Deep Learning for Agricultural Land Detection in Insular Areas

Eleni Charou
Institute of Informatics and Telecommunication
NCSR Demokritos
Athens, Greece
exarou@iit.demokritos.gr

George Felekis
Department of Mathematics
Kapodistrian University of Athens
Athens, Greece
geofele@yahoo.gr

Danai Bournou Stavroulopoulou
Rural and Surveying Engineering
National and Technical University of Athens
Athens, Greece
danaibournou@gmail.com

Maria Koutsoukou
Department of Physics
Kapodistrian University of Athens
Athens, Greece
marikou@gmail.com

Antigoni Panagiotopoulou
Institute of Informatics and Telecommunications
NCSR Demokritos
Athens, Greece
antigoni27aug@gmail.com

Yorghos Voutos
Department of Informatics
Ionian University
Corfu, Greece
george.voutos@gmail.com

Emmanuel Bratsolis
Department of Informatics and Computer Engineering
University of West Attica
Athens, Greece
ebrats@uniwa.gr

Phivos Mylonas
Department of Informatics
Ionian University
Corfu, Greece
fmylonas@ionio.gr

Laurence Likforman-Sulem
Institute Mines-Télécom/ Télécom ParisTech,
University Paris-Saclay
Paris, France
likforman@telecom-paristech.fr

***Abstract*— Nowadays, governmental programs like ESA's Copernicus provide freely available data that can be easily utilized for earth observation. In the present work, the problem of detecting agricultural and non-agricultural land cover is addressed. The methodology is based on classification with convolutional neural networks (CNNs) and transfer learning using AlexNet. The study area is located at the Ionian Islands, which include several land cover classes according to Copernicus CORINE Land Cover 2018 (CLC 2018). Furthermore, the dataset consists of natural color images acquired by Sentinel-2A multi-spectral instrument. Experimentation proves that extra addition of training data from foreign grounds, unfamiliar to the Greek data, serves much as a confusing agent regarding network performance.**

***Keywords*—Deep learning, Transfer learning, Ionian Sea, Agricultural land, CORINE database, Remote Sensing, Satellite Image Classification, Deep Convolutional Neural Networks**

I. Introduction

Climatic variations produce nuisances on the natural and human environment, more specifically they affect the primary sector of the economy. Agriculture, as one of the oldest and most important mean of production, necessarily demands continuous observation through remote and on-site monitoring. Furthermore, large scale spatial analyses require large datasets and specialized apparatus supported by analytical and statistical tools. Nowadays governmental programs like ESA's Copernicus provide freely available data that can easily be utilized for Earth Observation and Land Cover Classification.

Deep Learning (DL) is a branch of machine learning which tries to model the human brain function with the purpose of more efficient, faster and parallel processing of information. The idea of Convolutional Neural Networks (CNNs) was firstly introduced in [1], improved in [2] and refined as well as simplified in [3]-[4]. With the large-scale sources of training data and efficient implementation on GPUs, CNNs have recently outperformed some other conventional methods, even human performance, on many vision related tasks such as image classification, object detection and face recognition. It has been demonstrated that CNNs can provide even better classification performance than the traditional support-vector machine classifiers and the conventional neural networks.

Transfer learning [5] is a machine learning technique where a model, after having been trained on certain task, is re-purposed on another related task. In DL applications transfer learning is the process of considering a pre-trained model, thus considering the weights and the parameters of a network that has been previously trained on a large dataset, and fine-tuning the model with a current dataset. Fine-tuning a network with transfer learning is usually much faster and easier than training a network with randomly initialized weights from scratch. In the present work, the transfer learning technique was utilized through the network AlexNet [6]. AlexNet is considered one of the most influential networks published in computer vision, having spurred many more papers on employing CNNs and GPUs to accelerate DL. The particular network is able to classify images into 1,000 object categories, due to having been trained on over a million images and therefore, having learned rich feature representations for a big range of images.

