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Deep Learning-based Crops and Weeds Classification in Smart Agriculture

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Abstract--- *Today, agriculture remains the most important sector in the world. However, it faces a huge challenge: producing more and better with fewer resources while reducing the negative impact on the environment. Thus, to face this challenge, agriculture must become intelligent. In intelligent agriculture, the images collected from the monitored environment by various equipment's play an important role. In fact, aerial images of drones, for example, can be a valuable source of information. High-quality and real-time images can be used to correctly recognize and classify crops to monitor their growth, to prevent diseases, weeds and pests that can damage them. By monitoring crops, by targeting areas to be treated and by accurately managing quantities, farmers are able to reduce input consumption (pesticides and water), resulting in higher yield, reduced costs and environmental impact. As a result, image processing has received a lot of attention because of its strong ability to extract information from images and develop decision support tools. Convolutional Neural Networks (CNNs) as a particular type of Deep Neural Network have gained popularity in recent years as a powerful means of classifying or categorizing images. In this paper, we propose a vision-based classification system for identifying weeds and crops using AlexNet and ResNet Convolutional Neural Networks. Evaluation and simulation results showed that the proposed crop and weed detection method is effective.*

Keywords--- *Convolutional Neural Networks, Deep Learning, Image Classification, Smart Agriculture, Weed Detection.*

I. INTRODUCTION

Agriculture is one of the most important activities in the world. It is the most traditional of all productive activities. In order to produce more and better, it has gone through many technological evolutions and transformations over time. However, this sector is facing several problems such as climate change, water scarcity, poor application of inputs (fertilizers, liquids ...), depletion of fossil resources and loss of biodiversity.

As a result, agriculture needs to adapt and develop strategies to deal with these new conditions. It is therefore urgent to transform agricultural production processes in a more sustainable way, by properly allocating resources and using other intelligent farming practices that are resilient to climate change. To address these issues in a sustainable, cost-effective and environmentally friendly way, there is no alternative but to plant the seeds of a new agricultural revolution: Smart Agriculture.

The intelligence introduced in traditional agriculture allows the transition to a smart agriculture allowing the

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improvement of the yield and the palliation of most of the problems. This concept is embodied by the use of different kinds of automation technologies, capture, transmission, images processing and decision making [1] [2].

During the production cycle of a plant, abnormal conditions such as temperature and humidity of the surrounding environment allow the spread of several diseases caused by insects, weeds, nematodes and rodents... etc. which affect the good growth of the plant. To fight against these pests, phytosanitary products (insecticides, fungicides, herbicides, nematicides, rodenticides, etc.) have been used by farmers, nevertheless the random and irrational use of the latter leads to toxicity in case of overdose or deficiency in the opposite case.

Smart agriculture requires an understanding of the needs of each plot, and even each plant. Among the means used is remote sensing of images which provides very useful information for identifying and monitoring crops. With current resolutions, it is particularly well suited to the weeds analysis as a serious problem because they are responsible of most crop yield losses. To address this problem, farmers are using pesticide spraying throughout the field. Such a method not only requires huge amounts of herbicides, but also has an impact on the environment and human health.

With technological advances, a new way of fighting weeds, called precision spraying, is becoming increasingly popular. Precise spraying involves using new technologies (sensors, drones, artificial vision) to allocate the right amount of pesticides at the right time and in the right place. Thus, the amount of pesticide used can be reduced while increasing the yield. A real-time image processing and weed detection system can be the critical component of smart sprayers, used to detect targeted weeds and make spray decisions.

In addition, in recent years, Deep Learning combined with improvements in computer technology, particularly embedded processors graphics processing units (GPU) [3], has produced remarkable results in various fields of modern science as image classification and object detection [3] [4].

In this paper, we propose a new system for the detection and classification of agricultural images to identify weeds using Deep Learning, specifically Convolutional Neural Networks (CNN). From these images, we try to extract relevant information, so we developed an application that classifies these agricultural images in two classes as an initial work, according to their weed rate: class B for images containing a high rate of weeds and Class A for those containing very few weeds. Weed classification makes it possible to adjust the speed and the spraying pressure to achieve an automatic variable spraying depending on the intensity of the weeds.

