Precise Weed and Maize classification through Convolutional Neuronal Networks

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***Abstract*—-Deep Learning ha tenido un papel muy importante en los tiempos modernos, siendo muy utilizado en vision artificial y especialmente en reconocimiento de patrones, lo cual abre muchas puertas en los campos de aplicacion siendo uno de ellos la agricultura de presicion.En este paper presentamos el estudio una red neuronal convolucional aplicada a la clasificacion de plantas de maiz y de mala hierba en tiempo real, dirigida a campos de maiz en su etapa inicial.El algoritmo cuenta con dos etapas, segmentacion de imagenes y la clasificacion. En la segmentacion se busca separar de la imagen las plantas de forma individual. Mientras que la clasificacion se da a traves de la red neuronal convolucional, previamente entrenada con un dataset generado mediante la etapa de segmentacion. El rendimiento de la red se ilustra mediante analisis y comparaciones con diferentes arquitecturas de red, luego con la red que presento mejores resultados, se experimeto modificando su numero de filtros, para analizar su comportamiento. Finalmente con la red resultante se implemetó en diferentes procesadores para comparar tiempos de clasificacion.**

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 precision agriculture. In this paper the study of a convolutional neural network is presented, with two classes applied to the classification of plants of maize and weeds in real time, focused to fields of maize in its initial stage. The algorithm has two stages, segmentation of images and classification. Segmentation is intended to separate the target plant from the original image. While the classification is possible through a 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 in training, (revisar esta linea) 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, significant progress has taken place in science and technology developments. Significant milestones in diverse areas such as communications, numerical computer control and the miniaturization of components have benefited industrial sectors, providing new means to approach problems in a different manner.

The availability of leading edge technologies has considerably increased, thus becoming more accessible to people. This effect of globalization has allowed many countries to have access to state-of-the-art technological products, promoting its application in different areas to generate alternative and more efficient solutions to conventional problems.

Technological advances have caused industry transformations; manufacturing, food processing, and information industries among others, have gone through dramatic changes with industrial revolution. However there are fields that have not been significantly influenced by technological development in Ecuador, as it is the case of agroindustry. Agriculture in Ecuador has undergone some changes since colonial times; while it is true that there are efficient agricultural practices, the lack of technological resources make it impossible for the country to exploit its true potential as an agricultural producer. Also, the excessive use of pesticides have a negative effect on the production, soil, and water quality.

Nowadays, one of agriculture's 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 an algorithm [6], that through binarization methods of OTSU and Watershed for the segmentation of the images. While its classification was given through an 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.

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

El desarrollo del modelo para la identificacion de mala hierba y maiz usando Redes Neuronales Convoluciones se describe abajo:

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

A. Hardware

Para la etapa de entranamiento y captura de imagenes, los siguientes elementos fueron utilizados: Una Raspberry Pi 3 con su modulo de camara V2.1 para la adquisicion de imagenes, fue configurado para obtener video en resolucion de 1280x720 pixeles con el fin de obtener mayor detalle en la segmentacion de imagenes. Debido a la popularidad de la computacion por GPU(IDEA COMPLETADA) por sus ventajas en el desarrollo de modelos de Redes Neuronales Convolucionales, fue necesario consider hardware compatible con computacion paralela como las tarjetas graficas fabricadas por NVIDIA, estas tienen la ventaja de poseer mejores tiempos de procesamiento comparados con la CPU, con lo cual se logra optimizar los tiempos de clasificacion y entrenamiento de Modelos de Deep Learning, entonces, utilizamos un computador con una tarjeta Grafica NVIDIA GTX950M. Tambien fue necesario considerar el uso de un CPU Core i7 2.7Ghz, 8 Nucles and el CPU de la propia Raspberry Pi 3, un ARM 3, a ARM Cortex-A53, 1.2GHz, 4 nucles para probar el rendimiento de red en un sistema portable para su aplicacion en un sistema movil independiente . El hardware escogido sera probado para clasificar las imagenes y medir los tiempos de clasificacion para su posterior analisis. El hardware elegido ser probado para clasificar imgenes, en cada clasificacin se medirn los tiempos de procesamiento, para realizar un anlisis si el hardware puede procesar en tiempo real

