, increasing health care. To achieve this, robots able to detect plants and classify them into crop or weed are now introduced into agriculture (Dankhara, et al., 2019). This implementation has been done in multiples studies such as Dankhara, et al., (2019), where Internet of Things (IoT) is applied into an intelligent robot to differentiate crop and weed remotely; IoT is present in the communication between a Raspberry Pi, where the processing is done and the camera and sensors are connected, and the Data Server, where the Raspberry Pi sends the information obtained. This paper shows an accuracy of 90%-96% depending on if it is used a Convolutional Neural Network (CNN), a datasheet is being created or it is being used the training set.

Daman, et al., (2015) and Liang, et al., (2019) both introduce the use of automation into agriculture to identify weeds, and to do so, they make use of image processing techniques. Daman, et al., (2015) implement those techniques into an herbicide sprayer robot, capturing images from a Raspberry Pi camera and extracting pixels' colours to process them with diverse techniques in order to know whether it is a weed or not. Results were more than successful, after placing plants and weeds randomly, the robot was tested and weeds were almost totally identified and sprayed, taking the processing stage approximately 3 seconds. Liang, et al., (2019) implement image processing in drones instead of robots, that way, they not only detect weeds, but also monitor the growth of crops. By combining image processing and CNN in drones, they get different accuracies depending on the processing, which is from 98.8% with CNN to 85% using Histograms of Oriented Gradients (HOG).

All the previously mentioned processes can be done either in static by photos or in real-time by videos. Marzuki Mustafa, et al. (2007), have done a research about the implementation of a real-time video processing. The crop is recorded and processed, offline, using various image processing techniques and a new developed algorithm that respond correctly to real time conditions. Finally, they achieved an accuracy over the 80%.

Not only the weed as a plant can be differentiated, more advanced studies such as Wafy, et al., (2013), differentiate the weeds seeds using Scale-Invariant Feature Transform (SIFT), an algorithm that extracts the interest points from an image; by using this technique, the minimum accuracy they have is 89.2%.

B. Image processing

There is no correct technique to process images in order to obtain the characteristics needed to identify their elements, and weed detection is not an exception. There are many papers where different techniques are shown. Olsen, et al., (2015) makes use of segmentation and a rotation variant of HOG in order to process the images and get the same illumination so they are robust to variations in rotation and scale. By using these techniques, they got an accuracy of 86.07%.

Samarajeewa (2013) compares two techniques: Local Binary Patterns (LBP) and L*a*b thresholding. LBP thresholds pixels intensity according to its surroundings; this way, only high intensity values are visualised, separating plants from the background. L*a*b thresholding selects a threshold value for each channel in RGB based on histograms. Then, in both techniques, erosion is applied to remove the noise that can have appeared. This procedure is done with RGB and HSV images; the results obtained show that LBP has an accuracy of only 48.75% whereas L*a*b thresholding has an accuracy of 89.96%.

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Another technique usually used is Hough transform; Bah, et al., (2017) combines the Hough transform with simple linear iterative clustering (SLIC). This method focuses on the detection of crop lines; that way, what is not located in that line or differs from its neighbours, is supposed to be a weed. Firstly, the background is segmented and the shadows are eliminated; then the crop line is detected by using some operations that will end up in obtaining the 'skeleton' of the crop line, from that image, weed can be differentiated as said before. By following this method, it has been achieved an accuracy of more than 90% and an over-detection inferior to 2%.

Irias Tejeda & Castro (2019) comes up with a generic MATLAB algorithm for image processing of pictures with uniform illumination. The first step is a grayscale conversion with "rgb2gray" and green pixel subtraction from the converted image, in order to detect green plants in the images. Then filtering is done using "medfit2", which applies a median filter for a neighbourhood of 3x3 pixels with the intention of noise reduction. Image thresholding follows using the Otsu method with the command "graythresh", in order to do thresholding segmentation to get the binarized image. Morphological reconstruction comes next, with "imfill" and "bwmorph" to fill the image regions and holes. Next step is labelling and classification, where connected components are labelled with "bwlabel" and the smaller regions are removed since they are considered to be weeds. Finally, a threshold based on the classification values of the area for a crop or a weed is taken for further comparisons.

C. Deep Learning for weed and crop identification

Deep Learning neural networks range from deep neural networks, deep belief networks, recurrent neural networks and CNNs. The most usually used are CNN, whose layers apply convolutional filters to the inputs. The networks are rarely created from scratch and most of the ones used on papers are already existing networks such as LeNet, AlexNet, GoogleNet, SNET or CNET (Moazzam, et al., 2019).

