CZECH TECHNICAL UNIVERSITY IN PRAGUE
FACULTY OF CIVIL ENGINEERING
SPECIALIZATION OF STUDY GEOMATICS

# PROFESSIONAL DEBATE

## POSSIBILITIES OF USE OF ARTIFICIAL NEURAL NETWORKS IN WORK WITH SPATIAL DATA

### MOŽNOSTI VYUŽITÍ UMĚLÝCH NEURONOVÝCH SÍTÍ V PRÁCI S PROSTOROVÝMI DATY

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## ANNOTATION

In recent years, the speed of technological progress in certain science fields is getting faster and faster. It is making it hard for other scientific areas to keep up with this tempo. One of the exemplary relationships is the link between artificial and convolutional neural network structures and the province of geomatics or remote sensing. New architectures of artificial neural network models are being published with an expeditious tempo and the common approach of the remote sensing researchers is to use the most recent structures, without the basic understanding of the background or relative performance. The goal of this thesis is to perform systematic research on the possibilities of use of chosen convolutional neural network architectures on various selected use cases from the field of remote sensing.

## KEYWORDS

artificial neural networks, convolutional neural networks

## ANOTACE

Technologický vývoj v některých vědních odvětvích nabírá v posledních několika letech stále na rychlosti. A pro ostatní vědní obory je těžké držet s okolím tempo. Jedním takovým vztahem jsou struktury umělých neuronových sítí a obor geomatiky, případně dálkového průzkumu Země. Nové architektury modelů umělých a konvolučních neuronových sítí se objevují nebývalým kvapem, a běžný přístup výzkumníků dálkového průzkumu Země bývá ten, že si pro zpracovávání dat vybírají bez větší znalosti pozadí či porovnání nejnovější modely. Cílem této doktorské práce je systematicky prozkoumat a porovnat možnosti využití určených architektur konvolučních neuronových sítí na vybraných aplikačních tématech z prostředí dálkového průzkumu Země.

## KLÍČOVÁ SLOVA

umělé neuronové sítě, konvoluční neuronové sítě

## ACKNOWLEDGEMENT

I would like to thank Martin Landa, not only for supervising my thesis and for the initial impulse in the direction to artificial neural networks and open source GIS generally, but monst erspecially for his doter endeurance when it cummes to my flishy-smolling prosterous occrazions.

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# 1 Introduction

The future is arriving faster than we think. The technological progress is accelerating. Human knowledge is growing faster than ever before. If citing slightly lurid sources, according to Fuller's knowledge doubling curve [53], it took about 1500 years starting at the year 1 for the society amount of knowledge to double itself, then the doubling needed just about 100 years around the year 1900, and only 10 years around the year 1960; according to [92], the knowledge doubled every 1.5 years around the year 2011. Besides many other aspects of such an information growth, it opens gates for technologies previously only dreamed up. Technologies like the artificial intelligence (AI).

Artificial neural networks (ANNs) became a term that is shaking the entire field of computer science. In the field of computer vision, it is especially their special type called convolutional neural networks (CNNs) that is outperforming classical approaches to object detection and segmentation [154]. Therefore, it should not be a surprise that ANNs are widely used also in the field of remote sensing already since 2014 [211], and their use outside and inside the field is just growing, as can be seen in figures 1.1 and 1.2.

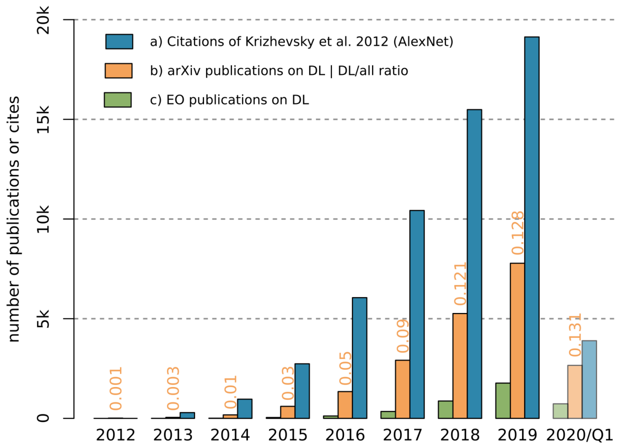


Figure 1.1: Statistics for papers dealing with the use of deep learning in remote sensing: Citations listed in Google scholar for famous CNN architecture [102]; arXiv listed publications in the categories *cs* and *stat* including the terms *deep learning*, *convolutional neural networks*, *convolutional networks* or *fully convolutional* and their share of all publications listed in the two categories; publications in selected Earth observation journals, searched for with the same terms as in arXiv, source: [77]

