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On behalf of an intelligent approach based on 3D CNN and multimodal remote sensing data for precise crop yield estimation: Case study of wheat in Morocco

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Abstract

Agriculture is a key sector in the global economy, and crop yield is a primary element in this field. Its estimation represents a troublesome task considering its link to market planning. Different techniques have been tested to estimate crop yield. However, they present several limits in terms of human effort and time. The agricultural world is now experiencing a digital revolution, for example the utilization of UAV (Unmanned Aerial Vehicle) provides high-resolution images of crops. Besides this, artificial intelligence techniques namely, DL (Deep Learning) enables today a revolution of the flow processing and improves the resulting information. This paper presents a case study of wheat yield estimation in Morocco using UAV multimodal remote sensing data and 3D CNN (3D Convolutional Neural Network). Our data was acquired during the growth season, and predicted yield was compared to in situ data. Based on our results, the RMSE value was 0.175 qx/ha. Our conclusions highlight the efficient role of convolutional neural network in capturing features in raw image data and the importance to improve resulting predictions by acquiring data over the entire period of growth, and the necessity to choose a temporal architecture, which is able to process temporal variations.

1. Introduction

Agriculture provides food, fuel, and natural substances, which are all fundamental for human life [1]. To meet this demand, farmers and policymakers are working hard to improve crop yield. Despite the existence of many possibilities of cropland extension [2], the accentuation ought to be on increasing the production within the actual agricultural lands to avoid harmful effects on the environment. Recent advances in sensor technology have infiltrated agriculture, so different remote sensing systems are now available and allow generating data and providing relevant results to optimize a variety of agricultural products. These systems provide temporally relevant spatial data on land surfaces at different scales [3]. Generally, the main objective of precision farming is improving the quality and optimizing the production processes of crops [4] and this by reducing environmental pollution and costs. The utilization and application of new technologies has resulted in a transformation of crop management from a qualitative science based primarily on observations to a more quantitative science based on measurements, including a variety of production factors such as soil, climate conditions, and irrigation management, that all have a significant impact on potential yield and growth, leading to the optimization of agricultural production. Total population is estimated to be more than 9 billion by 2050 [5], also current agricultural yields should increase up to 50% per unit in order to ensure food security. So as to achieve food safety and security, several stakeholders including national and international authorities, farmers, and other business units, expressed appreciation for timely and reliable information about crop management, production, and yield [6].

For a long time, yield squares have been among the conventional techniques for estimating agricultural yield. The principle of this method is the exploitation of a sample with square geometric shape which is placed at random in a plot to count all the plants that are in it [7]. To lay these squares, we determine the area of the plot as well as identify diagonals and location of samples. For a plot of minimum 1ha, each diagonal must have 5 plots while avoiding the edges, whereas plots having an area of less than 1 ha, it is necessary to place 2 to 3 squares per diagonal, without having less than 4 squares in total. In the end, to calculate the yield using the square, we divide the total amount of harvest weighted by the area of the considered yield square. Crop models aim to simulate the growth of agricultural crops [8]. They can work at different scales and help replicate key plant growth processes as well as the development in detail, and could therefore be used to determine crop yield [9] without forgetting the quantification and impact of individual factors in determining agricultural yield. To make future estimates and determinations, statistical models have been mainly used to develop an empirical relationship, combining a large number of current season yield characteristics with historical yield data [10]. More than a linear regression approach for predicting crop yield has been developed and used by studies dealing with estimating crop yields.

Remote sensing has facilitated crop monitoring by providing continuous data over large areas [11]. It offers the advantages of non-destructive, rapid and more profitable surveillance [12]. Satellite systems such as Sentinel and Landsat provide temporally interesting spatial data on visible land surfaces at very large scales [3]. Even though satellite images have been used extensively in estimating crop yield, we are facing many issues that still require resolution. For example, satellite images with high spatial and temporal resolution are rarely obtained at the same time [12], and sometimes it is not possible to obtain valid data during the critical phase of growth due to bad weather conditions. Remote sensing is now witnessing the expansion of UAV systems that have been rapidly developed and applied in the estimation of crop yield at the farm-scale over the past few years [13]. UAV platforms provide a cost effective and efficient way to meet the increasing demands of spatial, temporal and spectral resolution. Unlike satellites, Unmanned Aerials Vehicles are able to carry sensors at low cost and operate on very flexible schedules [14]. Drones data have been widely tested for agricultural monitoring of sugarcane, sunflower, soybean and triticale [12], as well as for forecasting yields of rice, wheat [15] and barley. Remote sensing sensors mounted on drones include RGB, NIR and multispectral cameras. With the advancement of imaging technology, hyperspectral cameras have gradually been equipped on drones to acquire remote sensing data which will make it possible to obtain more spectral bands and precise spectral information, and consequently improve the precision of the monitoring.