We also try to classify the images according to the typology of the plant. We have 12 categories (Garlic, Aubergine, Beet, Red Bean, Green Bean, Black Grass, Lentil, But, Mustard, Black Pepper, Salad, Tomato). Thus, accurate detection of weeds using Convolutional Neural Network models would allow precise herbicide spraying.

This paper is organized as follows: Section II presents the state of the art related to the application of Deep learning in agriculture. Section III presents the proposed approach. Section IV provides the experimental results. Section V concludes this paper.

II. Related Work

Significant Learning is a sub-area of AI that is predicated upon learning terrific tiers of depiction. It makes use of figurings to show raised degree look in records [5]. It regularly uses Artificial Neural Networks or Neural Networks with covered layers. Significant Learning has starting overdue have been given lots of top elegance especially inside the cultivating subject wherein it's been implemented to play out a couple of assignments which encompass the revelation of accumulate illnesses.

Makers in [6] proposed large Convolutional Neural Networks based version to understand ten rice diseases consisting of rice faux refuse (RFS), rice sway (RB), rice silly shaded spot (RBS), rice sheath scourge (RSHB), rice bakanae infection (RBD), rice bacterial leaf revile (RBLB), rice sheath rot (RSR), rice bacterial sheath break (RBSR), rice bacterial psychologist (RBW) and rice seeding curse (RSEB). The images are pre-organized problem to Principal Component Analysis (PCA) and lights up systems to get a planning and test comprise. Their model exhibited a precision of 95%.

Maker in [7] became large Convolutional Neural Networks models so you can apprehend plant sicknesses reliant on leaves photos. These fashions are AlexNet [8], AlexNet OWTBn [9], GoogleNet [10], Overfeat [11], VGG [12]. A couple of harvests and illnesses have been joined inside the version, except their shape remains fabric for 25 vegetation whose globality we find out 58 unmistakable commands alongside robust and contaminations vegetation (plant-sickness). The preliminaries showed promising consequences.

Makers in [13] used CNN fashions to understand ailments reliant on leaves tomato pics. The fashions used are AlexNet [8] and SqueezeNet [14]. Their structure is deliberate for use in cellular telephones. The models showed same effects.

Makers in [15] made CNN based structure for distinguishing cucumber leaves sicknesses (melon yellow spot contamination and Zucchini mosaic ailment). Makers used rectangular acquire and square bending approachs as a pre-planning step. Their dataset is based upon a unmarried supply. Their form showed an exactness of ninety four.Nine%.

Makers in [16] used LeNet [17] model to be able to understand diseases of banana leaves (banana seckle and banana sigatoka). Picture pre-managing steps are used together with resizing photographs to 60x60 pixels, exchange to lower scale photographs. They affirmed the proposed model the use of plant town pix of banana leaves. Interesting outcomes are confirmed up in their examinations.

Makers in [18] proposed CNN models (AlexNet, GoogleNet) to bunch nine tomato infirmities. They used a dataset of 14828 pictures. A portrayal machine is in like manner used to image and understand reactions. The investigations confirmed that the effects of CNN models (without or with pre-getting prepared) are higher than whatever the no longer on time consequences of Support Vector Machine (SVM) and Random Forest (RF).

Makers in [19] have proposed a Deep Learning based definitely model so that it will recognize 5 apple leaf contaminations logically. They used 26.377 images accumulated within the area and in the exploration network. The effects confirmed that the show of the proposed version INAR-SSD achieved seventy eight.Eighty% mAP with a revelation tempo of 23.Thirteen FPS.

The recognizable evidence of the plant (or an organ) can be beneficial as a basis enhance for the area of the illness. Yahata et al in [20] gift an image disclosure technique for spotting blooms and seed instances in outside conditions in Hokkaido, Japan. A cream approach to manage recognize Vegetation phenotyping is grasped, the use of Simple Linear Iterative Clustering (SLIC), Viola-Jones Object Detection Method, Features from Accelerated Segment Test (FAST), and Convolutional Neural Network. Customized checking of blooms and times truely regarded the method of soybean development. The paper exhibited promising results in which the precision of the sprout ID landed at 0.Nine and the survey price zero.826.