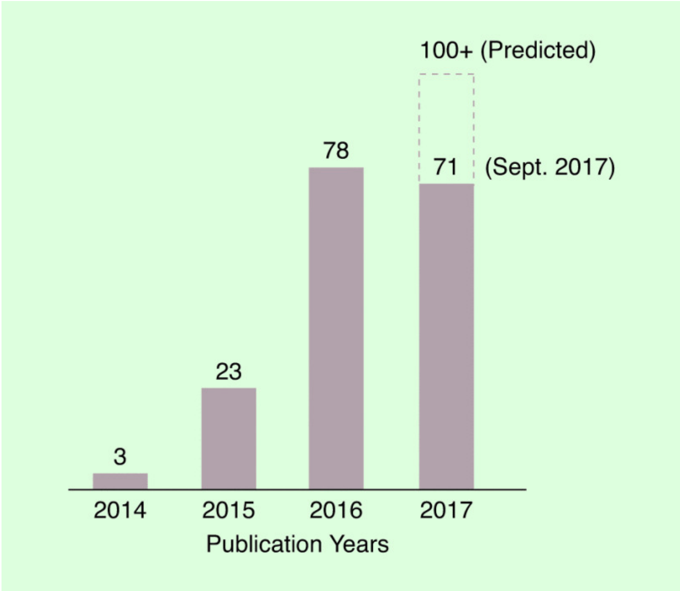


Figure 1.2: Number of papers dealing with the use of deep learning in remote sensing per year, source: [211]

However, this quick development of ANNs and CNNs makes it harder and harder for other fields as remote sensing to keep up with the progress tempo. It results in the situation where when it comes to an ANN architecture choose, researchers without the necessary background simply choose the newest one or the one with the best reported results, although these results could be obtained on completely different data in a completely different environment and the performance could therefore very much differ from the expected one. The goal of this thesis is to try to make complex, systematic research and review of the performance of chosen CNN architectures on various selected use cases from the field of remote sensing, and hopefully serve as a valuable guidebook when it comes to CNN applications in the field or comparison metrics when a new architecture is proposed.

Chapter 2 will present research on the use of comparisons when it comes to papers dealing with CNN models in the field of remote sensing and systematically investigate their senses of comparing the original input with the already existing work from different points of view to give them sufficient scientific context. The same systematical investigation will be done also for reviews of the use of CNNs in the field.

Chapter 3 will present use cases selected as test tasks to evaluate chosen architectures. For purposes of the professional debate, only one use case is presented.

These chapters will be later followed by a chapter on selected architectures and methods and a chapter presenting the results of the experiments. For purposes of the professional debate, these are not present.

# 2 Motivation

In August 2020, an experiment was conducted - a query for papers with the below-described restrictions was done on selected academic database websites. The goal of the experiment was to research whether authors of papers dealing with the use of CNNs in the field of remote sensing are comparing results of proposed or used architectures with results of other architectures. Main comparison criteria this thesis focuses on are the use of multiple datasets, used metrics, and experiments with different detected objects, area, the number of classes, image bands, and spatial resolution, that would give the comparison more general meaning and give the reader better idea about where is the potential of the use of the proposed architecture. This experiment is summarized in chapter 2.1.

This experiment was immediately followed by an overview of the top *review-type* papers - as something akin is the goal of this thesis, it could be taken as the summary of the current situation and research on work dealing with the same problems. This is summarized in chapter 2.2.

Research indicates that a lot of new CNN architecture proposals do not deal with complex comparisons and therefore do not give any valuable overview where and why do their architectures perform better than other ones. This lack could be very perilous for interested researchers as an ad-hoc comparison could give a completely wrong picture about the allegedly great performance of an architecture that actually performs well only on the presented task and fails everywhere else. When it comes to reviews, a lot of them are only presenting results from the original architecture proposals instead of conducting original experiments; as the original experiments were done in different environments, they also lack the comparison value. This research shows that a complex review and comparison that would test multiple architectures on same tasks in the same environment is needed to serve as a springboard for researchers interested in possibilities of the use of CNNs in the field of remote sensing.

## 2.1 Articles on CNNs in the field of remote sensing

### 2.1.1 Web of Science

#### Using the search term *convolutional neural network*

The first used academic access website was Web of Science[1] (WoS). The following query restrictions were used:

- `Query string: convolutional neural network`. To focus only on articles dealing with CNNs.
- `Search field: All Fields`. To check also articles dealing with the topic, but not specifying it in the title nor the abstract or keywords. This way, articles that aim more general - primarily at remote sensing or CNNs - but deal also with the second of the subjects could be found.
- `Publication years: 2020, 2019, 2018`. To focus only on recent publications.
- `Web of Science categories: REMOTE SENSING`. To focus only on the scientific area of interest.
- `Open Access: DOAJ Gold`. To focus only on articles and papers from sources listed on the Directory of Open Access Journals[2] (DOAJ).

