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Using Edge AI in IoT devices for Smart Agriculture: Autonomous Weeding

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Abstract

This paper presents the evolution of a vision system dedicated to automatic weeding, initially implemented on a NVIDIA Jetson Xavier board. This evolution aims to take advantage of a new computing board able to implement efficient artificial intelligence oriented computations, keeping a low power consumption, and a low cost, developed in the ANDANTE project. The paper presents the automatic weeding tool, the existing vision system and the weeding data used to train the system. It also describes the specifications of the new board and the adaptation needed in order to integrate the previous algorithm in this new board. The results obtained during the first step of this integration are presented and compared to those obtained with the previous vision system. These new results are encouraging and rich in lessons for the future.

Keywords: edge computing, precision agriculture, smart agriculture, automatic weeding, image processing, deep learning.

6.1 Introduction

Agriculture has to face many challenges in the 21st century. With the increasing artificialization of land and the augmentation of the global population, we have to produce more food using less surface. Another challenge in order to

preserve our natural resources and soil quality for agriculture, is to produce differently, with less inputs (fertilizers, phytosanitary products, herbicides...). In addition, climate change has a huge impact on production, yields, water availability and many more aspects.

To address those challenges, several solutions can be proposed, among which are smart farming, the usage of digital technologies in agriculture and precision agriculture, which can be summarised as applying to the crops the appropriate action, at the best moment, and at the right place and quantity.

In order to make those improvements in crop management, two key technologies can provide a significant help: in-field connected sensors and robotic processing of the crops.

In-field connected sensors have proven to be very useful for collecting data on the plots (vegetation index, soil composition, weather parameters...). These data are then processed and integrated in decision support systems to help the farmer manage the crops. Installing sensors in the field is not an easy task: outdoor conditions require robust material that can resist moisture, dust and shocks. Moreover, access to a power supply is not practical, so it is important to have low consumption devices, which limits the processing power available. Cloud computing could offer a solution: the sensor sends the data via internet in order to process it on a server. However, internet access is often limited in the fields and the amount of data can be large (images or videos). Another solution could be to use a long-range technology such as LoRa or SigFox. However, those technologies have a limited data rate and can't support huge amounts of data to send in the cloud.

Edge computing is a promising alternative, with the possibility to make computing on board, dramatically reducing the amount of data to be send (only the results), via LoRa for example. This makes it possible to use a connected sensor even in areas with poor network access. It also allows to reduce the power consumption involved in the communication in case of large amount of data. However, this latter advantage can be neutralized by the energy cost of the calculations carried out on board.

In the case of robotic processing of the crops, embedded sensors are necessary to provide real-time data to the system so that it can implement the operations needed to process the culture. This real time constraint favours the edge architecture, avoiding loss of time in data transfer and reception of results, especially for significant input data quantity (image or video).

In both cases, the constraints are similar: processing signals, images or videos of natural scenes require complex computations; the return on investment expected for the farmers limits the cost of the technologies used,

and the lack of availability of both network and energy imposes a certain electrical and communication frugality. Therefore, the edge architectures to be deployed in such use-cases must rely on low-cost circuits, capable of implementing the most efficient algorithms – such as deep learning based neural networks – with low power consumption.

The purpose of the European project ANDANTE is to create such circuits and to test them in various real-life situations, among which smart agriculture use cases.

In this paper, we will focus on a specific smart agriculture device: a mobile vision system dedicated to the perception task of an automatic weeding tool for market gardening (BIPBIP).

The paper will be organised as follows: Section 2, “Material and methods”, will describe the system. Section 3, “Reference results” will show the results obtained before the integration of ANDANTE circuits. Section 4 will show some results already obtained and will discuss the next steps.

6.2 Material and Methods

6.2.1 BIPBIP: the automatic weeding system

The automatic weeding use case within the ANDANTE project was based on the BIPBIP system developed in a previous project [1, 2]. BIPBIP is a precision weeding module designed to weed maize and bean crops in the intra-row without using any phytosanitary products. The state of the art of the weeding systems is illustrated in Figure 6.1.