Public research programs focus on providing access to satellite datasets under the scope of open and free use from the scientific community. In particular, Copernicus program engages the utilization of satellite imagery datasets for earth observation and land cover classification research purposes

[7]-[9]. Mediterranean insular areas present a fragmented pattern in landscape structure that requires advanced classification techniques. On the other hand, agriculture is an important factor in local economies and affects the natural environment.

In the present work a study on the direction of categorizing agricultural and non-agricultural land cover at insular environment namely the Ionian islands, Greece, is presented. Similar works can be found in [10]-[12]. CNNs and Transfer Learning were applied on existing data as well as on novel datasets created on the purpose of this work for the detection of agricultural lands. Experimentation proved that the extra addition of training data from foreign ground, unfamiliar to the Greek data, deteriorates the network performance.

The organization of this paper is as follows. Section I introduces the work. The area of interest and the data are presented in Section II. Section III gives the experimental set-up and results. Conclusions are drawn in Section IV.

II. Study Area and Data Used

A. Study Area

The area of study consists of the Ionian islands in Greece namely the islands of Corfu, Cephalonia, Zakynthos, Kithira, Meganisi, Paxoi and Lefkada as depicted in Fig. 1. This area of 2,400 Km^2 is big enough to be considered as a representative part of all the insular and close to the coastline areas of Greece.

B. Data Used

For the training and testing purposes two datasets were used and are described in the following: the freely available EuroSAT and the constructed on the purpose of this work Demokritos dataset. The EuroSAT dataset (Table I), publicly available at https://github.com/phelber/eurosat, is based on Sentinel-2 satellite images covering 13 spectral bands and consisting out of 10 Land Use Land Cover (LULC) classes with in total 27,000 labeled and geo-referenced images, that measures 64x64 pixels each. It was successfully used for LULC classification in state of the art CNNs and is intending to be a benchmark for this kind of studies [9]. The Demokritos dataset (Table II), publicly available at https://github.com/boreallis/NCSR_IonioNET/blob/master/README.md, was constructed for this study in a two steps procedure: Satellite Image Acquisition step followed by a Dataset creation step. In the Satellite Image Acquisition step, 125 Sentinel-2 tiles of the Study Area, between January 2017 and April 2019 with low cloud coverage were acquired. Since optical satellite imagery may be still contaminated with clouds and shadows, preliminary processing steps were taken to clean the data. As expected, noticeable differences were present in the fields at summer months, mostly dry soil, in comparison with the winter ones. The initial tiles were exported in a map scale of 1/30,000 through Qgis using Sentinel's Hub plugin in the following forms a) Georeferenced TIFF images (Reference System WGS 84 Pseudo Merctor) and b) JPG images. In the Demokritos Dataset Creation step, the obtained satellite tiles were divided into 2,925 non-overlapping image patches. Each patch is a natural color RGB image of size 227x227 pixels with spatial resolution of 10m per pixel and has been manually checked and labelled in one of the of two different classes (agricultural and non-agricultural). The labelling procedure was mainly based on the recently released CORINE Land Cover 2018 (CLC 2018) https://land.copernicus.eu/pan-european/corine-land-cover/clc2018 . The CLC inventory was initiated in 1990 by the European Environment Agency, for the recognition, identification and assessment of land cover classes in Europe. Updates have been produced in 2000, 2006, 2012 and 2018. The CLC 2018 is based on Sentinel -2 images and contains specific colored IDs of 44 classes belonging to 5 basic level land cover categories. In this work, the 44 classes have been merged in two classes, namely, agricultural and non-agricultural. The agricultural class includes the non-irrigated arable land, permanently irrigated land, rice fields, vineyards, olive groves, pastures, annual crops associated with permanent crops, complex cultivation patterns and land principally occupied by agriculture with significant areas of natural vegetation, while the non-agricultural class includes all the remaining CLC2018 classes. Special care was given when selecting images in the previous step for the tiles time interval to fall within the annotation period of CLC 2018 [6].