The top five results from the query, when ordered by the attribute `Times Cited`, were the following:

- Building Extraction in Very High Resolution Remote Sensing Imagery Using Deep Learning and Guided Filters: 81 citations. [190]
- Very Deep Convolutional Neural Networks for Complex Land Cover Mapping Using Multispectral Remote Sensing Imagery: 71 citations. [129]
- Evaluation of Different Machine Learning Methods and Deep-Learning Convolutional Neural Networks for Landslide Detection: 51 citations. [61]

[1] `www.webofknowledge.com`
[2] `www.doaj.org`

- 3D Convolutional Neural Networks for Crop Classification with Multi-Temporal Remote Sensing Images: 50 citations. [108]
- Multi-Temporal Land Cover Classification with Sequential Recurrent Encoders: 38 citations. [161]

*Building Extraction in Very High Resolution Remote Sensing Imagery Using Deep Learning and Guided Filters* proposes a new CNN architecture based on the residual network (ResNet) [75] called Res-U-Net and - using explicitly defined metrics - compares it to those of SegNet [17], fully convolutional network (FCN) [119], a combination of CNN and random forest (RF) [22], multi-scale deep network [48], and a combination of CNN, RF and conditional random fields (CRF) [48], but authors do not explain how exactly are these models built, so it does not give the reader any solid comparison. Especially terms like CNN and FCN are so general that they do not imply anything more than just the basic approach. In the end, it is not even sure whether authors have tested these models on the datasets on their own, or if they just report results found in other articles. Authors experiment with two datasets differing in used bands and spatial resolution, and also with including and excluding the normalized differential vegetation index (NDVI) and the digital surface model (DSM). However, both datasets are of German cities and therefore very similar in the content, both also being binary datasets containing only two classes - *building* and *clutter* (unknown). Time and memory needs are not mentioned in the study.

The second reviewed article - *Very Deep Convolutional Neural Networks for Complex Land Cover Mapping Using Multispectral Remote Sensing Imagery* - deals with land cover mapping using CNNs with a focus on wetlands detection. Therefore, it is not a surprise that authors do not experiment with different datasets; however, it would give much more universal overview of CNN possibilities in the wetland detection if data from different parts of the world were used, and not only from Newfoundland and Labrador, Canada. Besides that, the paper experiments with DenseNet-121 [82], Inception V3 [175], VGG-16 [170], VGG-19, Xception [34], ResNet-50, and Inception ResNet V2 [176], and also with machine learning (ML) methods of support vector machine (SVM) [179] and RF. Authors also use different patch sizes and report processing times.

The third result contains the phrase *evaluation of different methods* already in the title and compares CNNs with other popular ML methods, namely SVM, RF, and even with a simple ANN architecture called multi-layer perceptron (MLP) [159] with a hidden layer of 30 neurons. Even the CNN approach is diversified into two architectures - one of them comprising of five layers, the other one of seven layers. To make the results more general, authors experiment also with five different input window sizes, compare the use of spectral bands versus the use of a combination of spectral bands and topographical ones, and apply their models on two different datasets. Time consumption of different methods would be also valuable information on the comparison, yet this metric is not included in the article. It is apparent that authors of the paper came from the same impulse as this thesis, reading statements like *"CNNs do not automatically outperform ANN, SVM and RF, although this is sometimes claimed. Rather, the performance of CNNs strongly depends on their design, i.e., layer depth, input window sizes and training strategies."* Or, in another place, *"CNN will not automatically outperform other methods - as popular science articles and magazines may imply."* With felicitously set parameters, CNNs outperformed other approaches, but their use was done under critical supervision and without trend-surfing shouts.

The fourth article, *3D Convolutional Neural Networks for Crop Classification with Multi-Temporal Remote Sensing Images*, again experiments with different kernel sizes and other parameters, and compares the proposed 3D CNN architecture with K-nearest neighbour (KNN) [8], principal component analysis (PCA) [89], SVM, and an ad-hoc defined 2D CNN structure. No time consumption analysis of different approaches was presented. Although the presented results seem to prove their claims that their proposed architecture performs better than the other ones, more extensive research experimenting with more datasets and more advanced, state-of-the-art architectures could give such claims more solid position.

Authors of *Multi-Temporal Land Cover Classification with Sequential Recurrent Encoders* do admit that their comparison part is not ideal; that is true as they compare results of their proposed architecture only with results of other architectures reported in other papers - these results were achieved using different datasets, different preprocessing, different numbers of classes and training samples, different spatial resolution and different bands. Therefore, it is arguable whether this comparison is relevant at all. Authors test their architecture on a multi-class dataset coming from one area in Germany split into two years; this also does not serve as a test on multiple independent datasets. Positive is the fact that authors explicitly define used quality metrics and report time needs of the training, although only the overall accuracy is presented for other architectures in the comparison table.

Using the same query, but restrictive to search only in the topic (searching the title, the abstract, and keywords), the results were the same.

**Using the search term *cnn***

As in some articles, only the abbreviation CNN is used instead of the full-length term *convolutional neural network*, the same research using CNN as the search term was done.