In recent years, deep learning has proven to have a significant advantage in agriculture, especially in estimating yield. Mu et al. [16] reported that deep learning, specifically the convolutional neural network, has the ability to extract specific characteristics of crop growth, and used it with multitemporal MODIS (MODerate resolution Imaging Spectroradiometer) data to predict winter wheat yield. Their results showed that winter wheat yield based on remote sensing time series images correlates strongly with yield, having Pearson R and RMSE values of 0.82, 724.72 kgh.m-2, they conclude that CNN represents an essential technical reference for the large-scale crop yield while Wang et al. [17] estimated the winter wheat yield using LSTM (Long Short-Term Memory) networks for meteorological data with AVHRR (Advanced Very High Resolution Radiometer) inputs and convolutional neural networks for static soil characteristics inputs. Their model performed well, with an overall R^2 and an RMSE of 0.77 and 721 kg/ha, respectively. Garcia et al. [18] determined corn yield using UAV images with different multispectral vegetation indices, RGB, canopy cover and plant density in a multilayered perceptron model, their results demonstrated that neural networks had a high correlation coefficient and the spectral data collected by remote sensors mounted on UAV and processed into vegetation indices, canopy cover and plant density data is extremely useful and have more sense for agricultural characterization and estimation. Other authors tested deep learning approaches to predict rice yield, for instance Yang et al. [19] explored the ability of high resolution RGB images from drones with convolutional neural network and a new deep learning architecture with deep feature decomposition. Results demonstrate that the proposed network is more robust than the network without in-depth decomposition of the characteristics.

Through our study, we want to focus on methods for an intelligent estimation of agricultural yield, and present a case study carried out in Morocco, especially to estimate wheat yield, and the precision application of artificial intelligence, more particularly CNN architecture. Our study will present the results of 2D (two-dimensional) CNN applied to multispectral UAV data acquired during the season, and propose another architecture that can explain more yield variability, which is the third dimension of convolutional neural network.

2. Material and Method

In this section, we will present the area where our study was conducted and the main steps of our methodological workflow, starting from the UAV used for our acquisition, the followed methodology, and a description of the deep learning architecture used and our proposed model with its different layers.

2.1. Study Area

Our study area is located in the heart of Morocco, more precisely the region of Rabat Sale Kenitra (34°02′N, 6°50′W), which is known for its cereal production. It is one of the best-ranked regions for the annual production of this type of crops.

This region has several important natural resources, in particular those of the forest, in this case we have the Maamora forest, as well as an activity and a large-scale agricultural sector. it alone holds almost 11% of the useful agricultural area of the country with a greater contribution to the national cereal production. Figure 1 indicates the location of the considered region in Morocco country.