In [21], unmistakable Deep Convolutional Neural Network (DCNN) fashions are used to recognize weeds in turfgrass. They rely on weeds pix taken using a propelled digital camera. These fashions are VGGNet, GoogleNet, DetectNet. The consequences showed that giant convolutional neural framework is astoundingly realistic for weed disclosure.

Makers in [22] proposed Convolutional Neural Network got collectively with flowers strains estimation to recognize weeds in beet, spinach, bean issue. High vegetable pics taken about 20m through meanders aimlessly are used. The outcomes exhibited that the remarkable accuracy is come to in beet subject. The paper makes reference to specific difficulties in putting aside weeds in particular in the direction of the starting time of plant development or when weeds develop close to the yield.

Makers in [23] proposed Deep Convolutional Neural Networks and circulate making feel of a manner to expel created land information from UAV photographs had been given at excessive stature. The proposed method is diverged from ECLE gadget (eCognition for created land records extraction) and their assessments exhibited for all intents and purposes indistinguishable effects, with the exception of genuineness and lucidness, the proposed device defeats the following one.

In [24], a CNN is made to layout rice reliant on satellite TV for pc information (MODIS and Landsat 8). The CNN classifier is differentiated and two wonderful classifiers: SVM and RF. The proposed technique achieves the high-quality execution with a well-known accuracy of ninety seven.06% diverged from various techniques. The robust connection amongst's Landsat brought on rice a place and government real information confirms the consequences.

III. PROPOSED METHOD

A. Overview

We used extensively identified CNN plans which includes Resnet-50 [25] and AlexNet [8] for photograph request.

AlexNet is a pre-arranged Convolutional Neural Network on more than a million pix from the ImageNet database. The framework has a importance of 8 layers and can gather pix into a thousand precise instructions of factors.

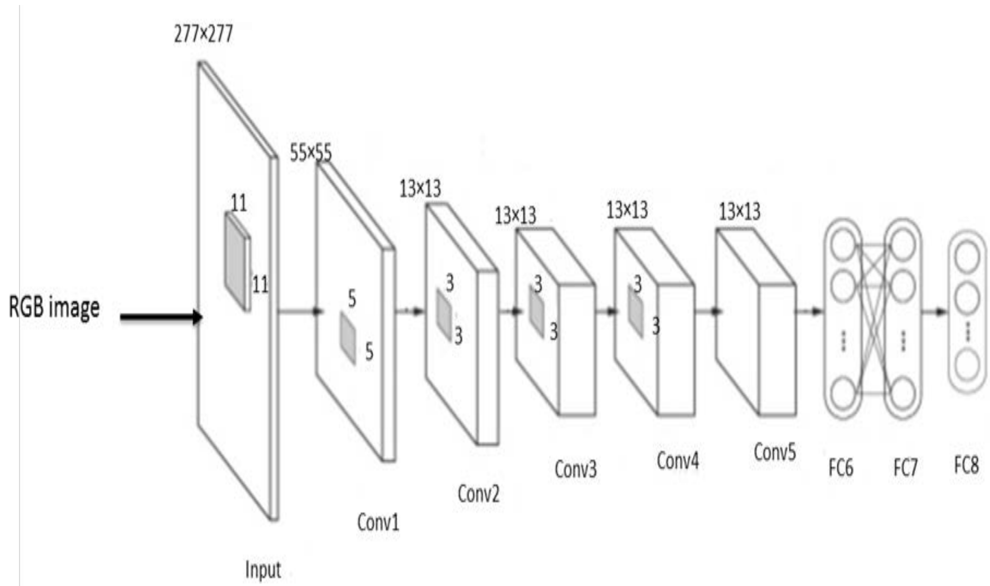

Fig. 1: AlexNet Network Architecture

The Residual Neural Network ResNet-50 is a pre-trained model that has been trained on a subset of an ImageNet database. The model is formed on more than one million images. It has 50 layers and can classify the images into 1000 categories of objects.