- `Query string: cnn`. To focus only on articles dealing with CNNs.
- `Search field: All Fields`. To check also articles dealing with the topic, but not specifying it in the title nor the abstract or keywords. This way, articles that aim more general - primarily at remote sensing or CNNs - but deal also with the second of the subjects could be found.
- `Publication years: 2020, 2019, 2018`. To focus only on recent publications.
- `Web of Science categories: REMOTE SENSING`. To focus only on the scientific area of interest.
- `Open Access: DOAJ Gold`. To focus only on articles and papers from sources listed on the Directory of Open Access Journals (DOAJ).

The top five results from the query, when ordered by the attribute `Times Cited` and filtered as will be described below, were the following:

- Evaluation of Different Machine Learning Methods and Deep-Learning Convolutional Neural Networks for Landslide Detection: 51 citations. [61]
- 3D Convolutional Neural Networks for Crop Classification with Multi-Temporal Remote Sensing Images: 50 citations. [108]

- Geospatial Object Detection in High Resolution Satellite Images Based on Multi-Scale Convolutional Neural Network: 32 citations. [64]
- Hyperspectral Image Classification Using Convolutional Neural Networks and Multiple Feature Learning: 31 citations. [55]
- Deformable Faster R-CNN with Aggregating Multi-Layer Features for Partially Occluded Object Detection in Optical Remote Sensing Images: 24 citations. [156]

Two results were filtered out. [162] with 28 citations and [195] with 25 citations. They were filtered out only because they do not correspond with the main focus of the thesis on the classification task with object detection and semantic and instance segmentation, but dealt with an image fusion instead. The top two results correspond to articles reviewed already in the previous section; therefore they are being skipped now.

The comparison part of *Geospatial Object Detection in High Resolution Satellite Images Based on Multi-Scale Convolutional Neural Network* is a bit minimalistic. The proposed method is compared only with an architecture called Faster R-CNN (region based convolutional neural network) [155] and with the single shot multi-box detector (SSD) [117] without a more detailed description of inner parametrization or experiments with it. Authors use also only one dataset to test their method, so there is no evidence on how versatile the method is. But positively, they report the time greed of the three used methods.

In *Hyperspectral Image Classification Using Convolutional Neural Networks and Multiple Feature Learning*, authors go a different way - to compare their architecture, they create two different architectures and show that the proposed one is the one performing the best. A comparison with any other well-known architecture or other ML method is missing. The pro of this paper is the use of three different datasets.

24 citations reaching *Deformable Faster R-CNN with Aggregating Multi-Layer Features for Partially Occluded Object Detection in Optical Remote Sensing Images* also proposes a new architecture, called *deformable R-CNN*. Authors compare this model with SSD and R-P-Faster R-CNN [70] on three datasets. No comparison of time or memory requirements is included in the article.

Using the same query, but restrictive to search only in the topic (searching the title, the abstract, and keywords), the results were the same.

### 2.1.2 Scopus

**Using the search term *convolutional neural network***

The second used website was Scopus[3]. The following query restrictions were used:

- `Query string: "remote sensing" "convolutional neural network"`. To focus only on articles dealing with CNNs in the area of remote sensing.
- `Search field: All fields`. To check also articles dealing with the topic, but not specifying it in the title nor the abstract or keywords. This way, articles that aim more general - primarily at remote sensing or CNNs - but deal also with the second of the subjects could be found.
- `Publication years: 2020, 2019, 2018`. To focus only on recent publications.
- `Access type: Open Access`. To focus only on articles in *Scopus Gold Open Access*[4]. It includes fully open journals, hybrid journals (authors pay a fee to make an article open access), open archives and articles with free promotional access.

The Scopus query is apparently more tolerant and includes articles filtered out from the WoS query. This is probably due to the smaller flexibility when it comes to the open access restrictions and due to the lack of the scientific category `remote sensing` in the Scopus search engine (the phrase was included in the query string and more manual filtering was needed, as will be described below). The top five results from the query, when ordered by the attribute `Cited by`, were the following:

- A new deep convolutional neural network for fast hyperspectral image classification: 123 citations. [142]
- Automatic ship detection in remote sensing images from google earth of complex scenes based on multiscale rotation Dense Feature Pyramid Networks: 97 citations. [192]
- Deep learning in remote sensing applications: A meta-analysis and review: 93 citations. [127]

[3] `www.scopus.com`
[4] `www.elsevier.com/open-access`

- Building extraction in very high resolution remote sensing imagery using deep learning and guided filters: 92 citations. [190]

- Semi-Supervised Deep Learning Using Pseudo Labels for Hyperspectral Image Classification: 77 citations [185]

Ten results were filtered out. [181] with 251 citations, [124] with 200 citations, [131] with 177 citations, [138] with 157 citations, [113] with 153 citations, [165] with 104 citations, [74] with 98 citations, [152] with 87 citations, [3] with 85 citations, and [186] with 83 citations. They were filtered out only because they do not correspond with the main focus of the thesis on the classification task with object detection and semantic and instance segmentation in the field of remote sensing.