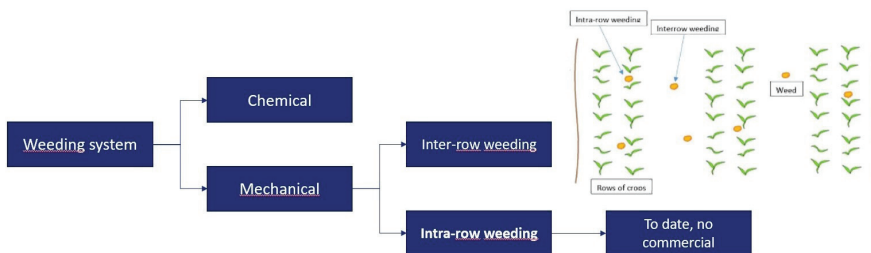


Figure 6.1 State of the art of the weeding systems.

To date, commercial intra-solution mechanical weeding solutions exists like the IC-weeder Lemkem [3], the RoboCrop InRow from Garford [4] or even the Robovator from VisionWeeding [5]. Those solutions are adapted

for lettuce, cabbage, celery etc, that are crops with higher distance between two plants, as opposed to beans and maize, that have small inter-plant gap, making the intra-row weeding more challenging (geometric precision, leaf overlapping, weed and crop closer and more difficult to differentiate, etc.)

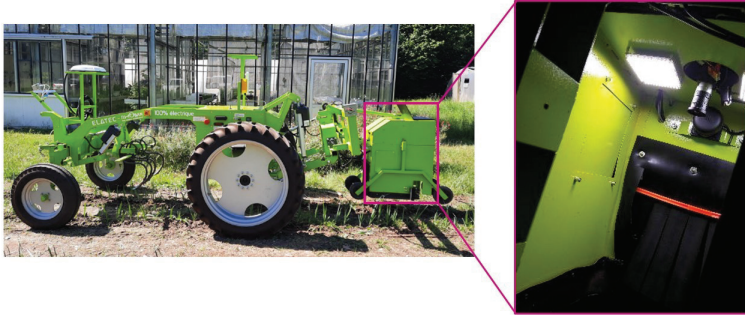


Figure 6.2 Left: BIPBIP weeding system behind a robotized tractor. Right: Inside BIPBIP, the camera and the lighting system [2].

BIPBIP is composed of a vision system that detects crops and locate crop stems and of a mechanical weeding tool (Figure 6.2 left). It targets market gardening crops such as bean, and field crops with large intra-row spacing such as maize. A similar vision-based approach is described in [6] but on lettuce and in laboratory conditions. Other approach exists like GPS-based weeding on tomato crop [7] but won't be integrated in our use case.

The system speed is 0.5 m/s. The mechanical weeding tool is composed of a metal tip that scraps the soil to remove all weeds without distinction around each plant of interest. Therefore, detecting weeds is not required for hoeing, only the crop stem positions need to be known as they are the only part of the crops to be avoided by the mechanical weeding system.

6.2.2 BIPBIP vision system

This crop detection system of the weeding module should operate in real-time and provide the stem position of crops with a great location accuracy which is required for the precision hoeing process. It is mainly based on one detector to identify the crop of interest and a second one to locate precisely its stem. These two detectors are intended to be transferred to the circuits developed in the ANDANTE project.

The initial implementation was done using a 3 megapixels RGB camera which can capture images at a rate of 15 frames per second. The camera is