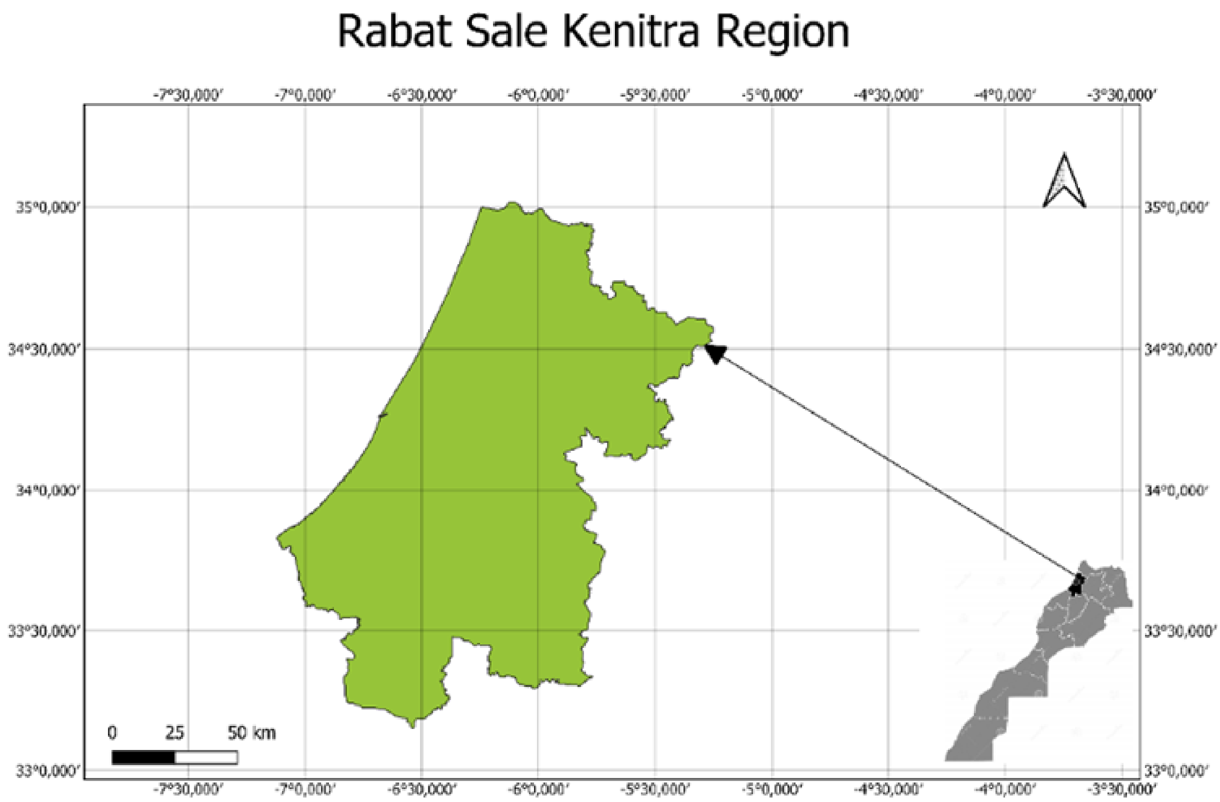

Figure 1. Localization map of the study area

2.2. Data acquisition and processing

Our study focused on estimating wheat yield in Morocco by exploiting remote sensing data. We started our methodology by acquiring UAV imagery with a HAGL (Height Above the Ground Level) of 60 m, and the processing of resulting images, then the extraction of necessary informations. Ground field yield collection was done, with a view to calibrating the model. The use of deep learning is especially proposed to capture the non-linearity that exists between yield data and predictors; in particular, convolutional neural network is proposed to process and extract features from our input images. A detailed methodological diagram is presented in (Figure 2). Remote sensing data was collected by a multispectral drone during the growth period, a single flight was performed, and a total of twenty plots were captured. All the plots considered in our study include wheat. Multispectral data was generated using the eBee Classic with MultiSPEC 4C as a camera, it is a special drone developed for precision agriculture (Figure 3). Almost hundred images covering all the plots have been acquired. Data processing was done in Pix4Dmapper, which allow us to generate orthomosaics by spectral band and also DSM (Digital Surface Model), and other special products especially for precision agriculture, for example reflectance maps and vegetation index maps.