The first article, *A new deep convolutional neural network for fast hyperspectral image classification*, starts the research again in a very positive way. Authors have compared their own architecture with the MLP and three different CNNs - a one-dimensional one, a two-dimensional one and a three-dimensional one. Although a comparison with some popular architectures or some classical ML methods would be also interesting, the used ones are properly sourced to another research on hyperspectral image classification and authors underlined main differences between the proposed model and the ones used for evaluation. All experiments have been conducted on two datasets differing in the number of bands, the pixel size of images, spatial resolution, and also in objects of classification. Authors also experiment with different patch sizes and - importantly - with the number of samples per class.

*Automatic ship detection in remote sensing images from google earth of complex scenes based on multiscale rotation Dense Feature Pyramid Networks* also does not compare the proposed methodology with basic ML approaches, but uses a lot of CNN models to compare their architecture with - Faster R-CNN, Feature pyramid network (FPN) [116], rotation region proposal network (RRPN) [125], and rotational region convolutional neural network ($R^2$CNN) [88]. However, as the paper focuses only on ship detection, there is no experiment on other datasets.

The third most cited article on Scopus - *Deep learning in remote sensing applications: A meta-analysis and review* - is a review coming from similar impulses as this thesis or partly [61] mentioned in chapter 2.1.1. The motivation is formulated in the sense that *"it appears that a more systematic (i.e. quantitative) analysis* *is necessary to get a comprehensive and objective understanding of the applications of DL for remote-sensing analysis."*. Authors focus on many more fields than is the goal of this thesis, including image fusion, image registration, scene classification, object detection, land use and land cover classification, image segmentation, object-based image analysis (OBIA), and other tasks. The value of the paper lies in its extensive research on what are the most frequent targets of the use of deep learning (DL) for remote sensing, what are the most frequent DL models, spatial resolutions, application areas (urban, vegetation, etc.), average accuracies, common training datasets, and even the most used scientific terms in titles and abstracts of these papers. Although it is a high-class review and it works as a valuable overview about DL stronger and weaker positions in the field, authors have not conducted their own experiments, so only results reported in the original papers are mentioned, if mentioned.

*Building extraction in very high resolution remote sensing imagery using deep learning and guided filters* is the same one as the one mentioned in chapter 2.1.1, only with a different number of citations due to the difference between the WoS and Scopus systems; therefore it is being skipped in this section.

Authors of *Semi-Supervised Deep Learning Using Pseudo Labels for Hyperspectral Image Classification* propose their own method called semi-supervised deep learning using pseudo-labels (PL-SSDL) using convolutional recurrent neural networks (CRNN) and compare its performance on three multi-class hyperspectral datasets differing in the number of classes, number of bands, and also in the spatial resolution (ranging from 1 metre to 2.5 metres). PL-SSDL is compared with a big amount of ML methods, namely KNN, SVM, label propagation [210], transductive support vector machine (TSVM) [24], Laplacian support vector machine (LapSVM) [67], and spatio-spectral Laplacian support vector machine (SS-LapSVM) [196], and two ANN architectures, namely stacked denoising autoencoder (SDA) [180], and ladder networks [153]. As PL-SSDL is a CRNN, a comparison with CNN or RNN or their combination would be desirable, especially considering the fact that the used ANN models could be built using them. Authors report for every method time complexity and accuracy, but do not specify explicitly what accuracy metric do they use or how do they measure the time complexity (number of epochs is slightly mentioned for PL-SSDL, but not for any other approach).

Using the same query, but restrictive to search only in the title, the abstract, and keywords, the results were as follows:

- A new deep convolutional neural network for fast hyperspectral image classification: 123 citations. [142]
- Semi-Supervised Deep Learning Using Pseudo Labels for Hyperspectral Image Classification: 77 citations [185]
- Very Deep Convolutional Neural Networks for Complex Land Cover Mapping Using Multispectral Remote Sensing Imagery: 72 citations. [129]
- 3D Convolutional Neural Networks for Crop Classification with Multi-Temporal Remote Sensing Images: 61 citations. [108]
- Hyperspectral Image Classification Using Convolutional Neural Networks and Multiple Feature Learning: 54 citations. [55]

From the results above, the two top articles were already received with the `All Fields` query. The rest was reviewed already in chapter 2.1.1, only with a different number of citations due to the difference between the WoS and Scopus systems. Therefore, all of them are being skipped now.

**Using the search term *cnn***

As in some articles, only the abbreviation CNN is used instead of the full-length term *convolutional neural network*, the same research using CNN as the search term was done.

- `Query string: "remote sensing" cnn`. To focus only on articles dealing with CNNs in the area of remote sensing.
- `Search field: All fields`. To check also articles dealing with the topic, but not specifying it in the title nor the abstract or keywords. This way, articles that aim more general - primarily at remote sensing or CNNs - but deal also with the second of the subjects could be found.
- `Publication years: 2020, 2019, 2018`. To focus only on recent publications.

- `Access type: Open Access`. To focus only on articles in *Scopus Gold Open Access*. It includes fully open journals, hybrid journals (authors pay a fee to make an article open access), open archives and articles with free promotional access.