For the training and image-capturing stages, the following elements were used: a Raspberry Pi 3 with a V2.1 Pi camera for image acquisition. The system was configured to obtain a video at a resolution of 1280x720 pixels in order to get more detail in the segmented images. Due to the popularity of GPU computing for its advantages in the development of models of Convolutional Neural Networks (COMPLETAR IDEA), it was necessary to consider hardware compatible with parallel computing such as the Graphic Cards manufactured by NVIDIA. These cards have the advantage of a superior processing speed compared to a CPU in order to optimize image-processing time and deep learning Model's training process, thus the selected device was a computer with a Nvidia graphics card GTX950M. Also, it was necessary to consider the use of a Core i7 2.7 Ghz CPU of 8 cores and the CPU of the Raspberry Pi 3, an ARM Cortex-A53, 1.2GHz, 4 cores (CLARIFICAR IDEA) for test its performance in this embedded system for a future aplication in a independent mobile system. The hardware chosen will be tested to classify images, in each classification a measure the times of processing will be performed, for make an analysis if the hardware can process in real time.

B. Software

Para la aplicacion en este documento, se requiere el uso de Poderosas librerias de desarrollo para el procesamiento de imagenes y Deep Learning, fueron requeridas debido a que se necesita de Vision Artificial para realizar la segmentacion de plantas del suelo y generar imagenes independientes de cada una y la otra libreria sirve para la clasificacion de las imagenes obtenidas y su analisis de precision en diferentes arquitecturas de red con el fin de elegir la mas adecuada para nuestro proposito. Consideramos el uso de software libre para extender su uso en futuros prototipos, debido a esta consideracion hemos escogido la libreria de OpenCV debido a su eficiencia computacional y su enfoque a aplicaciones en tiempo real, para este caso fue utilizada(en referencia a OpenCV) para la adquisicion y segmentacion de las imagenes de muestra. Tambien hemos considerado Caffe debido a que esta desstinado a el entrenamiento y desarrollo de Redes Neuronales Convolucionales de Proposito General y otros modelos de Deep Learning con soporte completo de la Libreria de Computacion GPU CUDA y una generosa base de datos de recursos para aprendizaje de aplicaciones como Simple Regresion, Robotica, large-scale visual classification, etc.

The use of powerful libraries of Image Processing and Deep Learning Development was required due to.... . The use of open software was required in order to provide the system with a certain level of flexibility to extend its use for future prototypes. Thus, OpenCV library was chosen due to its computational efficiency and focus on real-time applications [10]; it was used specificaly for sample images acquisition and segmentation. Also, Caffe was considered because it is intended to aid in the training and developing of general-purpose convolutional neural networks and other Deep Lerning models [11] with full support of CUDA GPU computation library and a generous database of resources for learning of applications such as simple regression, speech, robotics ,large-scale visual classification, etc.

Tambien el la etapa de desarrollo fue importante el suo del Sistema Operativo Linux, sus caracteristicas son: Sistema Operativo Ligero y Libre tambien completamente compatible con el software mencionado anteriormente. En la computadora principal fue usado la Distribucion Ubuntu Linux 16.04 por su soporte oficial a CUDA, Caffe y OpenCV, tambien en la Raspberry Pi fue usado el Sistema Operativo Pixel para adquirir imagenes y probar el rendimiento de clasificacion la Red Neuronal Convolucional

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 the Pixel OS were used for acquire images and test the classification performace of the CNN.

C. Dataset Description

Debido a la falta de datasets de plantas de Maize y Mala Hierba, Fue necesario buscar los cultivos de maz en su etapa de desarrollo inicial porque las acciones tomadas en esta etapa por el agricultor tendrn un impacto en el rendimiento futuro del cultivo, para ese proposito nos hemos traslatado a Pillaro, esta ciudad es localizada en la Provincia de Tungurahua, en el Centro de la Sierra Ecuatoriana. Pillaro es un productor reconocido de cultivos andinos como: Maiz, Papas y frutas, por lo que podemos encontrar aqui muchos cultivos de maiz que sean utiles para nuestro proposito

Due to the lack of weed and maize plant datasets, it was necessary to search maize crops in its initial development stage because the taken actions in this stage by the farmer will impact in the future yield of the crop (IDEA COMPLETADA). Fieldwork at a nearby town called Píllaro was arranged with the purpose of obtaining image samples. Píllaro it is a city located in the Tungurahua Province, in the center of the Ecuadorian Highlands region, it is a recognized andean-crop producer of species such as: maize, potatoes and a wide variety of fruits. Due to its year-long production season, many maize crops at its initial development stage were found in this area.

