Abstract
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'Development of methodology for automated crop mapping in Greece using Neural Networks and Sentinel-2 satellite imagery'

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1. Introduction

Reliable and accurate cropland mapping at national, regional and global level is essential within the framework of UN's 2030 Agenda for Sustainable Development, food security and sustainable environmental management. Earth Observation (EO) data, collected by satellite platforms of the European Union's Copernicus EO programme, provide the impetus for the development of automated high accurate methods for information extraction at regular temporal intervals.

2. Objective

Within the framework of the current study, computational approaches for cropland mapping in Greece using deep learning methods and high spatial resolution Sentinel-2 satellite images of the Copernicus programme were developed and evaluated. The study area was selected within the Regional Unit of Serres where reliable reference data from OPEKEPE (Greek Payment Authority of Common Agricultural Policy (C.A.P.) Aid Schemes) were collected for a complex classification scheme consisting of 20 classes. Furthermore, the effect of different methods of training sample extraction was examined and evaluated, not only in terms of classification accuracy metrics, but also considering classification uncertainty.

3. Methods

The experimental design included five supervised machine learning classification algorithms, including a Temporal Convolutional Neural Network (Temporal CNN), a bidirectional Gated Recurrent Unit Neural Network (Bi-GRU), a bidirectional Long Short-Term Memory Neural Network (Bi-LSTM), a combination of a Recurrent and a 2-D Convolutional Neural Network (R-CNN) and finally a Random Forest. In all these methods, two stratified sampling strategies for the acquisition of the training dataset – pixel-based and object-based – were developed and evaluated. The classification metrics of overall accuracy, Cohen's kappa, macro average precision, macro average recall and macro average f1-score were used for the comparative evaluation of the approaches. Finally, the normalized Shannon entropy of the test instances and a variant of the metric Root Mean Square Error (RMSE) were calculated in order to capture the spatial distribution of the classification error.

4. Results

Splitting the data based on the distribution of pixels among classes, the architectures of Temporal CNN and Bi-LSTM had almost equivalent performance in all the classification metrics assessed. Temporal CNN was the most effective in classifying classes of varying sample sizes. On the contrary, R-CNN didn't manage to reach the average levels of efficiency of the rest four architectures, performing the worst results in rarer classes. When the object-based splitting method was applied, the results were different, with the Bi-LSTM architecture having the highest value of macro average f1-score and subsequently being assessed as the best model. In both splitting approaches, Random Forests failed to keep the values of entropy low in the classification of test instances and had the highest percentage values of the variant RMSE. Thus, the tree-based algorithm, being the only one among the models which ignored the temporal dimension of data, offered more uncertain predictions in comparison with the neural networks.

5. Contribution

In this study, not only the traditional classification algorithm of Random Forest, but also four deep learning models, whose architectures belong to Temporal Convolutional Neural Networks, bidirectional Gated Recurrent Unit Neural Networks, bidirectional Long Short-Term Memory Neural Networks and combined Recurrent and 2-D Convolutional Neural Networks, were implemented for the classification of multi-spectral satellite images. In this task, the number of classes was relatively high (more than 10). Some of them were specialized types of crops while others were more general, a fact whose effect was investigated in the results. After exploring the influence of restructuring the training set, we suggest that the splitting should be on the basis of the objects' distribution among the classes, despite the higher values of classification metrics when applying the other splitting method. The main reason is the existence of similar spectral values of the pixels being included in the same objects.

The imbalance among the number of instances per class leads us to pay attention to macro average f1-score, with the proposed architecture of Bi-LSTM being this one which achieves the highest value in the case of object-based splitting approach. At the same time, the study proves and justifies why Random Forests in combination with the available data and methods are unable to provide reliable classification results from both perspectives of classification, accuracy and uncertainty. Moreover, the results made it clear that the number of instances belonging to the same class together with their spectral variability can have a significant impact to the values of uncertainty.

In general, this study designs from scratch the architectures of five different machine learning and deep learning algorithms for the classification of an extensive area of land covered mainly by crop and forest types. It uses a time series of Sentinel-2 images and it is not restricted to simply presenting the results given by classification metrics. On the contrary, it highlights the issue of sampling strategy for the extraction of the training set and it handles effectively both the imbalance of original data and the spectral variability of instances among classes. Furthermore, this study proposes a methodology of preprocessing of satellite images and it confirms the reliability of the final best architecture, not only from the traditional aspect of classification metrics. It is really significant that it is attempted to find and capture possible correlations between classes' size, the accuracy per class and the normalized entropy per class. All the computational results are also available in the form of classification maps of the specific area, providing, at the same time, a percentage distribution of the classes covering the area. This fact is very important for the purpose of crop mapping, decision-making and policy design for sustainable terrain management. Finally, this thesis is a first step of using an innovational methodology for the task of land cover mapping and the operational inventory of spatial information over agricultural areas.

The whole code of the thesis was created and developed in Python 3.8.5 and R Studio, with the concurrent support of the software packages called Quantum Geographic Information System (QGIS) and diagrams.net.

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