Besides CLC2018 data and in order to validate it, ortho photographs of the Hellenic Cadastre at 1m resolution as well as field checks were performed in the Study Area. Very few patches that were labelled as agricultural in CLC2018 found to be non-agricultural after checking and these paches were excluded from the Demokritos dataset. A labelled as agricultural patch in Demokritos dataset with its corresponding patch from CLC2018 is shown in Fig. 2.

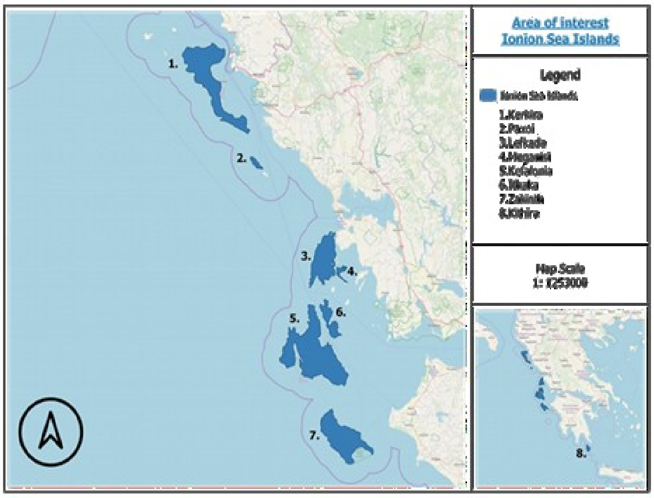

Fig. 1. Study Area.

Fig. 2. Raw image patch corresponded to its ground truth according to CORINE Land Cover 2018.

TABLE I. EuroSAT dataset.

Class Name	Number of Patches
Industrial	2,500
Residential	3,000
Annual Crop	3,000
Permanent Crop	2,500
River	2,500
Sea & Lake	3,000
Herbaceous Vegetation	3,000
Highway	2,500
Forest	3,000
Pasture	2,000

TABLE II. Demokritos dataset.

Class Name	Number of Patches
Agricultural	1,832
Non-Agricultural	1,903

III. EXPERIMENTAL SET-UP AND RESULTS

A. Dataset Description

Two datasets, namely EuroSAT and Demokritos, were utilized, Fig. 3. An adjustment of EuroSAT was performed in the present project. The binary EuroSAT, which is comprised of 20,493 images, was partitioned into only two categories, agricultural and non-agricultural from EuroSAT. Specifically, the agricultural category includes the following: annual crop, permanent crop, herbaceous vegetation and pasture. Regarding the non-agricultural category, Residential, Sea-Lake, Highway and Forest are included.

B. Networks

A series of CNNs was employed for classification at the Ionian islands region. Initially, EuroNet and EuroNet_exp networks were constructed. These are convolutional neural networks for deep learning classification created with transfer learning technique using the pretrained neural network Alexnet. Through transfer learning, EuroNet was re-trained on binary EuroSAT images and EuroNet_exp was re-trained on the union of Demokritos and binary EuroSAT dataset. Through an analytic optimization process, three more efficient CNNs were constructed. These CNNs were considered as more relevant at the research level. Below, a detailed description of the above-mentioned is given.

a)

b)

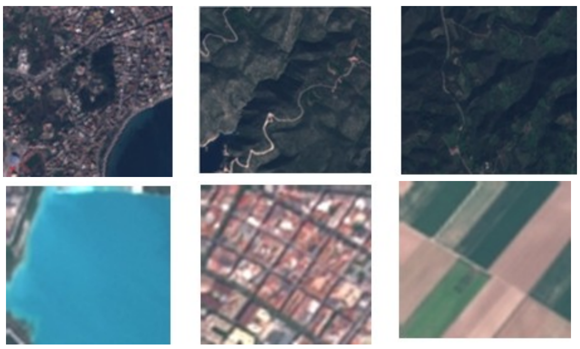

Fig. 3. Images from the datasets a) Demokritos b) EuroSAT.

