Precise Weed and Maize classification through Convolutional Neuronal Networks

Andrea Concepción Córdova Cruzatty *, Mauricio Daniel Barreno Barreno † and José Misael Jácome Barrionuevo‡
Department of Energy and Mechanics, University of the Army ESPE
Latacunga - Quijano y Ordoñez and Hermanas Paéz
Email: *accordova@espe.edu.ec, †mdbarreno@espe.edu.ec, ‡jmjacome1@espe.edu.ec

***Abstract*—Deep Learning has played a very important role in modern times, being very used in artificial vision and especially in pattern recognition, which opens many doors in the fields of application among which is agriculture of presicion. In this paper we present the study of a convolutional neural network applied to the classification of plants of maize and weeds in real time, directed to fields of maize in its initial stage. The algorithm has two stages, segmentation of images and classification. In the segmentation it is sought to separate from the image the plants individually. While the classification is given through the convolutional neural network, previously trained with a dataset generated through the segmentation stage.The performance of the network is illustrated by analysis and comparisons with different network architectures, then with the network that presented better results, we experimented by modifying its number of filters, to analyze their behavior. Finally, the resulting network was tested on different processors to compare classification times.**

I. Introduction

During the last centuries, huge progress has taken place in science and technology developments. Significant milestones such as Communications, Numerical Computer Control and the miniaturization of components have benefited social and industrial sectors on its approach to solve specific problems.

Globalization has permitted countries who are not leader technology developers, like Ecuador, to receive bleeding edge technological products in order to satisfy requirements and propose solutions to still-unresolved problems.

Industry transformation is a science evolution example; manufacturing, food, and information industries, among others, are signs of this industrial revolution. However there are fields still unexplored in Ecuador like agroindustry. Agriculture in Ecuador has not changed much since precolombine times; while it is true that there are efficient agriculture practices, the lack of technological resources make it impossible for the country to exploit its true potential as an agricultural producer.

Nowadays, one of agriculture challenges is the development of precision agriculture techniques focused on Weed and Crop segmentation. There are studies that show the impact of Weed in corn crops [1]; its yield is affected by 5000 kg/ha. Currently, growing development of Artificial Vision and Machine Learning algorithms allow researchers to propose solutions for Weed Segmentation in Crops.

One of the first approximations to the algorithms of detection of Crops was developed in 1996[2], this algorithm permitted to segment crops from weed, it could be possible by the use of IR Images, the image is processed by a hysteresis umbral and the method of Min Neighbouring to identify the row of crops. In recent years the implementation of Machine Learning has opened new possibilities for differentiate the Weed from the crops, recently [3] there had been developed an algorithm by the use of Harris Corner detector, Feature Detector and using the DBSCAN (Density-based spartial clustering of apllications with noise) , it demonstrates an effectiveness of 98% in the identification of Weeds in the Rice, Araguez *et. al* [4] performed their segmentation through the analysis of the green hystogram and performing the segmentation of the crop and weed by classifiers not specified in the document.

Hong and Lei [5] developed their approximation by using an optimal method for detection in various types of luminosity, they achived this by the use an ANN for weed and maize classification, with a precision of 92.5%, also there had been developed [6] through binarization methods of OTSU and Watershed for the segmentation of the images, while the classification was given through a areas analysis to perform a thresholding, although the method is computationally effective when the Weed distribution does not resemble the size to the crop plant, its error increases when there is more density of crop than of weed. Romeo *et. al* [7] propose to use a fuzzy clustering approach to correctly segment the crop green and the same algorithm to classify the soil crop.

The segmentation of weed and crops is not closed to color images, using a multispectral camera [8] permitted to obtain RGB and NIR images, for the segmentation and classification, then the images used a light CNN for the first process and a Deep CNN for classification in Crops, its accuracy is up to 98% in the identification of weeds. One of the most dificults things for the identification of crops is the generation of Datasets due to presence of Weed in the images of training, but there could be correctly generated by a Convolutional Neural Network [9] achieving a acceptable accuracy for the generation of Datasets

II. Matherials and Methods

The development of the model for the weed and maize detection algorithm using convolutional neural networks is described below.

A. Hardware

For the training and image capturing stages, the following elements were used: a Raspberry Pi 3 with Pi Camera V2.1 for image recording, it was configured to obtain a video at a resolution of 640x480 pixels in order to improve the performance of image processing. Due to the popularity of the GPU computing, it was neccesary to consider hardware compatible with Parallel Computing like the Graphic Cards manufactured by NVIDIA, they have the advantage of better times of processing compared to CPU, in order to optimize the time of image processing and training of Deep Learning Models, so we used a Computer with a Nvidia Graphics Card GTX950M.