Las muestras fueron obtenidas de imagenes capturas en esos campos de maiz, consideramos escoger cultivos de maiz donde podamos visualmente discrimiar las plantas del cultivo de la mala yerba para para facilitar la segmentacion de las imgenes y para proporcionar a red de muestras confiables que permiten al modelo aprender correctamente todas las caractersticas de la planta real. Las etapas del Maiz (V3-V7) fueron usadas para tomar muestras. Para obtener las muestra, centramos la camara sobre la platna objetivo, asegurandonos que la captura muestre todas las caracteristicas de la planta de maiz, esto fue posible al monitorear el proceso por una pantalla externa. Unas muestras de las imagenes capturadas son mostradas a continuacion:

Samples were obtained from images captured in different maize fields. Crops were weed and maize plants could be visually discriminated were chosen in order to easy segment the images and for provide to Net of reliable samples which permit to the model to correctly learn all features of the real plant (IDEA SUSTENDAD). Maize at a V3 to V7 develompent stage (3-7 leafs) [12] were used to take samples. To record the samples, a camera was centered over the target plant, insuring that the capture shows all features of the maize plant. This was achieved by monitoring the obtained samples through an external display. Examples of the images captured are shown below.

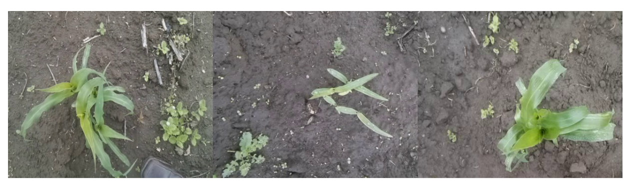

Fig. 1: Crops chosen to obtain samples, notice that it is easy to discrimante weed from maize

Tambien fue necesario obtener imagenes de las malas hierbas mas comunes en los campos de maiz de Pillaro, para permitir a la Red discrimiar entre las dos clases definidas en el Dataset.

Also, it was necessary to obtain images of the most common weed plants of the maize crops in Pillaro, to allow the network to discriminate between the two defined classes of the dataset.

Entonces, a traves de un proceso de procesamiento digital de imagenes, como primera fase, la imagen fue normalizada en su canal verde, esto mejora la deteccion del color verde porque elimina las luces y las sombras de la imagen, despues extrajimos el color verde de la imagen con la ecuacion descrita opr Wang, Men, Luo and Mei, para obtener una imagen final en escala de grises, despues se aplico una Umbralizacion de OTSU para obtener una mascara binaria

Then, through a first-stage digital image processing procedure, the images were normalized in its green channel. This was done in order to improve green color detection based on the elimination of light and shadow in the images. Later, the green color was extracted from the images to obtain a grayscale equivalent; this was done through the following equation described by Wang, Meng, Luo and Mei [13]. Following, an OTSU Thresholding was applied to the grayscale images in order to obtain a binary mask.

$$S = 2 * G - R - B \tag{1}$$

Despues de la imagen fue segmentada, para diferenciarla del suelo y otros elementos que no sean plantas, las imagenes originales fueron enmascaradas con la mascara binaria para proveer al Dataset caracteristicas de Color del Maiz y de la Mala Hierba. Una vez ue las imagenes segmentedas fueron obtenidas, removimos aquellas que tenian una resolucion menor a 64x64 pixeles debido a que son mas pequenhas que el tamanho de entrada de la red, ademas no es conveniente procesarlas debido a que su area total es mucho mas pequenha que la de las muestras de maiz, las cuales son el proposito de este documento, despues las imagenes se almacenan en un formato Png. El proceso se ilustra de mejor manera en la siguiente figura.

Afterwards, the images were segmented in order to differentiate them from the soil and other non-plant elements. Original images were masked with the binary mask to provide the dataset with color features of maize and weed plants. Once the segmented images were obtained, images that had a resolution lower than 64x64 pixels were removed because its size was smaller than the size of the network input layer. Besides, the processing of these small images was not convenient since its total area was much smaller than the maize sample images. Following, the images were saved in a png format. The entire process described before is illustrated in the next figure.

