EXPLORING THE CROPS CLASSIFICATION IN ROMANIA USING SATELLITE IMAGES

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Abstract

Crop classification is of enormous significance for agricultural management. Satellite remote sensing is considered an advanced technology for obtaining crop types on a regional scale, as it can regularly provide large-scale observations of ground objects. The paper aims to debate the problem of crop classification, and the findings can be used in complex commercial applications. Our analysis starts by presenting the progress made in the field of crop classification based on satellite imagery and proposes a general architecture for a crop identification system. The paper also discusses the challenges faced in crop classification, such as the complexity of crop spectra, the influence of environmental factors, and the need for ground truth data for validation. To address these challenges, the paper proposes using a combination of different data sources, including ground observations, meteorological data, and soil information, in addition to satellite imagery. Overall, the paper provides a comprehensive overview of the state-of-the-art techniques and methods used in crop classification based on satellite imagery. The findings of the analysis have significant implications for agricultural management and can be applied in various commercial applications, such as precision agriculture, yield estimation, and land-use planning.

Key words: crop classification, satellite remote sensing, agricultural management, machine learning

Technology is changing farming practices around the world. Satellite imagery, predictive analytics, large-scale data processing, and advances in biology and chemistry are working together to deliver better productivity and less pollution or soil degradation. Technological advances allow agronomists and farmers to monitor crop growth from desktop or mobile computers, assisting them in decision-making and better resource planning.

Machine learning algorithms are often used to analyse satellite images and classify crops. These algorithms can be trained using labelled data to recognise the spectral signatures of different crops and assign them to specific categories. Some commonly used machine learning algorithms for crop classification include Support Vector Machines (SVM), Random Forest (RF), and Convolutional Neural Networks (CNN).

Crop classification using satellite images has several applications in agriculture. It can be used to monitor crop growth and health, identify areas of crop stress or disease, estimate crop yields, and predict crop production. This information can be used by farmers, agricultural companies, and policymakers to make informed decisions about crop management, resource allocation, and food security.

Crop classification using satellite images has some challenges as well. Some of the challenges include the presence of cloud cover in the images, the variability of spectral signatures of crops within a region, and the need for high-quality labelled training data. Nonetheless, advances in remote sensing technology and machine learning algorithms have made crop classification using satellite images increasingly accurate and useful in recent years.

Furthermore, crop classification using satellite images can also help in monitoring the effects of climate change on agricultural productivity. The changing climate patterns are causing alterations in the timing of seasons, temperature, and precipitation. These changes can significantly impact crop yields, and the use of satellite images can help monitor and mitigate these effects.

Moreover, the classification of crops using satellite images can also be used to identify areas that are prone to natural disasters, such as droughts, floods, and wildfires. This information can be used to plan and implement appropriate measures to

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prevent or mitigate these disasters, thereby minimising their impact on crop production and improving food security.

In recent years, the use of artificial intelligence and machine learning techniques has significantly improved the accuracy and efficiency of crop classification using satellite images. These techniques can learn from previous classifications and make predictions based on past data. This helps in improving the accuracy of crop classifications and reducing the time and resources required for the process.

MATERIAL AND METHOD

Crop classification based on satellite imagery is currently a problem, as there are no operational field-level crop maps for Romania. There are, however, commercial initiatives and research that attempt to identify crop maps to facilitate farm management processes for farmers and also to manage resources better and understand agricultural processes at the national level.

The Sen2-Agri system uses Sentinel 2 (Sentinel website)imagery to create crop maps at 10 m resolution for crops such as maise, winter wheat, soybean, and sunflower. A similar initiative is described (Wu B. *et al*, 2015) and provides statistics at global, national or regional levels but does not have the facility to provide field-level crop mapping.

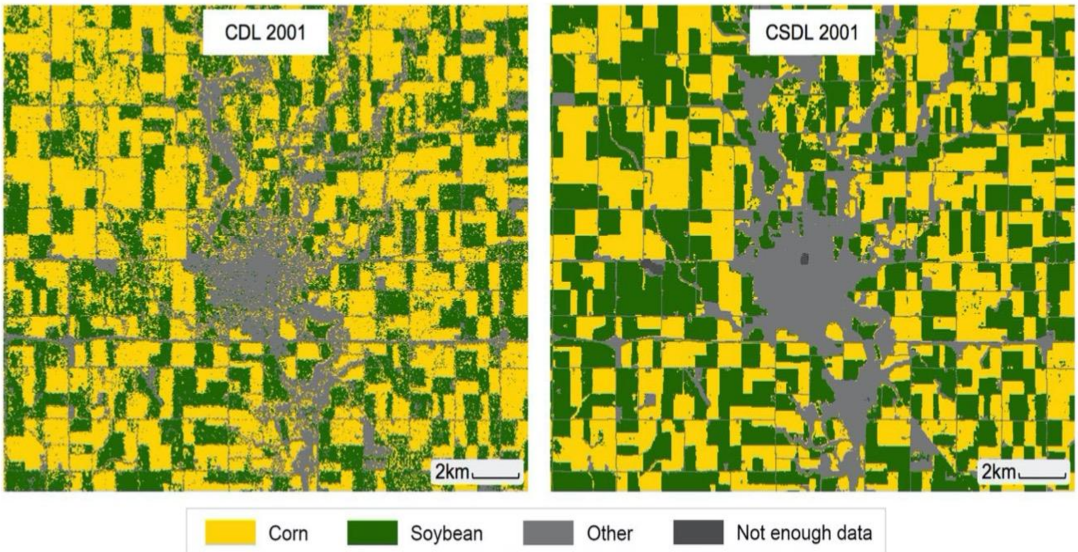

Figure 1. **Corn and soybean classification in Iowa in 2001.**

On the left is the USDA (United States Department of Agriculture) cropland data layer, and the result of the proposed method (Corn-soybean data layer) on the right is the crop type map.