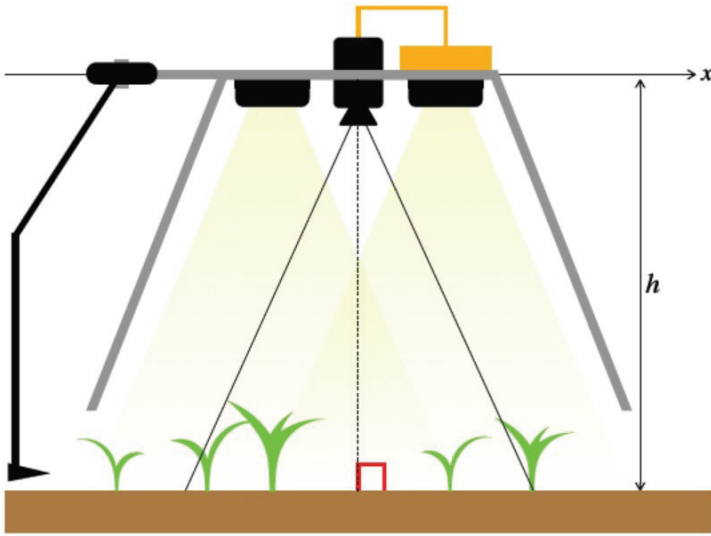


Figure 6.3 BIPBIP weeding module. The mechanical intra-row hoeing tool is represented by the rod on the left, the computing system in yellow, the two LED panels and the camera in black inside the vision chamber (in gray) which allows to isolate the vision system from changing light conditions [2].

confined in a hull avoiding natural lighting. Light conditions are controlled by 2 LED panels (Figure 6.2 right, Figure 6.3). The images are processed in real time on an NVIDIA Jetson Xavier which should be replaced by the ANDANTE board when available. The algorithms are developed in Python and deployed in C++ for faster processing speed. The software framework used for the neural network inference is written in C++ and CUDA. The detectors implemented in the weeding tool were based on a convolutional neural network YOLOv4 [8]. This model was chosen for its accuracy and speed. Indeed, the weeding operation needs to be very precise as the farmers cannot afford to lose a significant percentage of the crop during the weeding. Besides, the detection needs to be fast, as the image needs to be processed between the image acquisition and weeding operation. This allows a processing time on the embedded device within 50ms.

Regarding the training of the network, we used 4 databases (2 for maize and 2 for bean) composed of 15 fps videos saved as consecutive frames. These databases were annotated with bounding box ground-truths to provide labels for the neural network training and for the evaluation. The crop bounding

Table 6.1 Number of images and annotations for each crop.

Label	Images	Crop annotations	Stem annotations
Maize	1 034	2 095	2 133
Bean	748	2 820	2 824
Total	1 782	4 915	4 957

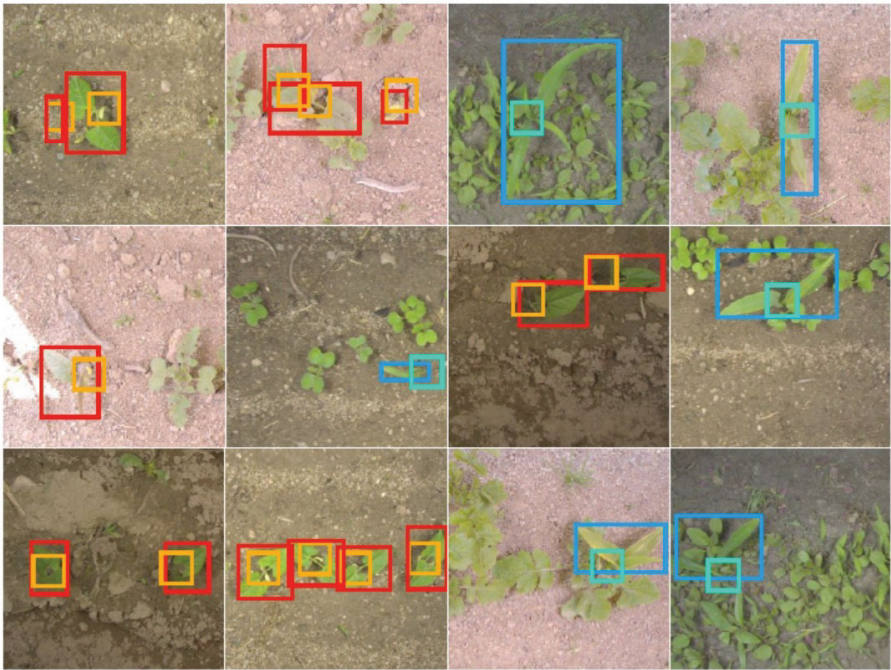


Figure 6.4 Example of annotations on the image database. Maize crops are annotated in blue and the stems in cyan, bean crops in red and the stems in orange [2].

box surround the whole crop (red and blue boxes in Figure 6.4) while the stem bounding box is centred on the stem entry point (orange and cyan boxes in Figure 6.4). Table 6.1 gives the number of images and annotations per crop.