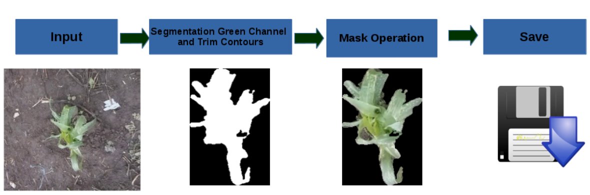

Fig. 2: Preprocessing to obtain samples for the dataset

Debemos acotar que hemos etiquetado manualmente las imagenes en dos clases, maiz y mala hierba, teniendo en cuenta que las imagenes no se repitan(**corregir**). En la presente imagen presentamos los resultados finales de las imagenes procesadas que conforman el dataset.

It should be noted that samples were manually labeled into two classes; maize and weed, making sure that the images are not repeated. In the following image, final results of the processed images that conform the dataset are shown.

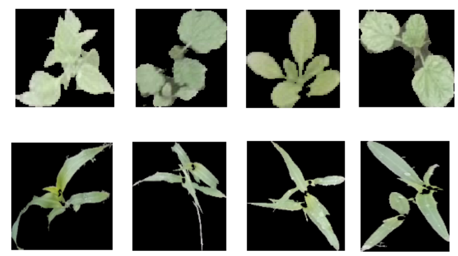

Fig. 3: Segmented and Masked images of dataset Above: Weed, Below: Maize

Una vez completada el procesamiento de imagenes, donde fueron obtenidas 2835 imagenes de maiz y 880 images de Mala Hierba, Lee et. Al dicen que una vez que la CNN ha alcanzado una precision aceptable, el dataset se puede extender por transformaciones geometricas, en adicion sladojevic mencionan que esto permite a reducir el sobreajuste y para mejorar la precision en el entrenamiento, razon por la cual hizimos 11 rotaciones cada 30 grados, obteniendo de esta forma el incremento(corregir) del dataset en 12 veces y tener mejores probabilidades de reconocer als plantas en cualquier orientaciones.

Once image processing was completed, a set of 2835 maize images and 880 weed images was obtained. Lee *et. al* [14] said that once CNN has reached an acceptable accuracy, the dataset can be extended by means of geometric transformations. In addition, the geometric transformations [15] (Si es verdad) allow overfitting reduction and improves(revisar correspondencia persona) the precision in the training process. For this reason, image rotations each 30 degrees were made, obtaining an increment of the dataset by 12 times, thus increasing the chances of recognizing plants that are in any orientation effectively.

Para la fase de validacion, hemos escogido aletariamente la quinta parte del total de imagenes de cada clase, asi que tenemos la siguiente tabla con la distribucion del dataset.

For the Validation Phase, a fifth part of the total image set of each class was chosen, resulting in the following chart with the distribution of the dataset.

D. Convolutional Neuronal Network

Despues que el ultimo paso ha sido terminado, fue necesario clasificar las imagenes del Maiz y Mala Hierba, un

Phase	Train	Validation	Test	Total
Maize	25695	8325	200	34220
Weed	8560	2000	200	10760

TABLE I: Distribution of the Dataset of each class

metodo muy preciso de Clasificacion de Imagenes son las Redes Neuronales Convolucionales(CNN), estos modelos son complejos pero eficientes con un alto grado de discriminacion y han demostrado que tienen unos buenos resultados en la Clasificacion de Imagenes, Deteccion de Objetos y Fine*Grained Classification. Tambien son aplicados en la Agricultura de Precision para la correcta identificacion de plantas

After the dataset was completed, it was neccesary to classify maize and weed images. Convolutional Neural Networks (CNN) can be used as a highly-accurate method for image classification, these models are complex but efficient with a high rate of discrimination and have proven to provide good results in image classification, object detection, and fine-grained classification [16]. CNN are widely used in precision agriculture [8] for the correct identification of plants.