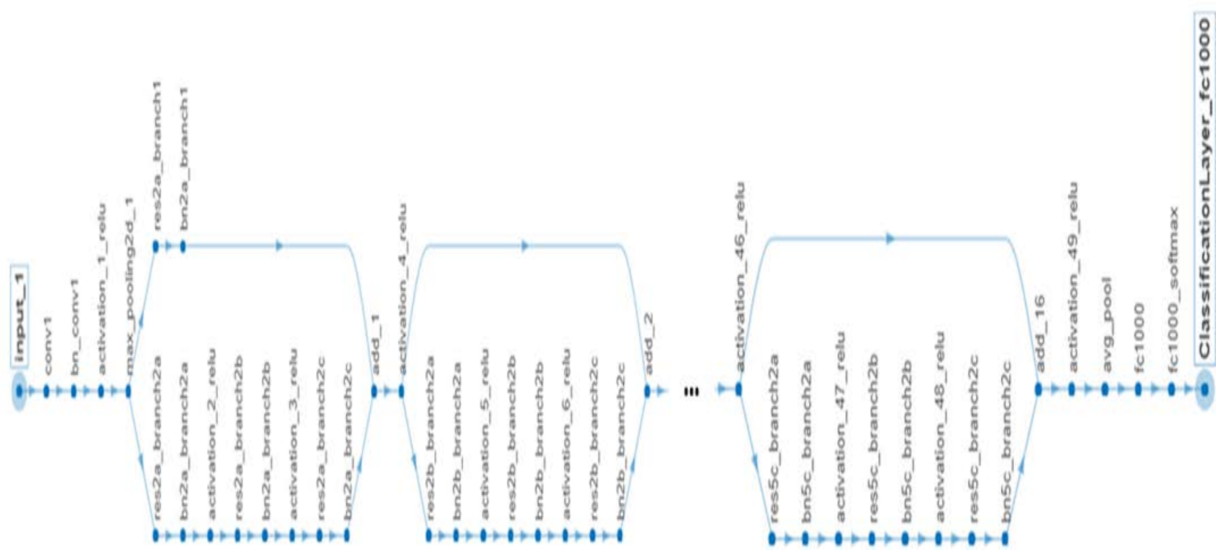

Fig. 2: ResNet-50 Network Architecture

Dataset

We have considered two publically available datasets: dataset 1 and dataset 2. The images in both datasets are in PNG format. Dataset 1 is partitioned into two main classes: class (A) which consists of images containing very few weeds unlike the class (B) which has images containing a lot of weeds. The number of images in each class is 100 and they have 1296 * 966 pixels. Fig. 3 shows some images of the dataset 1.

The second dataset used was dataset 2 which contains 12 classes of agricultural images which is further divided into classes (Garlic, Aubergine, Beet, Red Bean, Green Bean, Black Grass, Lentil, But, Mustard, Black Pepper, Salad, Tomato). Each class contains 100 images of a well-defined plant type with a size of 1435 * 1435 pixels.

Also, to perform our experiments, all the images were partitioned into two subsets: 70% for training purpose and the remaining 30% were reserved for testing.

Image Pre-processing

Due to the large size of the images, image preprocessing is performed. Pre-processing includes resizing the images. All images are resized to 300 * 300 pixels.

In order to reduce overfitting, data augmentation is applied to artificially generate additional training data via transformations of existing training examples. The most common augmentation methods are affine transformations (horizontal and / or vertical reversal, rotation), brightness and contrast variation, jitter (random noise), etc.