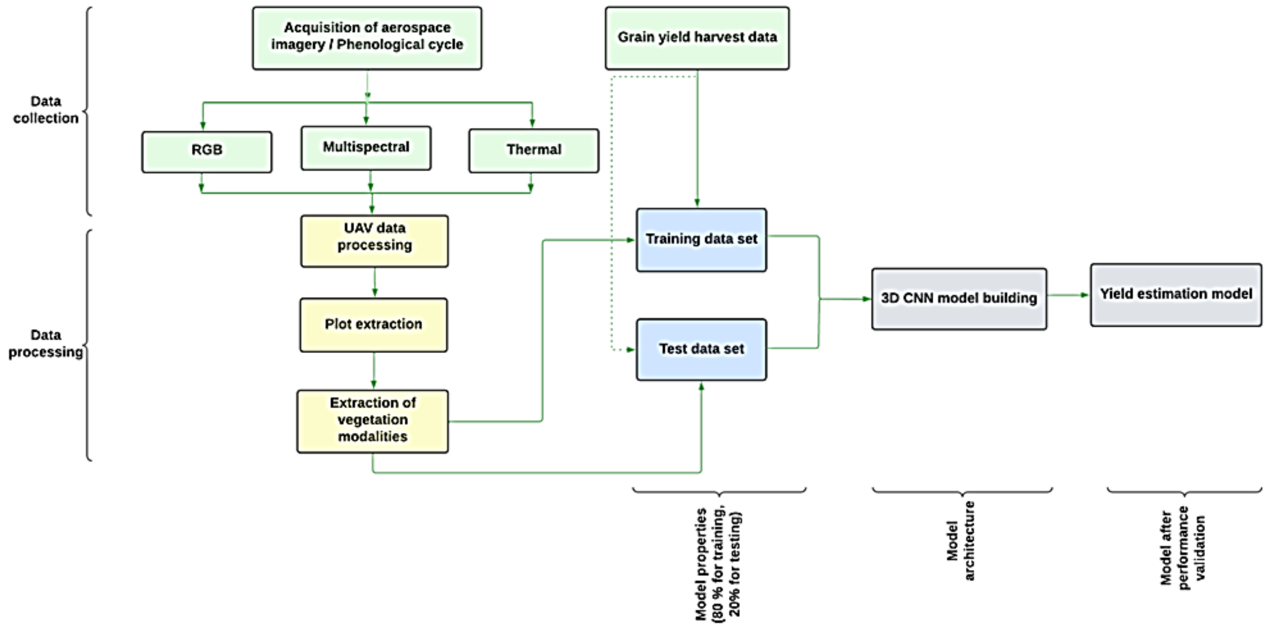

Figure 2. Methodological workflow of our study

(a) (b)

Figure 3. (a) eBee Classic UAV. (b) MultiSPEC 4C camera used

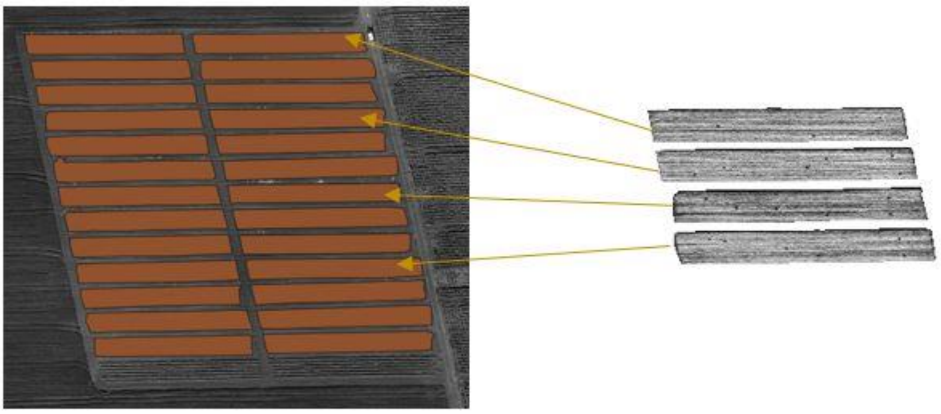

Figure 4. Shape of extracted plots

2.3. Convolutional neural network model

Artificial intelligence is an emerging technology that makes it possible to imitate human intelligence. It is based on the creation of applications and executable algorithms in computers and dynamic environments. It also makes it possible to meet a main goal, which is making computers able to act like human in terms of decisions in front of a special task.

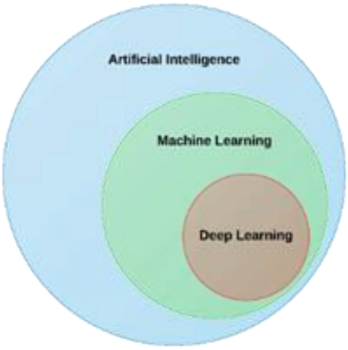

Figure 5. Artificial intelligence, machine learning and deep learning [20]

Machine learning is a branch of artificial intelligence that allows computers to solve tasks without having to be programmed in detail.