6.2.3 ANDANTE board integration

Our objective is to replace the NVIDIA Jetson Xavier computing system by the IA accelerator board and circuit developed in ANDANTE project, and to evaluate the performances of the resulting system. Figure 6.5 illustrates the

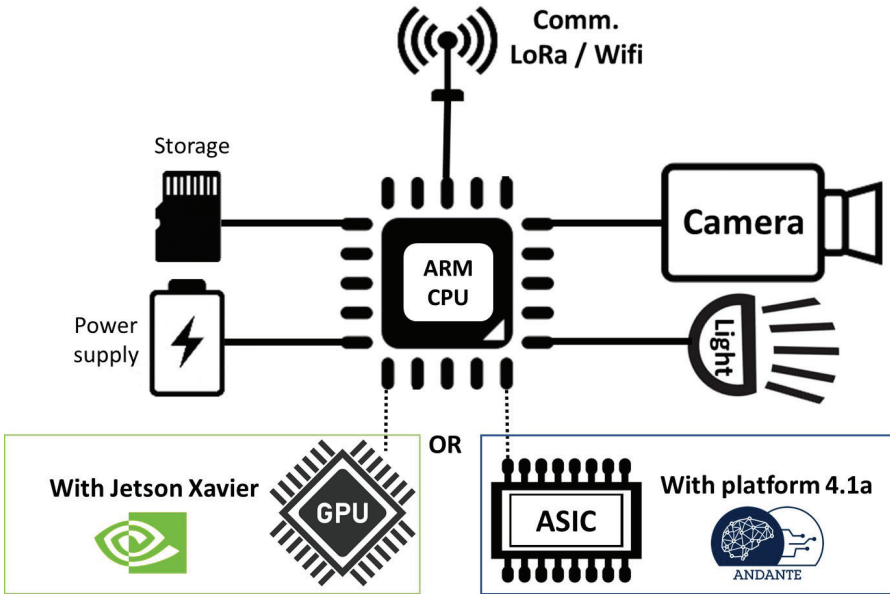


Figure 6.5 Schematic representation of the BIPBIP vision system with both hardware accelerator possible: a GPU for the NVIDIA Jetson case or an ASIC for the platform 4.1a.

future place of the ANDANTE board (*Platform 4.1a*) in the BIPBIP vision system.

The ANDANTE board consists of the NeuroCorgi [9, 10] ASIC and a Kria KV260 FPGA, running the network backbone and detection head respectively. The NeuroCorgi circuit implements a Mobilenet v1 network backbone [11]. The encoder uses hard-coded weights trained on the COCO dataset. The weights are quantized on 8-bit integers to lower the memory requirements and speed up the computation. To keep the possibility to adapt the circuit to different use cases, the FPGA is programmable and is able to run a PetaLinux distribution in order to deploy different software easily. The plant detection is performed by an SSD-Lite type head, providing similar results to the SSD detector [12] with a much lower number of parameters, by replacing the convolution layers by separable 2D convolution. The head of the SSDLite network uses 4M parameters, about half than the full SSD network's 8M parameters. This reduces the memory requirement and the computational cost for the network.

The NeuroCorgi circuit provides access to four layers of the encoder at different scales, to provide data at different levels of encoding. The output

layers are taken right before the down-sampling operations (max pooling). This allows the network head to access features of various resolutions and complexity.

6.3 Reference Results

In this section, we focus on the results obtained in the initial version of the BIPBIP vision system, with the NVIDIA Jetson board in order to get reference for comparison with the future vision system with the ANDANTE board. To date, the results of the ANDANTE board are from a simulated environment, with the SSDLite running on a classical computer. We split the image database in a training set and a validation set with an 80%-20% ratio.

In terms of power consumption, the current system work around 30W. In the case of the weeding platform, power consumption isn't a critical point. Having a system consuming less power, like the ANDANTE platform, is much more beneficial regarding energy sobriety and transferring for other IoT devices such as in field sensors for which it provides a much higher autonomy.