Una de las caracteristicas de las CNN is que estas pueden tener multiples arquitecturas, cada arquitectura puede alcanzar diferentes resultados dependiendo de la aplicacion, para el presente documento hemos considerado cuatro arquitecturas de CNN: Dos modelos fueron escogidos del Caffe Zoo Model(es un recurso libre liberado por los Desarrolladores de Caffe) Lenet y AlexNet, tambien Potena y Nardi han usado adicionalmente dos tios de modelos, sNET y cNET, estos han sido exitosamente probados en la clasificacion de plantas en cultivos, con las redes secogidas, cada una fue entrenada con un mismo Solver de Tipo AdaDelta, con el mismo Dataset y los resultados del entrenamiento son los siguientes:

One of the characteristics of the CNN is that these can have multiple architectures, each architecture can reach different results depending on the application. For the present document four CNN architectures have been considered: 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.

Dentro de los parametros mostrados en la Tabla, consideramos la red que alcanze la mas alta tasa de precision y mas baja tasa de perdida, claramente la cNET es la escogida, debido a que esta presenta una precision cercana a la clasificacion humana

Within parameters shown on table II, the network that

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	3000	3000
Accuracy(%)	86.48	93.86	95.33	80.4
Loss(%)	32.80	15.32	13.72	15.32

TABLE II: Comparison of the 4 types of CNN

achieved the highest rate of accuracy and lowest rate of loss was considered; clearly the cNET presented a superior performance due to its near-to-human classification precision.

Aunque lo resultados dados de la red fueron excelentes, uno de los propositos principales de este documento es una aproximacion de procesamiento en tiempo real, entonces el numero de parametros a ser computados va a ser un problema, entonces consideramos modificar la red para mejorar el tiempo de procesamiento. Para lograr esto, fue necesario reducir el numero de filtros de cNET de 64 a 16, en la tabla siguiente se muestran los resultados del entrenamiento para los dos tipos de red.

Although results given by this type of network are excellent, one of the main purposes of this paper is the implementation of this system in real time. The number of parameters to be computed by the selected network were numerous, so network modifications in order to improve processing time had to be made. To achieve this, it was necessary to reduce the number of filters of cNET from 64 to 16.

Parameters	cNET 16 filters	cNET 64 filters
Number of parameters	1651376	6421568
Iterations	9000	9000
Accuracy(%)	97.26	96.40
Loss(%)	8.39	14.48

TABLE III: Comparison between cNET of 16 and 64 filters

Esta reduccion permitio reducir el numero de parametros de 1651376(es un 25% de parametros de la red original), y acerca de la precision d ela red, fue affectada un poco pero asi consigue un 97.2% de precision en el entrenamiento.

This filter reduction permitted to decrease the number of parameters to 1651376 (this represents only 25% of the original network parameters) without compromising the network precision in a significant way; it still reached a 97.2% of accuracy.

Entonces el modelo completo de red se forma de la siguiente manera: La capa de entrada que recibe una imagen RGB de 64x64 pixeles, seguida por una capa de convolucion de 16 filtros, un kernel de 5 y stride de 1 pixel, esta capa obtiene solo las principales caracteristicas de la imagen, despues una capa de pooling es aplicada, la cual tiene la funcion de encontrar los maximos valores de las capas, con un tamanho de kernel y stride de 2, despues nuevamente se aplica una segunda capa de convolucion que tiene 16 filtros, ancho de kernel de 5 y un stride de 1, seguido nuevamente de una nueva capa de pooling con un tamanho de kernel y de stride de 2, obteniendo asi una imagen de salida de de tamanho 16x16x16 y finalmente se completa la red con tres capas consecutivas fully-connected, la primera con 384 neuronas, la segunda con 192 y la ultima con dos neuronas que representara la capa las dos clases que se busca clasificar, el modelo resultante se muestra en la siguiente imagen

So, the complete network model was conformed by the following components: an input layer where an RGB image of 64x64 pixels is received, followed by a convolution layer of 16 filters, a kernel of 5 and a stride of 1 pixel (this layer only obtains the main characteristics of the image), then a pooling layer is applied, which has the function to find the maximum values of the previous layer with a value of kernel size and stride of 2 (QUE? corregido), then again a second layer of convolution that has 16 filters is applied, the size of kernel is 5 and the stride is 1 (QUE corregido), followed by a new layer of pooling with a kernel size and stride of 2, so the resulting image was has size of 16x16x16. Finally the network is completed with three consecutive fully-connected layers; the first with 384 neurons, the next with 192 and the last with 2 neurons. The type of layers fully-connected contain a total of 478 neurons, where the last two neurons that are the output represent the two classes to identify, the result model is shown in the next graph.