Moazzam, et al., (2019) offers a summary of seven different studies, all of them use deep learning convolutional networks approaches for the weed/crop identification problem, as shown in Table 1. Even if all the papers mentioned focus on different types of crops, a common element is that most of them only focus on one crop. Studies using deep learning identification of multiple crops and weeds are not common.

Starting with Fawakherji, et al., (2019), this study focuses on the classification of sunflower crops and weeds using pixel-wise segmentation with a CNN. With a training dataset of 500 images, the first step taken is the pixel-wise classification of soil and vegetation, using UNet semantic segmentation network. The second step is background removal and extraction of Regions of Interests (ROI) for their later classification in the third and final step as a crop or weed using a thirteen-layer CNN model. The accuracy obtained with this method is of a 90%.

Knoll, et al., (2018) and McCool, et al., (2017) both study the usage of image-based CNN for the detection of carrot crops and weeds. The first paper uses an eleven-layered network to classify three categories: weed, carrots and background. The network is trained with 500 RGB images taken with a camera. As for the second paper, it uses GoogleNet pretrained on ImageNet and compresses it creating a deep CNN which is then trained on an online dataset. This method reported an accuracy of 90.5%, meanwhile the first paper reported an accuracy of 93%.

For soybean classification Tang, et al., (2017) uses k-mean classification pre-training prior to the CNN training. The CNN used consists of a ten layered convolutional network trained with a dataset of 820 RGB images to classify between soybean and three different types of weeds. The accuracy of this process is of a 92.89%. A similar accuracy percentage is found in the classification of maize crops and weeds, for this, Cordova-Cruzatty, et al., (2017) uses approximately 3600 maize and weed images taken by a Raspberry Pi 3 camera, and performed the testing on four CNNs: LeNet, AlexNet, SNET and CNET.

The best accuracy obtained was with CNET, with a value of 92.08%.

Miloto, et al., (2017) focuses on sugar beet and weed classification. With a 94.74% of accuracy, the training performed on the semantic segmentation-based CNN was done for 48 hours, using nearly 10,000 images. The last paper, Chavan, et al., (2018) is the only one that tries the classification of multiple crops, creating a hybrid version of AlexNet and VGGNET for weed and crop classification:

AgroAVNET, which is a CNN of five layers, trained with 5544 images, with an accuracy of 93.64%.

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In conclusion, crop and weed detection with the use of deep learning is not yet a usual topic of research, even if there are more and more attempts. There are still many research gaps not considered like the differentiation of different crops and weed combinations. Furthermore, even some major essential crops are lacking in this kind of investigation, as there is still a need of creating big datasets for these crops. Deep learning is still a new a tool for the autonomous agricultural applications, yet it seems to be a promising technique and more accurate than other approaches (Moazzam, et al., 2019).

From these researches the needed knowledge about the necessary pre-processing techniques that will be used in this work has been acquired; some of these are filtering, binarization and histograms, a deeper study on them will be done during the development to make sure they suit correctly. Also, through the study of ANNs, some papers using CNNs have been found, being one of those nets AlexNet, the one chosen for this work. by this research, a vision on how to work with these nets has been acquired, as well as the accuracy expected in this kind of works.

Table 1: CNN comparison (Moazzam, et al., 2019)

	Deep Learning Type	Crop	Training Setup	Time	Setup	Strength	%
Fawakherji, et al., 2019	Pixel wise segmentation using CNN	Sunflower	NVIDIA GTX 1070 GPU	Three weeks	Nikon D5300 camera	500 images	90
Knoll, et al., 2018	Image Based Convolutional Neural Networks	Carrot	GTX Titan having 6GB graphic memory	Not given	RGB CAMERA	500 images	93
McCool, et al., 2017	Image Based Convolutional Neural Networks	Carrot	Not mentioned	Not given	RGB CAMERA	20 training and 40 testing images	90.5
Tang, et al., 2017	K-means feature learning accompanied with CNN	Soybean	Not mentioned	Not given	Canon EOS 70D camera	820 RGB images	92.89
Miloto, et al., 2017	CNN based Semantic Segmentation	Sugar beet	NVIDIA GTX1080Ti	200 epochs in about 48 hours	JAI AD-130 GE camera	10.000 plant images	94.74
Córdova-Cruzatty, et al., 2017	Image Based Convolutional Neural Networks	Maize	Core i7 2.7 GHz 8 core CPU Computer with Nvidia GTX950M	Not given	Pi camera Version 2.1	2835 maize and 880 weed images	92.08
Chavan, et al., 2018	AgroAVNET	12 classes	Intel Xeon E5-2695, 64GB RAM and NVIDIA TITAN Xp with 12GB RAM	Not given	RGB CAMERA	5544 images	93.64