Table 6.2 Detection performance (%) and inference speed (fps) for Yolo v4 on the NVIDIA Jetson Xavier including video acquisition and post-processing for each crop.

Network	AP	AP ₅₀	AP ₇₅	mIOU	FPS
Yolo V4	53.87	89.71	54.59	80.96	13
SSDLite	51.6	84.6	52	80.5	N/A

Table 6.2 shows the performance using AP0.5:0.95 (AP), the AP50, AP75, AR100, the mean Intersection over Union (mIoU) [13] and the inference speed in frames per second (FPS). The YoloV4 results previously obtained gives us a reference for this use case. We can observe similar results with the SSDLite, which is satisfactory but on condition of an acceptable inference speed. However, as the SSDLite is running in a simulated environment, it isn't relevant to measure the number of FPS for this network. When available, the processing speed should allow at least 10 FPS.

Detailed results can be found in [1, 2].

6.4 Work in Progress and Future Work

6.4.1 Work in progress

Since the ANDANTE *Platform 4.1a* is not yet available, our network architecture described in section 1.2 has been implemented and tested using the

available development tools. The Mobilenet-based SSD detector was implemented using the Pytorch library, with separate classes for the backbone and the detection head. A simulator for the NeuroCorgi circuit was implemented on the N2D2 platform [14], which is a deep learning framework for creating artificial neural networks intended to work on constrained environments. The SSD network head was translated for the Kria KV260 FPGA using the VitisAI library.

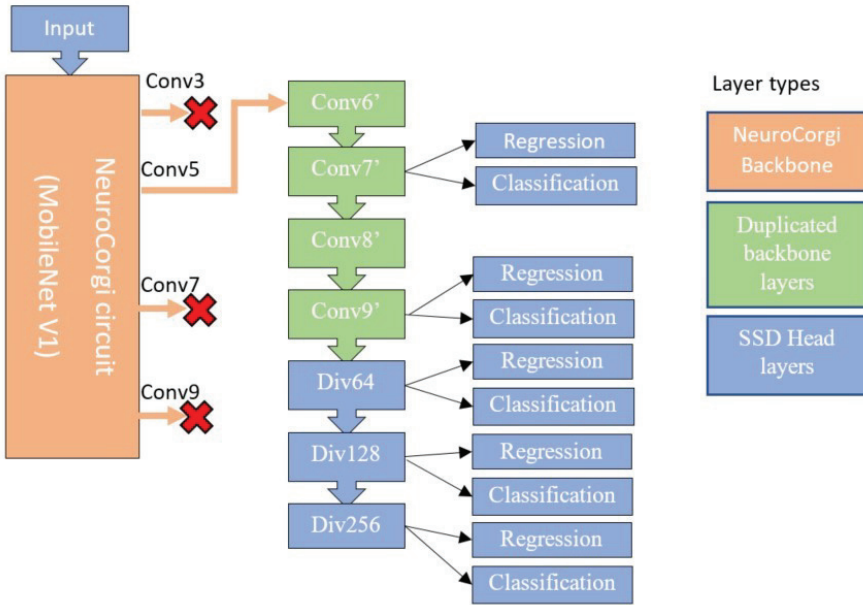


Figure 6.6 The adapted network architecture used for this application. The figure presents how the duplicated Mobilenet layers and the SSD head are connected to the NeuroCorgi backbone.

Some modifications to the network structure were necessary: as the training database for the encoder contains few examples of plants, the initial detection results were inadequate. Duplicating some of the encoder layers on the FPGA and making them trainable improved considerably the detection accuracy. The resulting network architecture is presented in Figure 6.6.

Table 6.3 shows the first results from the proposed architecture (these results are expressed in terms of loss function but the precision performances will be available soon). These results are promising, even if the SSD architecture is less precise than the reference Yolo V4 network. They also show

that it is necessary to use at least a partially retrained backbone. However, the improvement after retraining the first layers is marginal.

Table 6.3 Detection performance (loss function) using the new architecture.

Network training	Loss on SSD	Loss on SSD Lite
Head only	3.8	4.6
Partially retrained backbone	1.8	1.9
Retrained backbone	1.5	1.7

Figure 6.7 presents examples of detection obtained by the reference system and by the proposed network.