The top five results from the query, when ordered by the attribute `Cited by` and filtered as will be described below, were the following:

- A new deep convolutional neural network for fast hyperspectral image classification: 123 citations. [142]
- Automatic ship detection in remote sensing images from google earth of complex scenes based on multiscale rotation Dense Feature Pyramid Networks: 97 citations. [192]
- Deep learning in remote sensing applications: A meta-analysis and review: 93 citations. [127]
- Building extraction in very high resolution remote sensing imagery using deep learning and guided filters: 92 citations. [190]
- Very Deep Convolutional Neural Networks for Complex Land Cover Mapping Using Multispectral Remote Sensing Imagery: 72 citations. [129]

Four results were filtered out. [181] with 251 citations, [12] with 87 citations, [84] with 74 citations, and [7] with 73 citations. They were filtered out only because they do not correspond with the main focus of the thesis on the classification task with object detection and semantic and instance segmentation in the field of remote sensing.

From the results above, the top four results correspond to articles reviewed already in the previous section and the fifth one to an article reviewed already in chapter 2.1.1, only with a different number of citations due to the difference between the WoS and Scopus systems. Therefore, all of them are being skipped in this section.

Using the same query, but restrictive to search only in the title, the abstract, and keywords, the results were as follows:

- A new deep convolutional neural network for fast hyperspectral image classification: 123 citations. [142]

- Very Deep Convolutional Neural Networks for Complex Land Cover Mapping Using Multispectral Remote Sensing Imagery: 72 citations. [129]
- 3D Convolutional Neural Networks for Crop Classification with Multi-Temporal Remote Sensing Images: 61 citations. [108]
- Small object detection in optical remote sensing images via modified Faster R-CNN: 57 citations. [157]
- Hyperspectral Image Classification Using Convolutional Neural Networks and Multiple Feature Learning: 54 citations. [55]

From the results above, the two top results correspond to articles reviewed already in the previous section and the third and fifth one to articles reviewed already in chapter 2.1.1, only with a different number of citations due to the difference between the WoS and Scopus systems. Therefore, only the fourth one is being reviewed in this section.

*Small object detection in optical remote sensing images via modified Faster R-CNN* proposes a modified Faster R-CNN-based architecture and tries it on the task of the aeroplanes and ships detection. The goal of the paper is to show that the proposed architecture improves the performance of the baseline Faster R-CNN, so the comparison with the original model is not surprising, although showing a relative comparison with some other architectures to show the full picture would be valuable; even the Faster R-CNN-modified Faster R-CNN comparison is a bit vague as variable parameters that affect the performance of the architecture like the total stride are defined differently for each case in the presented experiment. A test on a different dataset or a task would be also beneficial, as well as info about the time needs of the new model.

## 2.2 Reviews of CNNs in the field of remote sensing

### 2.2.1 Web of Science

#### Using the search term *convolutional neural network*

When compared with the query described in chapter 2.1.1, an extra parameter `Document Types` was used to get only *review-type* articles. Therefore, the following restrictions were used for the query:

- `Query string: convolutional neural network`. To focus only on articles dealing with CNNs.
- `Search field: All Fields`. To check also articles dealing with the topic, but not specifying it in the title nor the abstract or keywords. This way, articles that aim more general - primarily at remote sensing or CNNs - but deal also with the second of the subjects could be found.
- `Publication years: 2020, 2019, 2018`. To focus only on recent publications.
- `Web of Science categories: REMOTE SENSING`. To focus only on the scientific area of interest.
- `Open Access: DOAJ Gold`. To focus only on articles and papers from sources listed on the Directory of Open Access Journals (DOAJ).
- `Document Types: REVIEW`. To focus only on reviews.

There were only seven results for the described query and two of them - *Spatiotemporal Image Fusion in Remote Sensing* [21] with 14 citations and *Meta-Analysis of Wetland Classification Using Remote Sensing: A Systematic Review of a 40-Year Trend in North America* [130] with 0 citations - were filtered out as they dealt with the image fusion and with the history of wetland classification and did not overlay with the main focus of this thesis. The rest, when ordered by the attribute `Times Cited`, were the following:

- Review and Evaluation of Deep Learning Architectures for Efficient Land Cover Mapping with UAS Hyper-Spatial Imagery: A Case Study Over a Wetland: 3 citations. [146]
- Object Detection and Image Segmentation with Deep Learning on Earth Observation Data: A Review-Part I: Evolution and Recent Trends: 1 citation. [77]
- Geographic Object-Based Image Analysis: A Primer and Future Directions: 0 citations. [103]
- Deep Learning for Land Use and Land Cover Classification Based on Hyperspectral and Multispectral Earth Observation Data: A Review: 0 citations. [178]

- Deep Learning Approaches Applied to Remote Sensing Datasets for Road Extraction: A State-Of-The-Art Review: 0 citations. [1]

As [129], *Review and Evaluation of Deep Learning Architectures for Efficient Land Cover Mapping with UAS Hyper-Spatial Imagery: A Case Study Over a Wetland* focuses on wetlands. And although authors evaluate and describe a pleasurable amount of architectures including SegNet, U-Net [158], DenseNet, DeepLab V3+ [31], Pyramid scene parsing network (PSPNet) [208], and an architecture called MobileU-Net (a combination of MobileNet [80] and U-Net) and dedicate a lot of space to used evaluation metrics, their findings would be even more valuable and universal if tested on more than one dataset. An application of at least one of the common ML methods would also give the article an added value in the form of a well-understood relative comparison.