IV. EXPERIMENTAL EVALUATION AND RESULTS

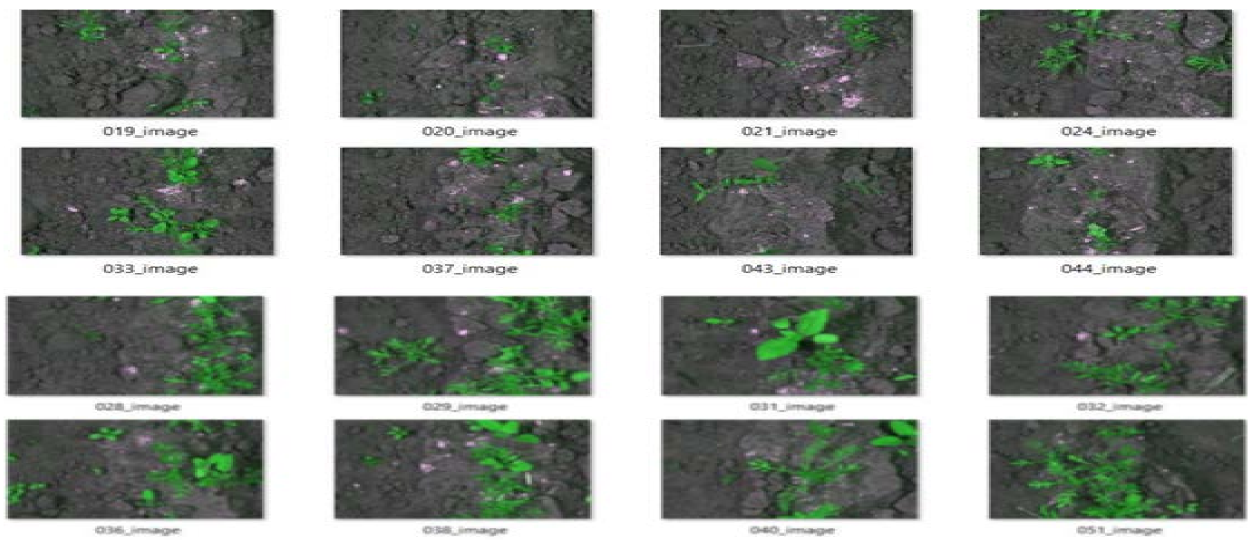

Fig. 3: A Sample of Images from the Dataset1

To carry out this work, we used MATLAB (Matrix LABoratory) and the following hardware configuration:

A laptop Dell i7, CPU 2.60 GHZ.

RAM size 8 GB.

Windows 10 (64 bit).

Intel® HD Graphics 5500 Graphics Card.

Performance Evaluation

In this section, ResNet50 and AlexNet models are trained and tested to evaluate their performance in classifying images into class A, class B, Garlic, Aubergine, Beet, Red Bean, Green Bean, Black Grass, Lentil, But, Mustard, Black Pepper, Salad, Tomato.