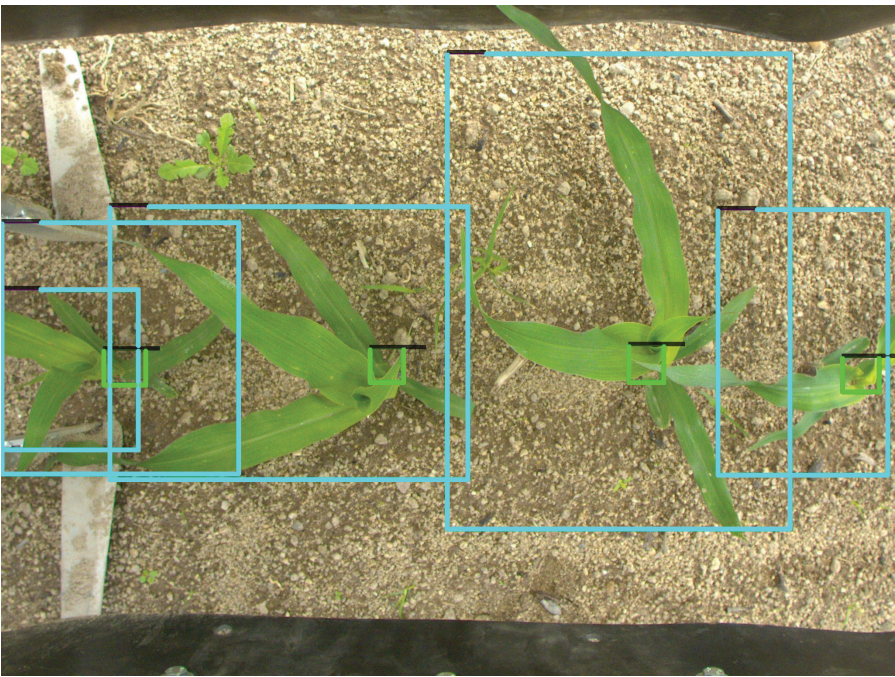


Figure 6.7 Results from the Yolo V4 network (left) and the proposed SSD network (right) on maize. Blue rectangles show the plants. Green rectangles show the stem locations.

6.4.2 Future work

The two parts of the network are currently being transferred on the *Platform 4.1a*. The performances, in terms of accuracy, processing time and power

consumption will then be measured and compared to the reference (NVIDIA Jetson Xavier board). If the accuracy and computing time are adequate, the implementation inside the BIPBIP weeding system will then be possible, allowing field testing.

6.5 Conclusion

In this paper we presented a vision system for automatic weeding (BIPBIP platform), and described the objectives and the progress of a project to evolve this vision system, through the integration of an Artificial Intelligence oriented computation board with low cost and low power consumption (ANDANTE project).

The existing vision system (BIPBIP) should allow easy hardware integration by replacing the NVIDIA Jetson Xavier with the new circuit. However, an adaptation of the Convolutional Neural Network model appeared to be necessary. Encouraging simulations have shown the overall feasibility of the transfer, and have been very informative, particularly about the need to adapt the initial architecture of the circuit to achieve the expected precision performance expected for weed control applications.

Furthermore, the availability of the new ANDANTE circuit makes it possible to address other “smart agriculture” use case such as a fixed vineyard monitoring vision sensor. The integration of the new ANDANTE board, even in its current architecture, should make it possible to improve the very simple vision processing algorithms carried out on board the existing prototype, while keeping a low power consumption inherent to this type of device, thus allowing to extend its uses.

Acknowledgements

The ANDANTE project has received funding from the ECSEL Joint Undertaking (JU) under grant agreement No 876925. The JU receives support from the European Union’s Horizon 2020 research and innovation programme and Belgium, France, Germany, The Netherlands, Portugal, Spain, Switzerland. www.andante-ai.eu.

The BIPBIP project has been funded by the French Research Agency (ANR) (grant ANR-17-ROSE-0001 - BIPBIP) and has been supported by the organizers of the ROSE Challenge and all the partners of the BIPBIP project.

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