3. Sustainability

Nowadays, humanity's lifestyle is using up their resources leading to a lack of them in the future. Sustainable development is the solution to this problem, controlling the usage of actual resources without compromising the future generation needs (Brundtland, 1987). In order to achieve sustainable development, as said by Samaan (2020), it is crucial to balance its three pillars: economic growth, social inclusion and environmental protection, as it is shown in Figure 1. This balance tries to be achieved by accomplishing the 17 goals.

As this research focuses mainly on the development of a software that autonomously detects both weeds and crops, the sustainability will depend on how it is implemented in real life. Nowadays, this implementation is mainly done with the help of automation.

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Figure 1: Sustainable development pillars (Kurry, 2011)

A. Environmental sustainability

From an environmental point of view, sustainable development aims to balance the actual consumption of resources and their production rate. When it comes to the usage of energy and CO2 emissions, Nouzil, et al., (2017) states that automation in industry is not environmentally sustainable; the amount of energy used needs to be reduced and so do its emissions, which are approximately the 24% of the total CO2 emitted. On the other hand, a positive aspect of automation is the waste management; reducing waste by dealing with recycling in industry, including agriculture. Another important aspect is the reduction of chemicals used, as the precision of a machine surpasses a human worker, the usage of pesticides is reduced since it will only be used exactly where needed. As mentioned in Chapter 1, this work makes use of a FarmBot, its use is not only helpful for waste reduction, using resources such as water and fertilizers in a more efficient way and pesticides only if needed, but also with CO2 emissions. According to estimations done by FarmBot Inc., (2018) the CO2 emitted to produce a FarmBot is between 100 and 150kg, and the yearly CO2 emissions caused by its use is only of approximately 60kg. Furthermore, the existing possibility of powering the FarmBot with solar energy also reduces the CO2 emissions (FarmBot Inc., 2018).

B. Economic sustainability

Economically speaking, sustainability refers to the most optimal use of the existent resources in order to attain economic growth. Automation has increased gains for the industry by increasing productivity and accuracy. The cost of this technology has been reduced since its beginning, but it is still a high investment for small entrepreneurs. Nevertheless, economic sustainability is guaranteed.

The economic sustainability of this study related to FarmBot can be based on its return on investment. FarmBot Inc., (2018) estimates a period of three years for its products, comparing the costs of producing FarmBot grown products against the costs of store-bought products.

C. Social sustainability

Social sustainability cares for health and wellbeing of humans. Nouzil, et al., (2017) talks about how the introduction of automation in people’s daily life aims to improve human quality of life and reduce safety risk by replacing manual work in repetitive and dangerous tasks by autonomous systems. Even though it seems like this technology only brings benefits, nowadays it is one of the most discussed dilemmas since many may say it only causes unemployment and others that it creates new jobs opportunities.

FarmBot also improves quality of life, by reducing the amount of necessary human supervision needed on orchards. With this technology no jobs are substituted since it has been developed for personal use instead of industrial. In this paper, besides FarmBot, social sustainability also focuses on the reduction of time a person needs to control the weeds; this job will be simplified by the use of a computer only needing human intervention to take out those detected weeds. In a larger scale if weed elimination was totally automated this would suppose some job loss, but the workers could be relocated by taking care of the maintenance and supervision of the robots used to do that elimination.

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- In addition to the three sustainable development pillars, this paper also tries to achieve some of the 17 sustainable development goals. The ones that are most related and relevant are explained below:
- Quality education since the FarmBot will later be used for educating farming students
- Industry, innovation and infrastructure introducing the new technology of artificial intelligence into backyard robots
- Responsible consumption and production as the FarmBot is used to grow food for the personal consumption reducing overconsumption

4. Solution for development of prototype

The main focus of this research is the training of a neural network in order to differentiate crops and weeds. To achieve this, MATLAB is used as the principal programming software for the image processing and the network training. Other software such as Python and FarmBot are needed to help with the acquisition of images. To store the pictures, the computer storage is used as well. The following image (Figure 2) shows a representation of how these software are connected:

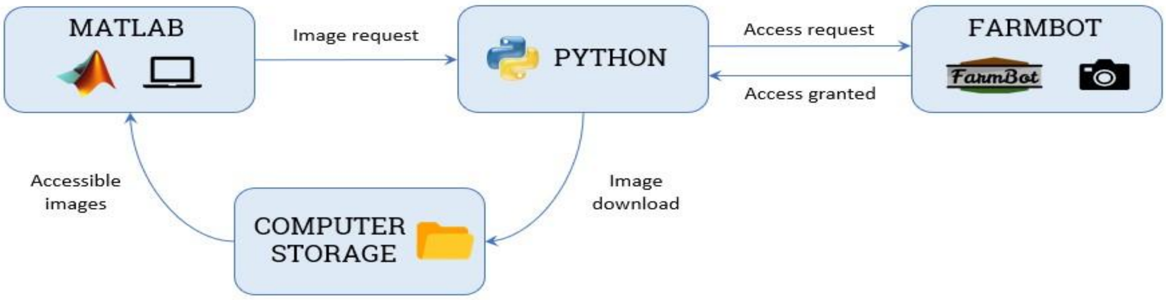

Figure 2: System overview

In Figure 2, each block has its own functionality, being all of them crucial to the development of the work. To have a deeper understanding of each point, they are explained bellow.

MATLAB is the principal software of the system. It takes images as its input, processes them to improve their characteristics and finally trains and evaluates an ANN with those images; the ANN correctly trained is the output of the program. The trained network will be later used to detect crop and weed from any picture.

The images used are the ones captured by FarmBot; to make this possible, the first step of the MATLAB programming is the acquisition of those images by executing a Python code.

- Python works as the intermediary between MATLAB and FarmBot. Once it is executed, it connects to FarmBot REST API and requests access to download the pictures taken by the robot. After the access is granted, the Python code downloads those pictures into the computer where MATLAB is running in order to make them accessible.
- FarmBot is the only source of image capturing for this work. The robot is programmed on its UI in order to take the needed pictures, which are stored waiting for the python code request to access them. FarmBot is also used as a comparison source for the results, comparing the accuracy and characteristics of its own weed detector software with the one developed.
- All the downloaded images are stored in the Computer Storage, where they will be accessible for MATLAB to retrieve them.

The work has been developed using three different software, therefore there are three different codes that, linked together, conform the final work. For the initial design of the work, a prototype for each code has been created accordingly to the expected function of each software.

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The programs chosen were the FarmBot software, MATLAB and Sublime Text 3 as a Python programming environment. The FarmBot UI was used because it is the programming interface from where the robot and the camera used can be controlled. As the pictures taken are stored in the FarmBot REST API, to access them easily Python was chosen following the advice from this study supervisor and some posterior research. Finally, MATLAB was chosen as the main program because of previous experience working with this software, and the great amount of available information resources.

To choose the pre-created ANN for this study was carried out in the literature review. AlexNet was the chosen network, due to the accuracy shown in various papers similar to this paper. From the literature review it was also decided that image classification was a suitable method for the identification of crops and weeds.

Finally, for the network training, the pictures used were not only from the FarmBot but also from pictures taken onsite with other cameras. Those pictures were used to prevent a lack of time while developing the work, in fear the crop or weeds would not grow on time.

The development of the final work has been done based on the prototype previously explained in Chapter 6. As the prototype results were not as good as they could have been, some changes have been done to it in order to achieve better results, these modifications lead to the final work and it is going to be explained in this chapter.

The modifications, in order to have an overview of all the changes, are the following:

- The number of photos taken by the FarmBot has increased from 25 to 54.
- In Python, a command to erase older photos has been added in order to work only with the latest pictures.
- In MATLAB there have been two big changes: the introduction of pre-processing techniques to the pictures in order to improve their characteristics, and a change of network from a CNN to a RCNN to perform object detection instead of image recognition; therefore, all the MATLAB code has been updated.

The aim of this paper is to study a weed detection system able to differentiate between crops and weeds using neural networks. To make the study more specific, a crop and two different weeds have been chosen, spinach as crop and dandelions and cleavers as weeds; these can be seen in Figure 3. This means that the neural network of this research will differentiate spinach (circle 2), dandelions (circle 1) and cleavers (circle 3).

Figure 3: Crop and weeds chosen for this study

The structure of the study is the same as in the prototype. It has three phases: the picture taking done with FarmBot's software, the image download done in Python and, finally, the image processing and network training done in MATLAB. Every part is going to be explained taking into account the modifications previously mentioned.