IonioNet_PI is a CNN which was created with transfer learning using the pretrained neural network Alexnet. Demokritos was used for both training and testing. Additionally, binary EuroSAT served for testing. The training options were as follows: initial learning rate α = 0.01, number of epochs = 6, mini batch size = 10, Optimizer: Stochastic Gradient Descent with Momentum (SGDM) = 0.9 (default) | scalar from 0 to 1. The accuracy on Demokritos was 96.58%. Regarding binary EuroSAT, the overall accuracy was 47.3 % or 9,683 out of 20,493. In specific, on agricultural images there was accuracy 0.33% or 35 out of 10,501 and on non-agricultural images accuracy 96.5% or 9,648 out of 9,992.

IonioNet_PD is a CNN created from scratch. It has an image input layer, three convolutional layers, three batch normalization layers, three ReLU layers, two max pooling layers, a fully connected layer, a Softmax layer and a classification layer. Demokritos was used for both training and testing. Additionally, binary EuroSAT served for testing. The training options were as follows: initial learning rate α = 0.01, number of epochs = 20, shuffle in every epoch, optimizer: SGDM = 0.9 (default) | scalar from 0 to 1. The accuracy on Demokritos was 93.75%. Regarding EuroSAT, the overall accuracy was 24.3% or 4,981 out of 20,493. Particularly, on agricultural images there was accuracy 26.43% or 2,778 out of 10,501 and on non-agricultural images accuracy 22.06% or 2,205 out of 9,992.

Enet is a CNN created from scratch and trained on EuroSAT. It has an image input layer, three convolutional layers, three batch normalization layers, three ReLU layers, two max pooling layers, a fully connected layer, a Softmax layer and a classification layer. EuroSAT was used for both training and testing. The training options were as follows: initial learning rate α = 0.01, number of epochs = 20, shuffle in every epoch, optimizer: SGDM = 0.9 (default) | scalar from 0 to 1. The accuracy on EuroSAT was 80.34%.

IonioNet_PE is a convolutional neural network for deep learning classification created with transfer learning technique using the pretrained neural network ENet. Demokritos was used for both training and testing. The training options were as follows: initial learning rate α = 0.001, number of epochs = 20, mini batch size = 64, shuffle in every epoch, optimizer: SGDM-Stochastic gradient descent with momentum = 0.9 (default) | scalar from 0 to 1.

The accuracy-iteration and accuracy-CNN tables are depicted in Fig. 4 and Fig. 5, respectively. The accuracy was computed on patches. Table III gives the training schemes as well as the training and testing datasets regarding each CNN. All parameter values were optimized for best performance.

Particularly, EuroNet had 40.89% success on Demokritos dataset (correctly categorizing 1,221 out of 2,925 images) while EuroNet_exp showed a slightly increased accuracy of 62.30%. It is fairly obvious that the extra addition of data of foreign grounds (EuroSAT), unfamiliar to Greek ones, in the training set serves more as a confusing agent rather than an enhancement in the performance of the network. To sum up, the IonioNet_PE is the most effective network for the purposes of the present study and what will be preferred for future works.