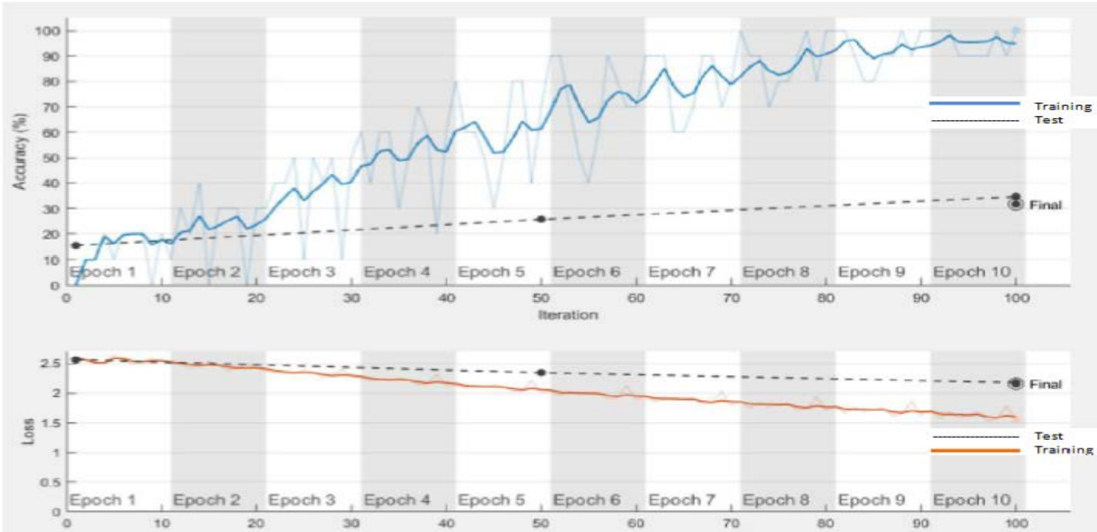

Fig. 4: Accuracy and Loss Curve of ResNet 50 without Data Augmentation

In order to measure the performance of each classification method used we used the confusion matrix and the Receiver Operating Characteristic (ROC) curve.

A confusion matrix is a summary of the results of predictions on a classification problem. Correct and incorrect predictions are highlighted and divided by class.

A ROC curve is a graph representing the performance of a classification model for all classification thresholds. This curve plots the true positives rate based on the false positives rate.

Fig. 4 shows the precision and loss curves with the maximum epoch set to 100 without using data expansion techniques. We notice a significant gap between training and test after 20 epochs because of the overfitting. The highest accuracy of the test images was 31% and the training accuracy was 95%. We notice that there is an overfitting during the training process. High loss is shown for test and training with low accuracy for the test set.

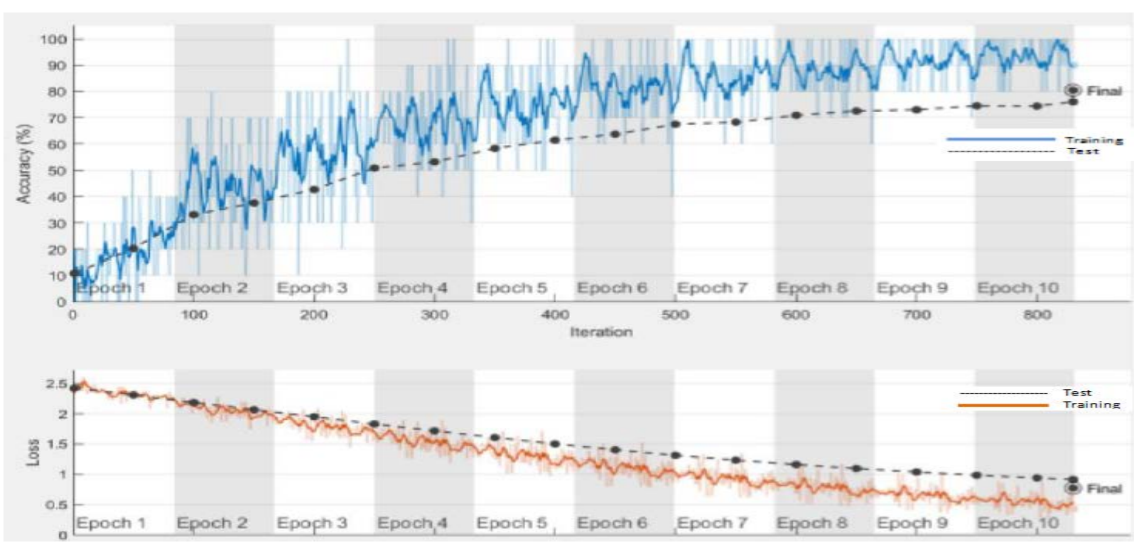

Fig. 5: Accuracy and Loss Curve of ResNet 50 with Data Augmentation

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As discussed earlier, data augmentation techniques are used in order to improve the performance of the model and prevent overfitting. Fig. 5 shows the loss reduction for the training process and even in the test set.

We also note an improvement in the accuracy of the test which has been considerably increased; reaching 80%, as well as the overfitting problem observed with a non-expanding dataset is completely eliminated.

The classification accuracy of a model can be estimated using the confusion matrix. Fig. 6 presents the confusion matrix on the test images (the average of true positive and true negative rates) for all the categories.