Deep learning another field of AI (Artificial Intelligence) is a sub-branch of machine learning, and a particular form of ANN (Artificial Neural Networks) which has the particularity of being deep [21]. It is generally composed of an input layer, two or more hidden layers and an output layer. Figure 6 shows us the structure of this architecture. Here the depth is represented by the number of hidden layers. DL is one of the fields that have shown a great revolution through the different architectures, in particular convolutional neural networks [7], recurrent networks [22] and other more advanced architectures [23].

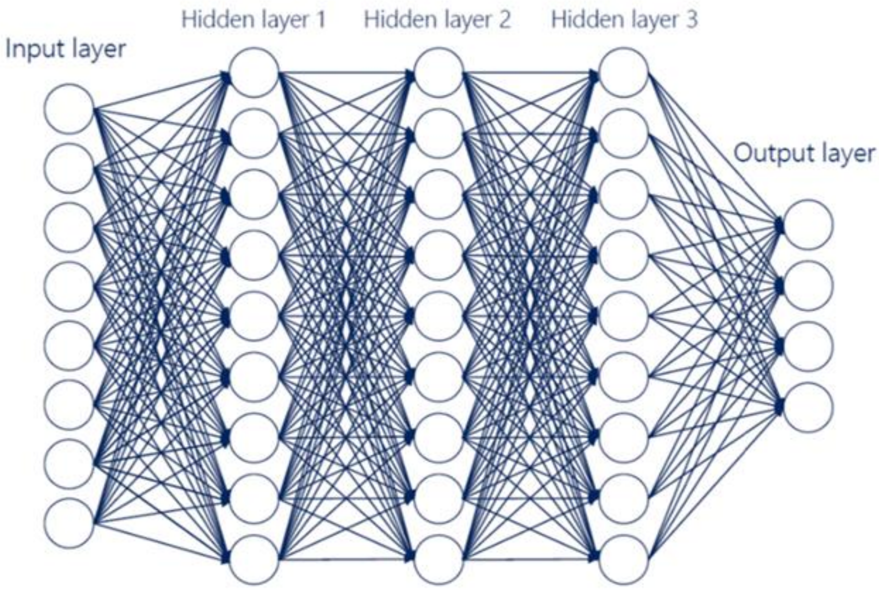

Figure 6. Deep Neural Network architecture [24]

The convolutional neural network architecture is one of the very advanced revolutions of this technology. Indeed, it allows an extraction of what is called features from images. A CNN model mainly comprises several layers of different natures namely [25]:

Convolution layer: which perform convolution operations on the input images and generate nonlinear activation maps.

Pooling layer: which aim to decrease the size and dimensions of the feature map and keep the main changes from feature maps. It is much more a compression role of this layer.

Flatten layer: A flatten layer has the role of creating a one-dimensional output from its inputs, and this to allow its use by the next layer which is the fully connected layer.

Fully connected layer: This layer is placed at the end of the CNN architecture; it allows to generate results relating to the tasks of classification or regression on the basis of its inputs.