B. Software

For the application in this documents requires the use of powerful libraries of Image Processing and Deep Learning Development, we considered to use Open Software for extend its use in future prototypes, due to this considerations we had chosen the OpenCV library for its computational efficiency and focus on real-time application [10] in this case, it was used for acquisition and segmentation of the sample images. Also we had considered Caffe because it is intended to use in training and developing general-purpose Convolutionals Neural Networks and other Deep Lerning models [11] with fully support of CUDA GPU Computation and a generous database of resources for learning,

Also in the development stage was important the use of Linux OS , its features are: lightweight and free OS also fully compatible with the software mentioned above. For the main computer was used Ubuntu Linux 16.04 for its official support to CUDA, Caffe and OpenCV, also in the Raspberry Pi we used the Pixel OS for acquire images and processing of the CNN.

C. Dataset Description

Due to the lack of datasets of Weed and Maize plants, it was neccesary to search crops of maize in its initial stage, for that purpose we had traslated to Píllaro, it is a city located in the Tungurahua Province on the center of the the Ecuadorian Highlands region, Píllaro is recognized producer of Andean Crops such as: Maize, Potatoes and Fruits so here we could find many crops of Maize useful for our purpose.

¡¡¡¡¡¡¡ Updated upstream Samples were obtained from images captured in those maize fields, we considered to choose maize crops where we could visually discriminate the plants of the crop and the weed. Maize in stages V3-V7(3-7 leafs) [**?**] were used to take samples. To record the samples we centered the camera insuring that the capture shows all features of the maize plant, it was possible by monitoring the get of samples by an external display. An examples of the images captured are shown below. ======= Samples were obtained from images captured in those maize fields , we considered to choose maize crops where we could visually discriminate the plants of the crop and the weed. Maize in stages V3-V7(3-7 leafs) [12] were used to take samples. To record the samples we centered the camera insuring that the capture shows all features of the maize plant, it was possible by monitoring the get of samples by an external display. An examples of the images captured are shown below. ¿¿¿¿¿¿¿ Stashed changes

Fig. 1: Crops chosen to obtain samples, notice that it is easy to discramante weed from maize

Then, through a digital image processing, the images were segmented to differentiate them from the soil and other non-plant elements, then the images were masked to provide the dataset features of color of the Maize and Weed. Once the segmented images were obtained, they were removed those that had a resolution lower than 64x64 pixels, because it's smaller than size of input layer of the network, besides it was not convenient its processing since its total area was much smaller than the samples of corn, which is the purpose of this document.

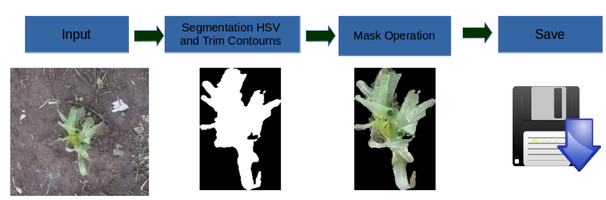

Fig. 2: Preprocessing to obtain samples for the dataset

To highlight we had labelled the samples manually in two classes. In the following image we present the final results of the processed images that conform the dataset.

Once we completed the processing of the images were obtained 2369 images of Maize and 632 images of Weed, **Seng**

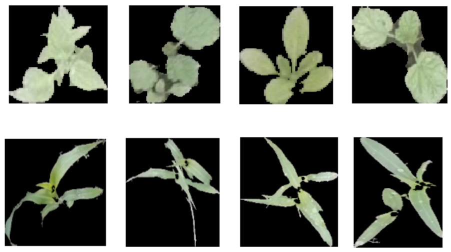

Fig. 3: Segmented and Masked images of dataset Above: Weed, Below: Maize

[13] said that once CNN has reached an acceptable accuracy, the dataset could extend by Geometric Transformations, in addition [14] they measure that this allows to reduce the overfitting and to improve the presicion in the training, reason why we use rotations that go from the 30 to the 330 degrees in steps of 30, obtaining in this way to increase the date for 12 times and have better chances of recognizing plants that are in any orientation.

For the Validation Phase, we had chosen randomly a fifth part of the total images of each class, so we have the following chart with the distribution of the dataset.

Phase	Train	Validation	Test	Total
Maize	7581	1895	787	9476
Weed	2023	505	300	2528

TABLE I: Distribution of the Dataset of each class

D. Convolutional Neuronal Network

After the last step have been terminated, it is neccesary classify the images of Maize and Weed, a high accurate method of Image Classification is Convolutional Neuronal Networks(CNN), those models are complex but efficient with a highly rate of discrimination and its demostrated that they have good results in Image Classification, Object Detection and Fine-Grained Classification [15]. Their are also applied in Precision Agriculture [8] for the correct identification of plants.