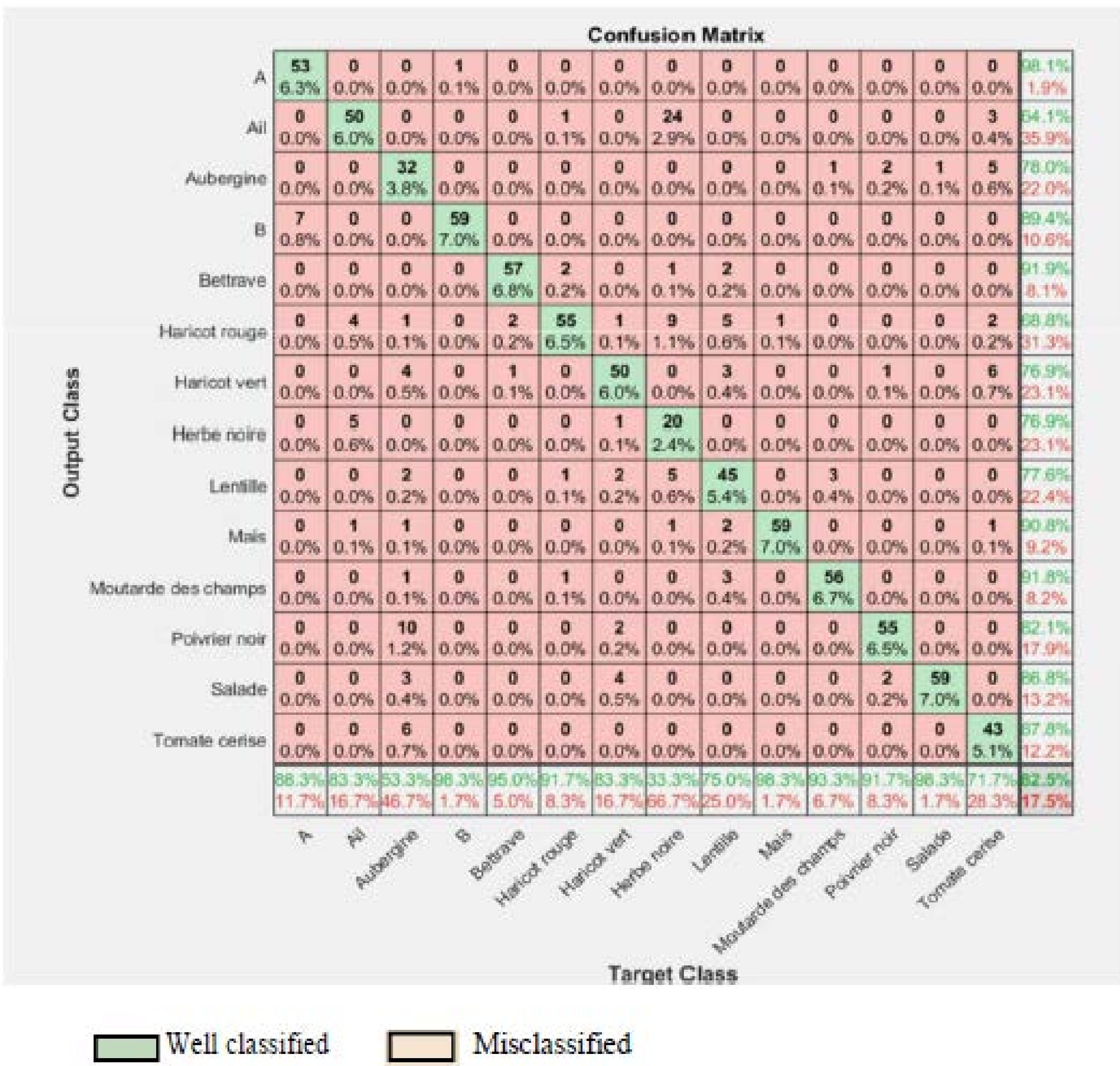

Fig. 6: The Confusion Matrix of the AlexNet

As we see in this figure, the results show that the total misclassification rate is 33.1% (278 misclassified) while the total fair classification rate is 66.9% (562 well ranked images), which is good but we are far to say that the network performs well.