FarmBot is the main source of picture taking, by using the Logitech camera attached to the robot, it is programmed on its UI in order to take photos of the field. Every picture has dimensions of 385x280 mm and the field 1575x1320 mm (Figure 4), therefore 54 photos are taken.

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Figure 4: FarmBot's field dimensions

The number of pictures taken has been increased from the prototype, then the number of movements the robot must do has also changed. In the programming this is reflected as an increment on the number of different positions the robot has to achieve, and as consequence, the number of commands sent to it.

The code follows almost the same sequence as before, changing just the number of times it repeats each sequence and the distances it moves (Figure 5). The robot is sent home to {0, 0, 79} where 79 mm is the height from where all the pictures are going to be taken. Then, until the robot arrives to the end of the first row (Y axis), it executes five times the picture taking and moves to the next position in that axis. When it arrives at the end of the axis, a last picture is taken, and it moves to the beginning of the next row. This is done nine times, moving over the whole field and taking pictures of it. When it arrives to its last position, it takes the last photo and moves straight to the home position again, ready to start over.

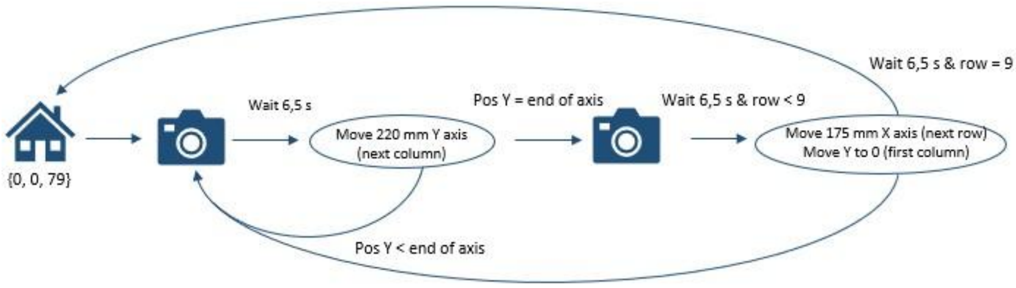

Figure 5: FarmBot's sequence diagram

As MATLAB is the core programming environment for this study, it is the most different from the initial design shown in Chapter 6. The main change to highlight is the switch of approach for the plant recognition from image classification to object detection. The prototype was based on taking a picture and classifying it, object detection on the other hand studies the contents of the image and recognizes and classifies each element. To do this the concept of RCNN is introduced.

RCNNs work different than CNNs in a way that it first extracts region proposals from the given images, and then classifies each region as a CNN would do with a normal image. The final result of this detection is a bounding box corresponding to the object location within the image, as well as its associated label, which determines the class the detected object should belong to.

In this subchapter, a quick update on the MATLAB code is presented to understand how the program has been developed taking into consideration all the changes made. This update involves the image processing, the network training and the plant detection.

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5. Limitations

To establish the boundaries during the development of the work, some factors will be taken into account. The FarmBot programming will not go further than the basic programme needed to take pictures wherever it is necessary. The ANN to be used will be a previously created network available on MathWorks community, it will not be created from the beginning in this paper, only the last layers will be modified, and then the network will be trained. This paper will be developed to differentiate between crop and weed with MATLAB in order to evaluate the differences between MATLAB's ANN and Raspberry Pi's ANN. The crop and weeds used in this work will be grown in Sotasen, being the crop specifically spinach and the weeds dandelions and cleavers.

Some hardware limitations can be found on the development of the work, such as the camera resolution or the computer characteristics. The camera resolution will limit the quality of the image, which interferes with the final result of the image processing stage. The computer characteristics will affect the ANN training speed. These characteristics will determine the accuracy of the work, so the better they are, the more precise the results will be.

6. Conclusion

In conclusion, the study in this work has successfully achieved the principal aim set in Section 1.3. The principal aim of this thesis was the study of a system able to identify crops and weeds using ANNs with images captured by the FarmBot, which will later be compared with FarmBot built-in weed detector. The accuracy obtained is not of a 100%, but the network differentiates well enough the different type of plants it has been trained on. Therefore, the main aim of the thesis is considered as accomplished.Through the awareness step of the methodology,and this study gives an initial idea of how to obtain the images with FarmBot and Python, and an as well as a possible approach to the network training and testing.

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