One of the characteristics of the CNN is that they can have multiple architectures, each architecture can reach different result depending of the application , for the present document we have considered four CNN architectures: Two models were chose of the Caffe Zoo Model(it's a free resource provided by Caffe Developers), LeNet and AlexNet also Potena and Nardi had used two additional types of Models, sNET and cNET, they were sucessfully proved in identification of plants in crops[8], with the Nets chosen, each one was trained with a same Solver of type AdaDelta and with the same dataset, the results of training are the following.

Inside of the shown parameters in the Table table:2, we considered the net who achieved the highest rate of accuracy

Parameters	LeNet	AlexNet	cNET	sNET
Input size of images	32x32	64x64	64x64	64x64
Layers numbers	9	11	8	4
Number of parameters	652500	20166688	6421568	135872
Iterations	3000	3000	4500	3000
Accuracy(%)	78.84	95.266	99.33	90.4
Loss(%)	44.8471	12.7256	5.86	781.3

TABLE II: Distribution of the Dataset of each class

and lowest rate of loss, clearly the cNET is the chosen due it shows a precission equal to human classification. The following picture shows the process of training of the cNET
Inside of the shown parameters in the Table III, we considered the net who achieved the highest rate of accuracy and lowest rate of loss, clearly the cNET is the chosen due it shows a precission equal to human classification. The following picture shows the process of training of the cNET.

Although results given for the net are excellents, one of the main purposes of this paper is the implementation in real time, so the number of parameters to be computed must be a problem, so we considered to modify the net in order to improve the processing time. To achive this, it was neccesary to reduce the number of filters from 64 to 16, this permitted to reduce the number of parameters to 1651376(it's a 25% of parameters than the original net), and what about the precision of the net, it was slighty affected but it reach a 97.2% of accuracy, the results of the processing will be explained with more detail in the next section.

III. Test

For this stage, we considered an extra dataset with 200 images of maize plants and 203 images of weed, the results were comparated between cNET with 64 and 16 filters, each one would be

GPU			
cNET	% Accuracy Weed	% Accuracy Maize	Average time of classification
64 Filters	81.6	88.36	2.34 ms
16 Filters	85.71	87.13	951 μ s
CPU			
	% Accuracy Weed	%Accuracy Maize	Average time of classification
64 Filters	81.6	88.36	51.6 ms
16 Filters	85.71	87.13	17.23 ms
CPU Raspberry Pi 3			
	% Accuracy Weed	%Accuracy Maize	Average time of classification
64 Filters	81.6	88.36	615 ms
16 Filters	85.71	87.13	161 s

TABLE III: Test

IV. Conclusion

In this paper we have studied the application of Convolutional Neuronal Networks for Classification between Maize and Weed Plants, for that we have used some CNN

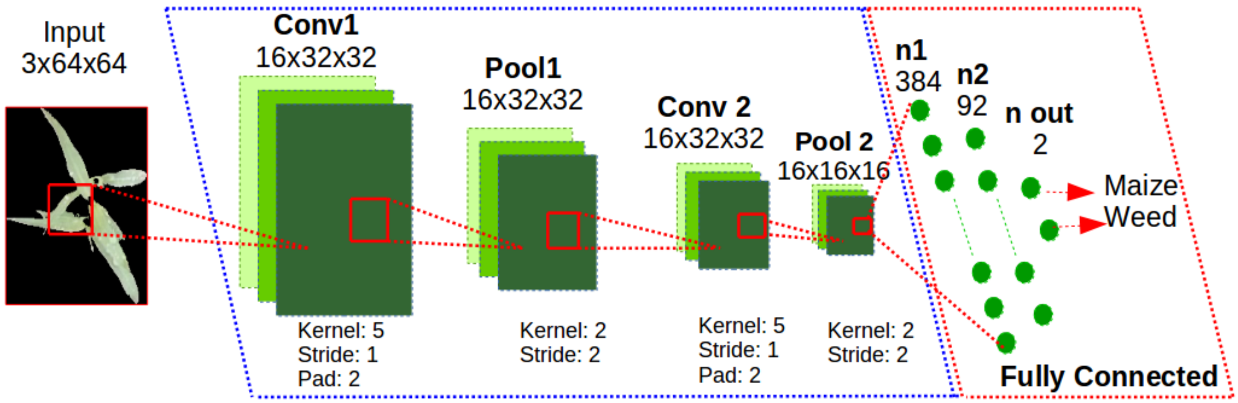

Fig. 4: The schematic of CNet

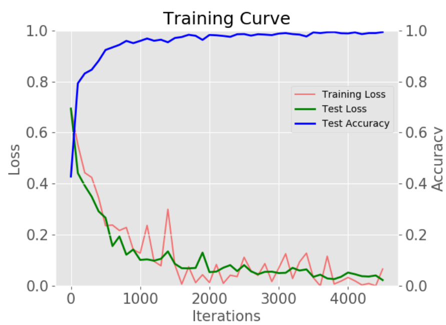

Fig. 5: Graph of the Training Process

Architectures, the Network with best results in precision was cNET, with a 99.33 % of accuracy of training, using a dataset of both classes of 44580 segmented images.