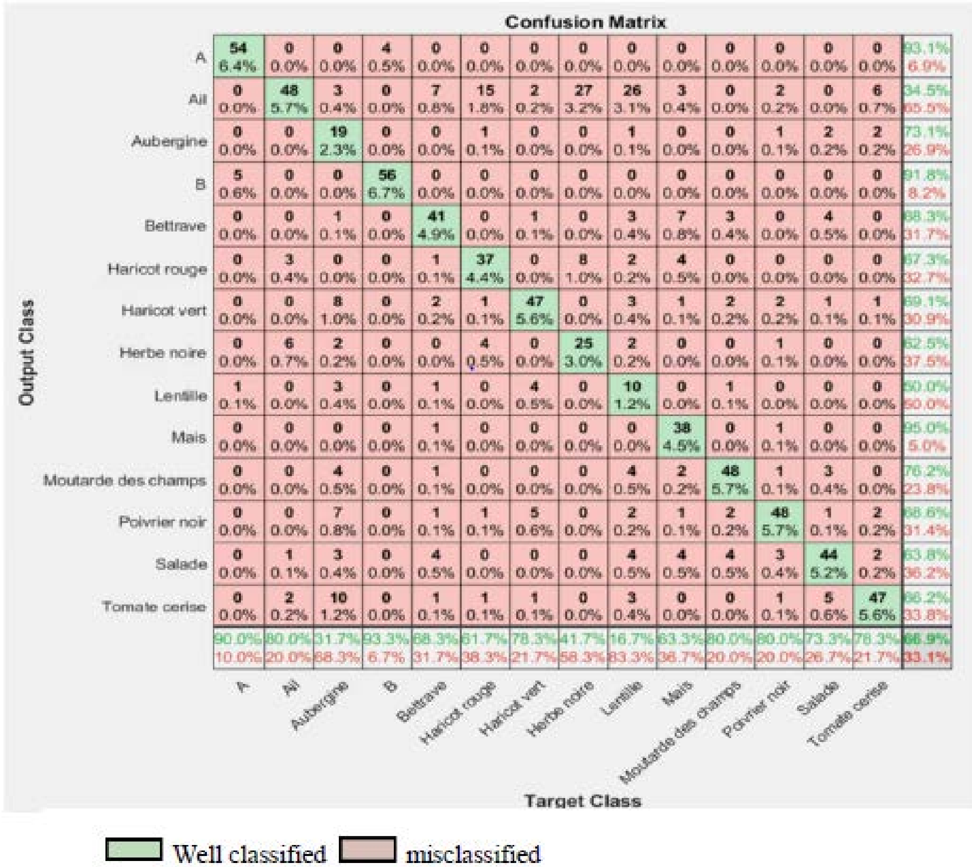

Fig. 7: The Confusion Matrix of the ResNet50 Model

According to this matrix, the accuracy rate of the algorithm is 82.5% , so 693 well classified images on the 840 images (of 30%), while the error rate is 17.5%, which makes 147 poorly ranked pictures out of 30%. The good performance of ResNet50 compared to AlexNet is explained by its deep.

We consider also the ROC analysis showed. The ROC representation puts forward a new indicator which is the area under the curve, the closer the curve is to the top-left corner, the better the classifier. In our work, as shown in ResNet50 has better performance than AlexNet.

V. CONCLUSION

A deep learning model for crops and weeds classification can assist farmers in maximizing crop yields and consequently minimizing the losses.

In this paper, we applied deep learning technique to classify crops and weeds by using convolutional neural networks. The AlexNet and ResNet models were used for conducting this work. The results of the comparison of the two models showed that ResNet has a better performance than AlexNet model with an accuracy of 82.5%.

Due to limited training data, the two CNN models suffered from overfitting. By expanding the training data through various transformations, this problem was solved, increasing the overall accuracy to more than 90%. Further improvements of accuracy can be obtained by collecting more training data.

Based on the high performance level, we conclude that CNN-based weed recognition can be an effective decision-making system in the artificial vision system of a precision herbicide applicator for weed control.

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