Several algorithms were tested for research purposes in creating crop maps: SVM, Decision Trees, Gradient Growth Trees or Random Forest and as features surface reflectance, spectral indices, statistical textures and temporal features were considered. Several strategies (Inglada J., *et al*, 2015) were tested and compared using SPOT4 data on 12 sites worldwide.

The random forest also showed the best results (Wang S., *et al*, 2020), where the authors created crop data layers (Figure 1) for the US Department of Agriculture. Crop classification maps using this approach achieved 90% accuracy in some cases. Another approach, presented by Nasrallah A. (Nasrallah A. *et al*, 2018), uses Mean-Shift segmentation applied on NDVI -Normalised Difference Vegetation Index (Rouse J.W. *et al*, 1973) values to achieve 82% to 87% accuracy. The novelty is that the approach allows the identification of wheat crops before harvest.

The literature suggests that it is possible to identify crop types using satellite imagery. Based on all the approaches reviewed, we propose in this paper an architecture for a crop identification system for different purposes, such as buying or selling land or just improving the rotational crop process.

In section 2, we present the use case for this application and the architectural proposal. The last section briefly presents the conclusions and shows how it can be further developed into other commercial applications.

RESULTS AND DISCUSSIONS

Buying or renting an agricultural field is sometimes a risky business. Particularly in Romania, data on the history of arable land is scarce and not always reliable. APIA - Agency for Intervention and Payments in Agriculture (APIA, website) has data on fields and what farmers grow each season, but the data is not publicly available and cannot always be trusted, as farmers sometimes change crops without notification. Therefore, a farmer/investor wanting to learn more about a field can just visually inspect it and get a few soil samples to perform an analysis, which is costly and time-consuming.

We propose a scenario that can be realised using a mobile app. The farmer visually inspects a field. He opens the app, and the app detects its location. The farmer can mark the field around him, the field he is interested in buying or renting. The app shares the shape of the field (geospatial vector data format) with the crop classification system for field analysis. Fields are extracted from Sentinel-2 imagery by querying the Copernicus (Copernicus, website) open access centre for Sentinel-2 L1C and L2A products. The images are analysed, and various vegetation indices, cloud cover, shadows, et.al. are computed (Sentinel, website). Based on these and a machine learning algorithm, a field history is generated with the crops that have been grown in the field for each season.

A proposed high-level system architecture is shown in Figure 2.

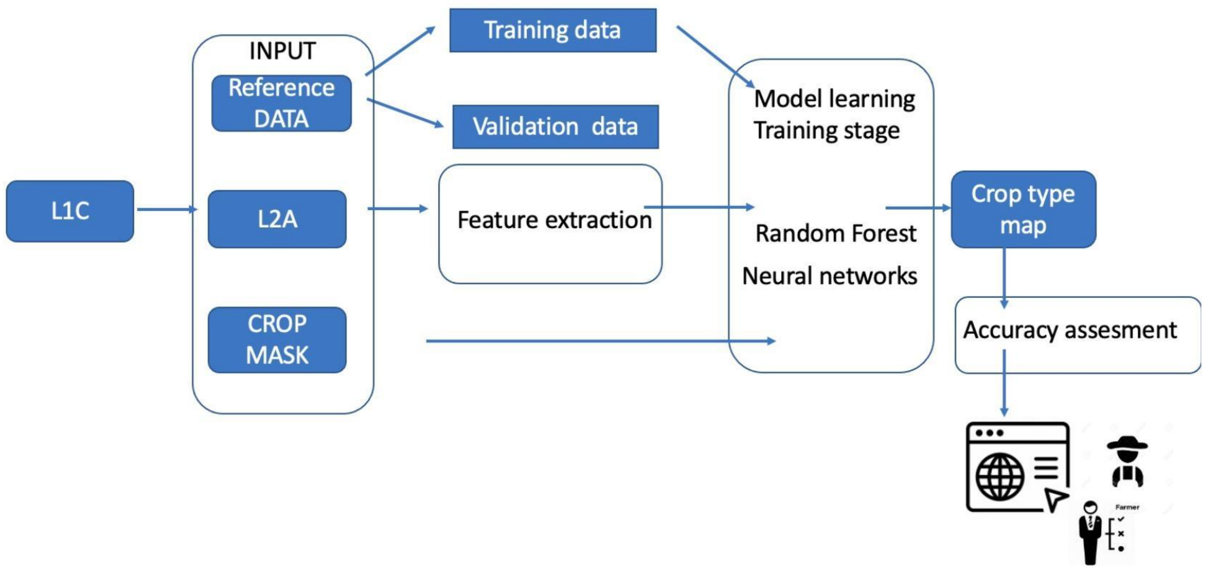

Figure 2. **High-level system architecture**

CONCLUSIONS

Crop classification plays a crucial role in agricultural management. For this reason, satellite remote sensing is considered an advanced technology that allows information on crop types to be obtained on a regional scale through regular large-scale observations of ground objects. Our review starts by presenting the progress made in the field of crop classification based on satellite imagery. Therefore, we propose a general architecture for a crop identification system for different purposes, such as buying or selling land or just improving the rotational crop process.

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