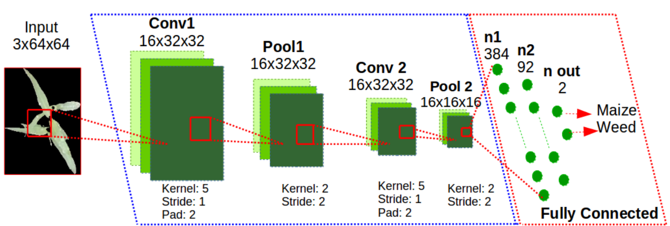

Fig. 4: The schematic of cNET

En la grafica de entrenamiento que se muestra a continuacion podemos apreciar el resultado final de precision de la red, la 9000 iteraciones fueron necesarias para reducir el la capa de Loss al minimo y la arquitectura demostro alcanzar rapidamente un valor aceptable de precision, notose que reduciendo el numero de filtros la red gano en precision porque las imagenes del dataset no tienen demasiadas caracteristicas para procesar, por lo que la red fue mejor solucionable con un numero menor parametros de red

In training graph shown below the final result can be appreciated of the net accuracy; 9000 iterations were neccesary to reduce the loss value to its minimum and the architecture shows that it can reach an acceptable accuracy with few iterations. Note that by reducing the number of filters the network gained accuracy because the dataset does not have too many features to process, so the network obtained a better solution with a fewer number of parameters.

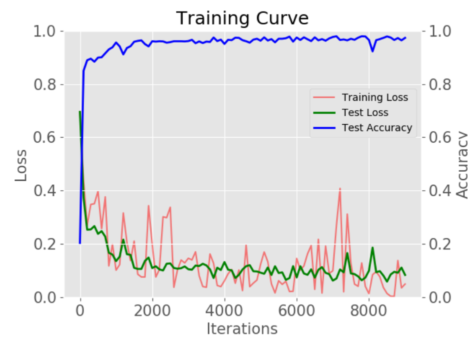

Fig. 5: Graph of the Training Process

III. Test

Para esta etapa, consideramos otro dataset con 202 imagenes de plantas de maiz en la etapa V3-V7 y 202 dos imagenes de mala hierba obtenidas en campos de maiz diferentes a los que pertenecen al dataset de entrenamiento, para esta prueba se ha medido los tiempos de clasificacion promedio de diez clasificaciones de este dataset en los distintos hardwares que poseemos, empezamos con la clasificacion en Caffe sin modificaciones de software. Los resultados fueron comparados entre la red cNET de 64 y 16 filtros y se muestran en la siguiente Tabla

For this stage, another dataset with 202 images of maize plants in stage V3-V7 and 202 images of weed were considered, obtained in different maize crops that the training dataset. For this test and in order to have a reliable value its considered to classify ten times the dataset, so the average time of classification by image were obtained with the chosen hardware, we started the classification in Caffe without modifications in Software. The results were comparated between cNET with 64 and 16 filters and there are shown in the next Table IV.

Como la tabla muestra, los mejores resultados en tiempos de clasificacion fueron alcanzados por el procesador por GPU, esta es la mejor opcion para clasificar una gran cantidad de imagenes, sin embargo este proyecto esta psenado para ser portable, por lo que consideramos al Raspberry Pi para el analisis del rendimiento de classificacion. Con la cNET de 64 filtros, los ersultos de tiempo de clasificacion fueron de 615 milisegundos, pero este tiempo no es optimo para nuestro objetivo que es la aproximacion de clasificacion en tiempo real.