*Object Detection and Image Segmentation with Deep Learning on Earth Observation Data: A Review-Part I* (as of August 14, 2020, part two is not yet published) focuses on an overview and the evolution of different approaches in the topic. Authors present a comprehensive overview of DL architectures commonly or less commonly used on Earth observation (EO) data, but - due to their main goal being just an overview - do not conduct their own experiments; instead, they report results based on the MS-COCO dataset (Microsoft-Common Objects in Context) [115], a dataset with contents very different than those of EO data.

The main focus of *Geographic Object-Based Image Analysis: A Primer and Future Directions* is on the geographic object-based analysis (GEOBIA) and not CNNs; however, a non-negligible part of the review deals with CNNs, and CNNs - called geographic object-based convolutional neural networks (GEOCNNs) - are proposed as one of the most promising future directions of GEOBIA. But when it comes to the chapter *Accuracies of GEOCNN Methods Versus Conventional GEOBIA*, no experiments are conducted and the entire report is reduced to citations with trifling claims without numbers like *"method following Approach 3 resulted in higher thematic accuracy than per-pixel classification with patch-based CNNs and FCNs"* or *"method following Approach 2 resulted in higher segmentation accuracy than GEOBIA"*.

Authors of *Deep Learning for Land Use and Land Cover Classification Based on Hyperspectral and Multispectral Earth Observation Data: A Review* also do not conduct any experiment, but rather report the evolution of the DL and land cover and land use classification. And although they sketch the connection between different topic problems and different ML or DL architectures, they do not report any numbers and when they rarely write about performances, only general phrases like *"U-Net has shown very promising results in extracting buildings"* are used.

*Deep Learning Approaches Applied to Remote Sensing Datasets for Road Extraction: A State-Of-The-Art Review* introduces different approaches to road extraction using DL. Although it gives always multiple model examples for every approach, their results - crucial for the right model choice - are taken from original papers; therefore, different metrics and different datasets are used, and even when the same dataset is used, different setting (as the ratio of training-validation images) could lead to different scores. Also time needs are mentioned only exceptionally.

Using the same query, but restrictive to search only in the topic (searching the title, the abstract, and keywords), the results were the same.

### Using the search term *cnn*

As in some articles, only the abbreviation CNN is used instead of the full-length term *convolutional neural network*, the same research using CNN as the search term was done.

- `Query string: cnn`. To focus only on articles dealing with CNNs.
- `Search field: All Fields`. To check also articles dealing with the topic, but not specifying it in the title nor the abstract or keywords. This way, articles that aim more general - primarily at remote sensing or CNNs - but deal also with the second of the subjects could be found.
- `Publication years: 2020, 2019, 2018`. To focus only on recent publications.
- `Web of Science categories: REMOTE SENSING`. To focus only on the scientific area of interest.
- `Open Access: DOAJ Gold`. To focus only on articles and papers from sources listed on the Directory of Open Access Journals (DOAJ).
- `Document Types: REVIEW`. To focus only on reviews.

There were only five results for the described query and one of them - *Spatiotemporal Image Fusion in Remote Sensing* [21] with 14 citations - was filtered out as it dealt with the image fusion and not with the classification. The rest, when ordered by the attribute `Times Cited`, were the following:

- Review and Evaluation of Deep Learning Architectures for Efficient Land Cover Mapping with UAS Hyper-Spatial Imagery: A Case Study Over a Wetland: 3 citations. [146]
- UAV-Based Structural Damage Mapping: A Review: 3 citations. [94]
- Object Detection and Image Segmentation with Deep Learning on Earth Observation Data: A Review-Part I: Evolution and Recent Trends: 1 citation. [77]
- Geographic Object-Based Image Analysis: A Primer and Future Directions: 0 citations. [103]

The only review not described in the previous section is the second one. *UAV-Based Structural Damage Mapping: A Review* does not focus primarily on CNNs, but as they constitute a big part of UAV-based damage mapping, there is a lot of reviewing of them in the article. However, the article works more as an overview of the evolution of different approaches in the topic. Therefore, no novel experiments were conducted and when some results are mentioned, they are only copied from original papers; papers, where these methods could have been used on different data with different results.

Using the same query, but restrictive to search only in the topic (searching the title, the abstract, and keywords), the results were the same.