In order to search a right processing to work in real time, we have experimented to reduce the number of filters of the Layers of the Net from 64 to 16 filters, achiveiving to reduce the number of parameters to be computed during the classification , we obteined a classification time 2.5 times less than the original Net of 64 filters , this change had a small impact in the training accuray of the net, it value fell 1 % in comparation with the original net.

Also, by using different methods to classify the images in our experiments, the results showed that the best time of classification was achieved by using a Nvidia Graphic Cards, this is due the Parallel Architecture that this GPU has and also it has fully support for the computation platform CUDA, it demostrated to be 18 times faster than a normal CPU and 170 times faster than a Raspberry Pi 3.

The study demostrated that is better to perform some geometrical tranformations to the Dataset images due it benefits to improve the classification of plants because the plants ever have different orientations in the crop field.

Acknowledgment

The authors would like to thank to the ”Granja Agroecológica y Demostrativa” of Píllaro City and owners of corn crops of the city which allowed us to take samples of plants, to obtain to conform the dataset of the project.

This work has been supported by the University of the Army ”ESPE” Latacunga.

References

[1] R. SUÁREZ and J. P. Y. J. VALLADARES, “Distintos sistemas de escarda en maíz forrajero,” *Producciones agroganaderas: Gestión eficiente y conservación del Medio Natural. Actas de la XLV RC de la SEEP. Gijón*, 2005.

[2] R. Brivot and J. Marchant, “Segmentation of plants and weeds for a precision crop protection robot using infrared images,” *IEE Proceedings-Vision, Image and Signal Processing*, vol. 143, no. 2, pp. 118–124, 1996.

[3] B. Cheng and E. T. Matson, “A feature-based machine learning agent for automatic rice and weed discrimination.” in *ICAISC (1)*, 2015, pp. 517–527.

[4] S. Equipo Técnico, “Proceedings of vii seae congress spanish society for organic farming,” 2006.

[5] H. Y. Jeon, L. F. Tian, and H. Zhu, “Robust crop and weed segmentation under uncontrolled outdoor illumination,” *Sensors*, vol. 11, no. 6, pp. 6270–6283, 2011.

[6] S. H. Hlaing and A. S. Khaing, “Weed and crop segmentation and classification using area thresholding,” *IJRET*, vol. 3, pp. 375–382, 2014.

[7] J. Romeo, G. Pajares, M. Montalvo, J. Guerrero, M. Guijarro, and A. Ribeiro, “Crop row detection in maize fields inspired on the human visual perception,” *The Scientific World Journal*, vol. 2012, 2012.

[8] C. Potena, D. Nardi, and A. Pretto, “Fast and accurate crop and weed identification with summarized train sets for precision agriculture,” in *International Conference on Intelligent Autonomous Systems*. Springer, 2016, pp. 105–121.

[9] M. Di Cicco, C. Potena, G. Grisetti, and A. Pretto, “Automatic model based dataset generation for fast and accurate crop and weeds detection,” *arXiv preprint arXiv:1612.03019*, 2016.

[10] G. Bradski, “The opencv library.” *Dr. Dobb’s Journal: Software Tools for the Professional Programmer*, vol. 25, no. 11, pp. 120–123, 2000.

[11] Y. Jia, E. Shelhamer, J. Donahue, S. Karayev, J. Long, R. Girshick, S. Guadarrama, and T. Darrell, “Caffe: Convolutional architecture for fast feature embedding,” *arXiv preprint arXiv:1408.5093*, 2014.

[12] A. Fassio, “Maíz, aspectos sobre fenología, alberto fassio, ana inés carriquiry, cecilia tojo, ricardo romero,” *Serie técnica. 101.*, 1998.

[13] S. H. Lee, C. S. Chan, P. Wilkin, and P. Remagnino, “Deep-plant: Plant identification with convolutional neural networks,” in *Image Processing (ICIP), 2015 IEEE International Conference on*. IEEE, 2015, pp. 452–456.

[14] S. Sladojevic, M. Arsenovic, A. Anderla, D. Culibrk, and D. Stefanovic, "Deep neural networks based recognition of plant diseases by leaf image classification," *Computational intelligence and neuroscience*, vol. 2016, 2016.

[15] A. Sharif Razavian, H. Azizpour, J. Sullivan, and S. Carlsson, "Cnn features off-the-shelf: an astounding baseline for recognition," in *Proceedings of the IEEE conference on computer vision and pattern recognition workshops*, 2014, pp. 806–813.