Like the table shown the best results in times of classification were achieved by the GPU processor, it is the

GPU			
cNET	**Accuracy Weed**	**Accuracy Maize**	**Average time of classification/image**
64 Filters	95.05%	74.75%	2.34 ms
16 Filters	94.55%	87.13%	951 μs
CPU			
cNET	**Accuracy Weed**	**Accuracy Maize**	**Average time of classification/image**
64 Filters	95.05%	74.75%	51.6 ms
16 Filters	94.55%	87.13%	17.23 ms
CPU Raspberry Pi 3			
cNET	**Accuracy Weed**	**Accuracy Maize**	**Average time of classification/image**
64 Filters	95.05 %	74.75%	615 ms
16 Filters	94.55%	87.13%	161 ms

TABLE IV: Test with the three types of Hardware

best option to classificate a large amount of images however this project is thought to be portable, so the Raspberry Pi were considered for the analysis of classification performance. With cNET of 64 filters the results of time of classification was 615 miliseconds, so it time isnt́ the optimum for our objective that it is the approximation to classification in a real time.

Los resultados presentados anteriormente no son definitivos, pues Caffe presenta algunas formas de optimizar la clasificacion de datasets de imagenes, para este documento se ha utilizado el Agrupamiento de Imagenes en una sola estructura(Batch) para clasificar el dataset de cada clase en un single forward pass y la utilizacion de Multithreading a traves del software matematico OpenBLAS. Para cada hardware se volvio a compilar Caffe con OpenBLAS en lugar de Atlas y en el programa se ingresaron todas las imagenes en un vector para ser clasificado un solo grupo de imagenes por cada clase, ademas se configuro a OpenBLAS para que use 4 Nucleos del cada hardware para obtener resultados parejos, los resultados obtenidos son los siguientes.

The results shown previously are not definitive because Caffe has ways to optimize the classification of datasets of images, for this document Batching were used to classify the dataset of each class in a single forward pass and the use of Multithreading by OpenBLAS math software. For each hardware, Caffe were recompiled with OpenBLAS instead of Atlas, in the program all images were entered in a vector to be classified in an only batch per each class, also OpenBLAS was configured to use the 4 cores of each hardware to obtain fair results, the obtained results are the following

Los resultados muestran que para el tiempo de Clasificacion por GPU ha empeorado un 66%, principalmente debido a que la Libreria de OpenBLAS hace extenso uso de los hilos del CPU causando que no todos los parametros seran computados

Hardware	Accuracy Weed	Accuracy Maize	Average time of classification/image
GPU	89.11%	92.08%	1.58 ms
CPU	89.11%	87.13%	10.92 ms
CPU(Raspberry Pi)	89.11%	87.13%	150.8 ms

TABLE V: Test of cNET 16 filters with optimized software

por GPU como en la anterior prueba. En cambio, cuando se utiliza el CPU los resultados son mejores, debido a que las operaciones se ejecutan utilizando cada uno de los nucleos disponibles, en el caso de la CPU se noto un 22% y para 6.3% para el Raspberry Pi

The results shown that classification time by GPU get worse by 66%, mainly due OpenBLAS make extense use of CPU Threads causing that not all the parameters of the net were computed by GPU like

IV. Conclusion

-Este paper estudia una red neuronal convolucional para la clasificacion entre maiz y mala hierba, para lo cual se utilizo algunas arquitecturas de red, de donde la que proporciono mejores resultados fue la Cnet, con un 99% de presicion en el entrenamiento al usar un datasetc de 44580 imagenes conteniendo las dos clases.

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 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.

Para buscar un procesamiento apropiado para trabajar en tiempo real, se experimento reduciendo el numero de filros de las capas de la red desde 64 hasta 16, logrando con esto disminuir el numero de parametros a ser computados durante la clasificacion, obteniendo tambien un tiempo de procesamiento de 2,5 veces menor al de la red original, este cambio tuvo un bajo impacto en la precision de entrenamiento de la red, pues este valor cayo en un 1%, con respecto a la red original.

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.

-Ademas nuestros experimentos al utilizar diferentes procesadores, demostraron que se obtienen mejores resultados en cuanto a velocidad al trabajar con una a tarjeta grafica

ENVIDIA que posee soporte CUDA debido a su arquitectura de computacion paralela, siendo este 10 veces mas rapido que el CPU normal y 100 veces mas rapido que una RaspBerry Pi3.

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.

-El estudio demostro que es mejor obtener las imagenes para el dataset realizar algunos giros en las imagenes de las plantas del dataset, debido a que esto aporta mejoras en la identificacion de plantas, pues estas siempre tienen orientaciones diferentes.

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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.

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