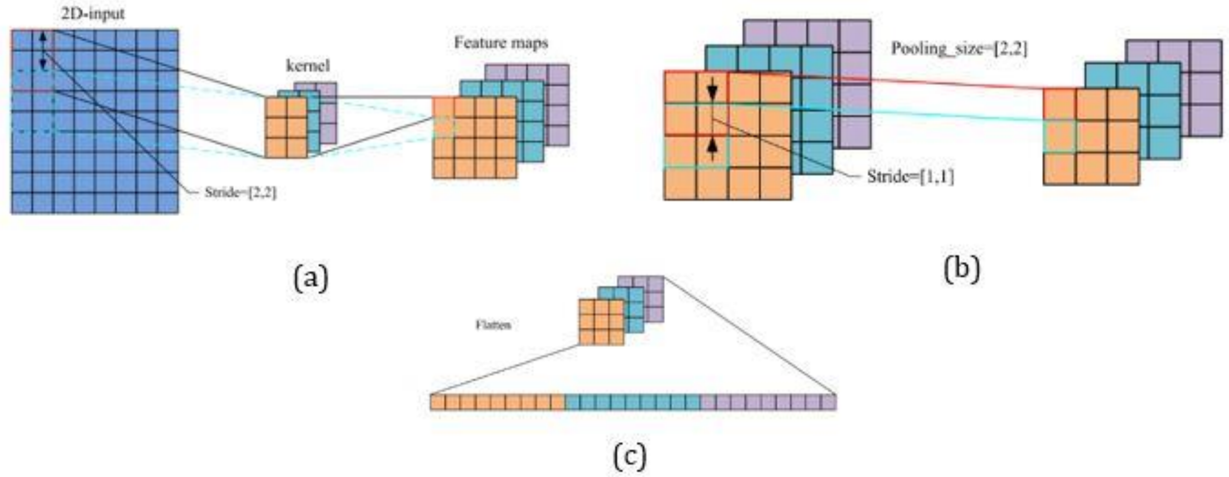

Figure 7. (a) Convolution layer (b) Pooling layer (c) Flatten layer [26]

3D convolutional neural network is an architecture generally characterized by a capacity for processing both spatial and temporal data [27], and this thanks to the addition of a dimension allowing the processing of time series. Using three-dimensional filters, 3D CNN performs a convolution on images while considering their appearance in different temporal resolutions. In the case of a 3D CNN architecture, the results are 3D maps, which will be the input of the next layer of pooling as in a simple convolution neural network. Figure 8 shows us this architecture.

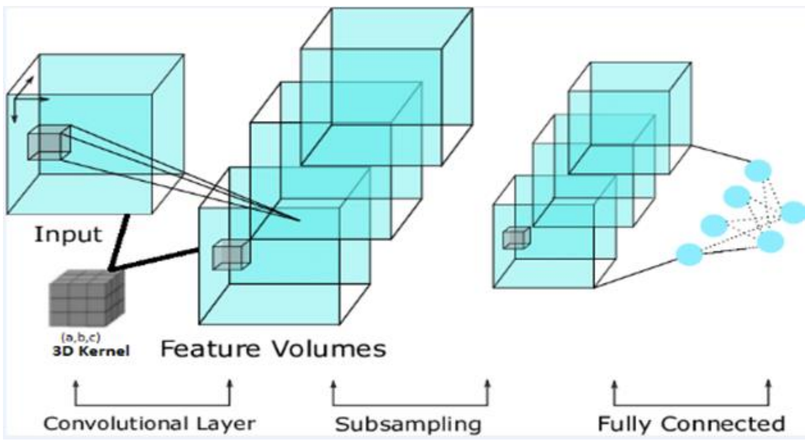

Figure 8. Convolutional neural network architecture used (modified from [28])

For the parameterization and the configuration of our convolutional neural network, we worked on the environment of jupyter. We used two convolution layers, each of them is connected to a max pooling layer, then an average pooling layer was used, and finally flatten and fully connected layers. The first convolution layer has 32 kernels while the second one has 64. The activation function used was ReLU (Rectified Linear Unit), and for the last layer we chose a linear function, since we are dealing with a regression application.

3. Results

In this section, we will present the results of an intelligent approach based mainly on the use of high-resolution aerospace images, particularly data from a multispectral camera. We will also present the results of crop yield estimation using the red edge spectral band, which is well-known for its sensitivity to agricultural applications, in particular those related to the estimation of crop yield. It often improves the results of processing [29]. Results presented in the following paragraphs concern the convolutional neural network architecture, more particularly the second dimension, and this given the availability of aerospace images of a single phenological stage. We were able to implement our deep learning model by using python programming language with its various libraries. Figure 9 shows us the variation of the loss function related to training data with increasing epochs. The agricultural yield estimates established by our convolutional neural network were compared with the results of yield values estimated by in situ methods. The generated RMSE was 0.175 qx/ha and the coefficient of determination was 0.4. Table 1 shows us the in-situ values and the predicted values. Our results confirm that a deep neural network is able to predict yield even before harvest and this by using non-destructive methods that can help farmers to obtain informations about their crops and their production.

