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Towards 3D CNN for precise crop yield estimation using multimodal remote sensing data: Case study of wheat in Morocco

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Abstract

Crop yield is a primary measure in Moroccan agriculture, with various connections to human needs. Its estimation represents a troublesome task in light of its fundamental relation to crop market planning. Conventional techniques are simple, but require human effort and time. Advancement has been made in remote sensing by using deep learning architectures. This paper discusses different estimation techniques and presents a methodology to estimate wheat yield based on multimodal remote sensing data and exploiting 3D CNN (3-Dimensional Convolutional Neural Network) architecture which can be used to extract dynamic features over consecutive time. Unlike the 2D convolution kernel, which only moves in the two dimensions of height and width and passes through images horizontally and vertically, the 3D kernel establishes convolution while adding an additional dimension generally represented by time and therefore moves through these three dimensions. Our paper suggests this architecture as a methodological solution to develop a precise yield determination.

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 possibility of cropland extension [2], the accentuation ought to increase production within actual agricultural lands to avoid harmful effects on the environment.

For a long time, yield samples have been among conventional techniques to estimate agricultural yield. The principle of this method is the exploitation of a piece of iron with a square shape placed at random in a plot to count all the plants in it [3]. To lay these squares, we determine the area of the plot and identify the diagonals. For a plot of a minimum of 1 ha, each diagonal must have five samples while avoiding edges, whereas for plots having an area of less than 1 ha, it is necessary to place two to three squares per diagonal, without having less than four squares in total. To calculate yield using the square, we divide the total amount of harvest weighted by the area of the considered yield square. Crop simulation models can simulate the growth of agricultural crops [4]. They can work at different scales and help replicate key plant development processes in detail. Statistical models have been mainly used to develop an empirical relationship combining many current season yield characteristics with historical yield data [5]. More than a linear regression approach for predicting crop yield has been developed and used by studies dealing with crop yield estimation.

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 various agricultural products. These systems offer temporally relevant spatial data on land surfaces at different scales [6].

Deep learning, a subfield of machine learning, has a significant advantage in agriculture, especially in estimating yield. Mu et al. [7] reported that deep learning, specifically convolutional neural network, can extract specific characteristics of crop growth and use 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. They had Pearson R and RMSE (Root Mean Square Error) values of 0.82, 724.72 kg.m-2 and concluded that CNN represents an essential technical reference for the large-scale crop yield prediction. At the same time, Wang et al. [8] 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. [9] determined corn yield using UAV (Unmanned Aerial Vehicle) 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 in characterizing and estimating agricultural crops.

Material and Method

Our study focused on estimating wheat yield in Morocco by exploiting multimodal remote sensing data. Our study area concerns the region of Rabat-Sale-Kenitra, which is considered among the best ranked in cereals production in Morocco. We started our methodology by acquiring UAV imagery using different sensors and the extraction of multimodal informations, ground field yield, and other auxiliary data collection, which can improve the DL (Deep Learning) model results. The use of deep learning is especially proposed to capture the non-linearity that exists between yield data and predictors; in particular, the 3D CNN (Fig. 1) is proposed to allow the processing of temporal data and, at the same time, the ability to explore the spatial information and its variety when it comes to crop yield. A detailed methodological diagram is presented below (Fig. 2).

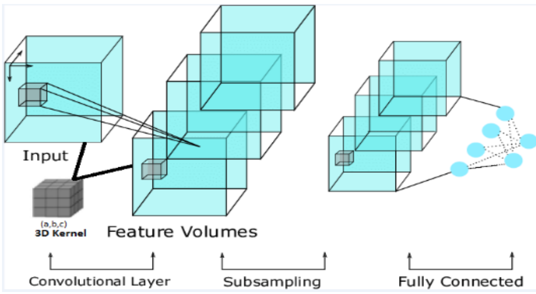

Figure 1. Architecture of 3D CNN (modified [10])

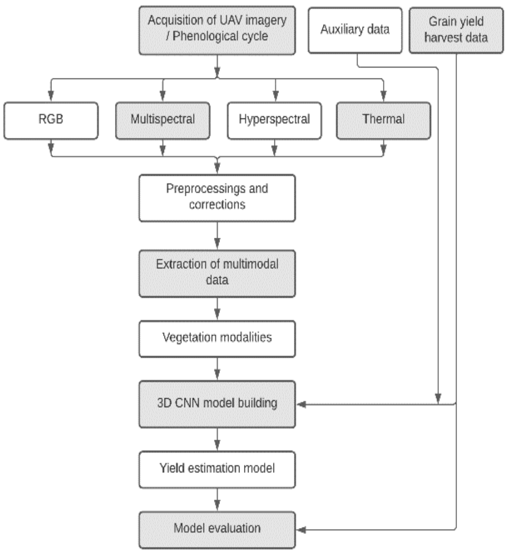

Figure 2. Methodological workflow of our study

Results and perspectives

Our research project particularly aims to demonstrate the advantage and the accurate estimation provided by deep learning algorithms, in particular three-dimensional convolutional neural networks. The latter will undoubtedly make it possible to determine the agricultural yield, whether it is that of wheat or another crop, given its particularity in capturing different dimensions of aerospace imagery. Our research project is still in progress and aims to demonstrate all these hypotheses.

Discussion

We have focused on estimating crop yield through our methodology, more specifically wheat as a crop. The reason behind the choice of combining remote sensing multimodal data is, in particular, to group together all the characteristics that describe a crop as long as the majority of studies have focused on vegetation indices which consider them alone to be able to reflect the relationship between plants and their yields, this is the case for example of the work carried out by Astaoui et al. [11]. Also, the choice of features which corresponds perfectly to the type of crop considered and not to vegetation and its cover, in general, have been little explored. To collect all these multimodal data, it is indeed remarkable that they are spread over the entire period of growth, and this is why we have opted for the 3D CNN architecture, which can process both spatial and temporal aspects when it comes to crop yield.

Conclusion

This study explored the precise estimation of agricultural yield by exploiting remote sensing imagery, particularly multimodal data. Our methodology is mainly based on acquiring images from various UAVs sensors, ground field data, and other information that may improve our determination. We chose to obtain our data in the region of Rabat, which is well known for its annual wheat yield production. Our project focused on the 3D CNN architecture as an algorithm to process spatial and temporal variations. In our future work, we will apply similar architectures for estimating the yields of other crops.

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