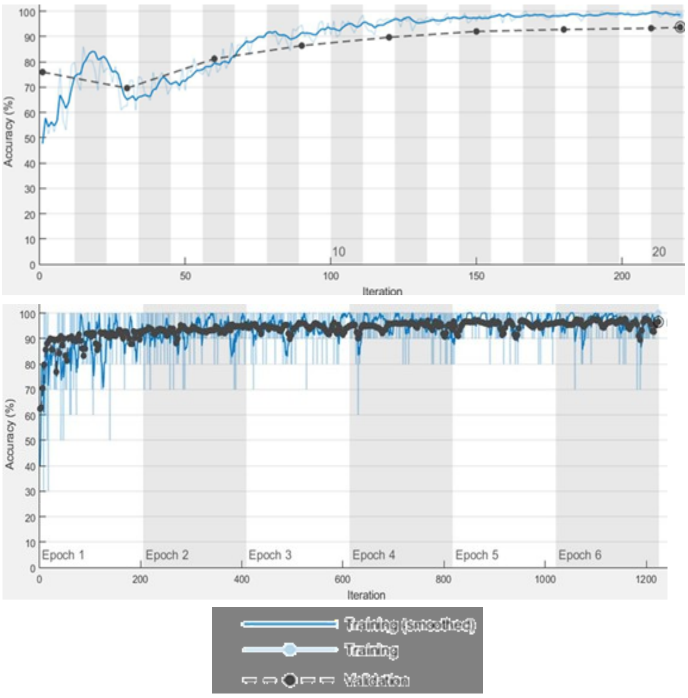

Fig. 4. Accuracy-Iteration tables for IonioNet_PD (first) and IonioNet_PI (second).

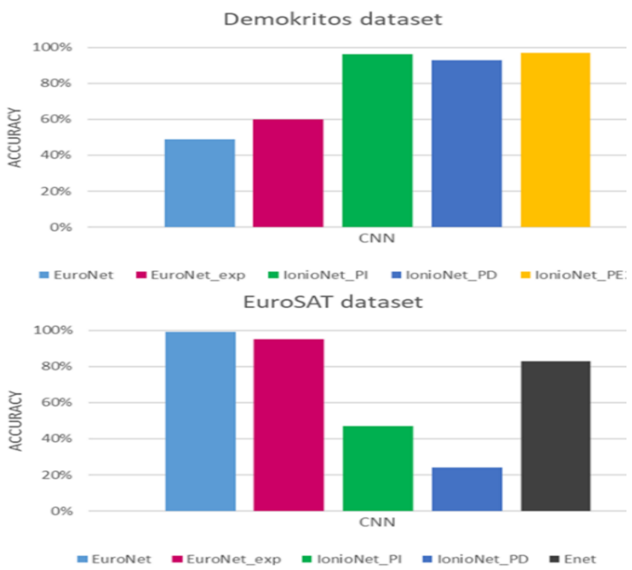

Fig. 5. Accuracy of CNNs on both Demokritos and EuroSAT datasets.

TABLE III: Training schemes and training/testing datasets for the various CNNs.

CNN Name	Training Scheme	Training Dataset	Testing Dataset
EuroNet	Transfer Learning	Binary EuroSAT	-
EuroNet_exp	Transfer Learning	Union of Demokritos and Binary EuroSAT	-
IonioNet_PI	Transfer Leaning	Demokritos	Demokritos, Binary EuroSAT
IonioNet_PD	Randomly Initialized	Demokrtos	Demokritos, Binary EuroSAT
Enet	Randomly Initialized	EuroSAT	EuroSAT
IonioNet_PE	Transfer Learning	Demokritos	Demokritos

IV. CONCLUSIONS

In this work, the detection of agricultural land in insular environment was addressed. The methodology used is based on CNNs and transfer learning. A new dataset of image patches, called Demokritos and based on Sentinel-2 images of the study area, was created and made publicly available. An existing dataset of image patches, called EuroSAT and based on Sentinel-2 images of European cities, was tested. Preliminary results show that this extra information of training data that are unfamiliar to the Greek ones, serves more as a confusing agent rather than an enhancement in the performance of the CNN. The CLC 2018 was validated in the study area with synergistic use of ancillary data as well as field checks and found to be in a good consistency.

Since this work is a preliminary one, the EuroSAT dataset was tested as a whole. However, in the immediate future, EuroSAT will be limited to only images from regions in southern Europe. Additionally, the *IonioNet_PI* training will be reconsidered. Regarding implementation, the various important elements of architecture and the parameter factors of the CNN should be studied in future work. Considering parameters such as the learning rate, the improvement threshold and the number of iterations to the end of learning epochs could improve time efficiency and accuracy.

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