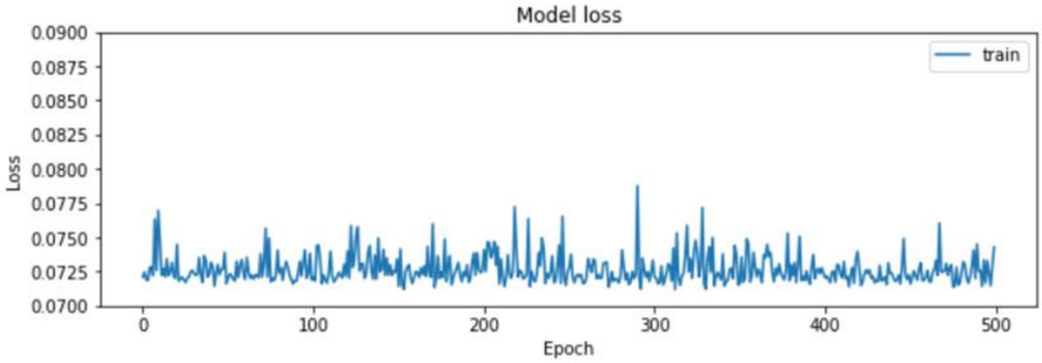

Figure 9. Variation of the loss function of our convolutional neural network

Table 1. Estimation results of DL model compared to in-situ data

N° plot	Difference between actual and predicted yield (Qx/ha)
1	0.34
2	2.11
3	3.78
4	3.44
5	5.14
6	4.46
7	1.61
8	14
9	12.73
10	1.57
11	19.24
12	7.27
13	4.94
14	8.89
15	0.53
16	14.11
17	4.31
18	4.06
19	0.06
20	4.66
21	0.11
22	2.07
23	3.78
24	3.66
25	5.54
26	4.78

4. Discussion

Through our study, we focused on estimating agricultural yield, more specifically that of wheat in Morocco. we opted for aerospace imagery first, for its ease of acquisition as well as the spectral and also the spatial richness it provides. Our study focused on the spectral band of the red edge from a multispectral camera, as long as it presents a great importance in remote sensing of agricultural crops, particularly with regard to the classification but also the prediction of physical and biological parameters of crops.

We have also chosen to manipulate our images by using deep learning, and this in order to capture all the non-linearities that may exist between our input data and the resulting output. Regarding the chosen architecture, we have opted for convolutional neural networks. It is one of the most powerful architectures that have revolutionized the deep learning field, given their ability to process unstructured data, including images.

The two-dimensional CNN architecture and drone images acquired only during one stage of the growth period were used. This explains on the one hand, the value of the correlation coefficient which was about half. We can say it was due mainly to the fact that, plants during the same growth period can have the same spectral characteristics, and other variations will appear and exist after the date of acquisition of our images. Moreover, choosing plots that are close and do not have a great variability explains the point of having very similar estimates by the model.

All this leads us to propose new possibilities for improving the results of this study, these are mainly:

* Using several spectral information describing a specific agricultural crop.

* Identifying more information of different natures and which can enrich the developed model, in particular texture information.

* Using drone images acquired throughout the wheat growth cycle to allow a detailed description of the plants and their yield as a result.

* Using deep learning architectures that allow capturing both spatial and temporal variations and, in this sense, 3D CNN is one of the architectures that can respond to this point.

5. Conclusion

This study explored the precise estimation of agricultural yield by exploiting remote sensing imagery. Our methodology is mainly based on acquiring images from multispectral UAV sensor, more precisely the red edge spectral band and ground field data, and this in the middle season of growth. We chose to obtain our data in the region of Rabat, which is a well-known territory for its annual wheat yield production. Our project was focused on exploring the convolutional neural network architecture as an algorithm to process spatial variations. Our results highlight the importance of such architecture in capturing features from raw image data and before harvest. However, more input images should be considered and this by acquiring data over the entire period of growth and not only in one stage. Furthermore, more advanced architectures should be used, namely temporal networks, which will process different aspects and specificities of an agricultural crop. Based on this, in our future work, we will apply similar architectures for estimating the yield of wheat and also other crops.

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Author contributions:

Khadija Meghraoui: Conceptualization, Methodology, Software, Data curation, Writing-Original draft preparation, Validation. **Imane Sebari:** Conceptualization, Methodology, Software, Data curation, Writing-Original draft preparation, Validation, Visualization, Investigation, Writing-Reviewing and Editing. **Saloua Bensiali:** Visualization, Investigation, Writing-Reviewing and Editing. **Kenza Ait El Kadi:** Methodology, Visualization, Investigation, Writing-Reviewing and Editing.

Conflicts of interest:

The authors declare no conflicts of interest.

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