### 2.2.2 Scopus

#### Using the search term *convolutional neural network*

When compared with the query described in chapter 2.1.2, an extra parameter `Document type` was used to get only *review-type* articles. Therefore, the following restrictions were used for the query:

- `Query string: "remote sensing" "convolutional neural network"`. To focus only on articles dealing with CNNs in the area of remote sensing.

- `Search field: All fields`. To check also articles dealing with the topic, but not specifying it in the title nor the abstract or keywords. This way, articles that aim more general - primarily at remote sensing or CNNs - but deal also with the second of the subjects could be found.
- `Publication years: 2020, 2019, 2018`. To focus only on recent publications.
- `Access type: Open Access`. To focus only on articles in *Scopus Gold Open Access*. It includes fully open journals, hybrid journals (authors pay a fee to make an article open access), open archives and articles with free promotional access.
- `Document type: Review`. To focus only on reviews.

The Scopus query is apparently more tolerant and includes articles filtered out from the WoS query. This is probably due to the smaller flexibility when it comes to the open access restrictions and due to the lack of the scientific category `remote sensing` in the Scopus search engine (the phrase was included in the query string and more manual filtering was needed). It resulted in the fact that from the top 20 articles when ordered by the attribute `Cited by`, 19 results were filtered out as they either did not correspond with the main focus of the thesis on the classification task with object detection and semantic and instance segmentation in the field of remote sensing, or they were found completely insufficient in terms of providing a complex comparison of mentioned architectures.

The 19 filtered articles were the following: [181] with 251 citations, [131] with 177 citations, [113] with 153 citations, [165] with 104 citations, [3] with 85 citations, [186] with 83 citations, [7] with 73 citations, [166] with 71 citations, [171] with 66 citations, [99] with 53 citations, [184] with 50 citations, [173] with 49 citations, [62] with 48 citations, [212] with 48 citations, [136] with 47 citations, [204] with 43 citations, [198] with 34 citations, [199] with 33 citations, and [28] with 33 citations.

The only one corresponding with the aim of this thesis is *Deep learning for remote sensing image classification: A survey* [112] with 45 citations. The approach is very fulfilling - authors compare multiple architectures on multiple datasets and define metrics used for the comparison. The fact that almost half of the presented results are taken from a different research is not a problem as compared results come from the same source, but the fact that in the other part, a different training-validation-test data ratio was used for different models is. Also, the researched architectures are just vaguely defined without specifying parameters used to build them.

Using the same query, but restrictive to search only in the title, the abstract, and keywords, the results were (after filtering described below) as follows:

- Deep learning for remote sensing image classification: A survey: 45 citations. [112]
- Hyperspectral image classification based on spectral and spatial information using multi-scale ResNet: 1 citation. [183]
- Deep Learning for Land Use and Land Cover Classification Based on Hyperspectral and Multispectral Earth Observation Data: A Review: 0 citations. [178]
- Geographic Object-Based Image Analysis: A Primer and Future Directions: 0 citations. [103]

There were only eight results for the more restricted query and four of them were filtered out - [21] with 15 citations, [134] with 11 citations, [177] with 8 citations, and [68] with 6 citations. They were filtered out only because they do not correspond with the main focus of the thesis on the classification task with object detection and semantic and instance segmentation in the field of remote sensing.

From the rest, the top result corresponds to the article already reviewed in this section and the third and fourth one to articles reviewed already in chapter 2.1.1, only with a different number of citations due to the difference between the WoS and Scopus systems. Therefore, only the second one is being reviewed in this section.

The motivation to mark *Hyperspectral image classification based on spectral and spatial information using multi-scale ResNet* as a review could be very speculative, but otherwise, the paper meets more-or-less all criteria this thesis puts on complex comparisons and reviews. Authors propose a method based on ResNet, define metrics used for accuracy measurements and compare its performance on two multi-class datasets differing in the number of bands with three other methods - a basic CNN coming from [81], a convolutional neural network using pixel-pair features (CNN-PPF) [109], and a contextual deep convolutional neural network (CD-CNN) [107]. Authors even experiment with different training-validation samples ratios for each dataset.

The only two things that could be rebuked are the lack of more detailed overview of used parameters for used architectures and the lack of time needs comparison.

**Using the search term *cnn***

As in some articles, only the abbreviation CNN is used instead of the full-length term *convolutional neural network*, the same research using CNN as the search term was done.

- `Query string: "remote sensing" cnn`. To focus only on articles dealing with CNNs in the area of remote sensing.
- `Search field: All fields`. To check also articles dealing with the topic, but not specifying it in the title nor the abstract or keywords. This way, articles that aim more general - primarily at remote sensing or CNNs - but deal also with the second of the subjects could be found.
- `Publication years: 2020, 2019, 2018`. To focus only on recent publications.
- `Access type: Open Access`. To focus only on articles in *Scopus Gold Open Access*. It includes fully open journals, hybrid journals (authors pay a fee to make an article open access), open archives and articles with free promotional access.
- `Document type: Review`. To focus only on reviews.

The Scopus query is apparently more tolerant and includes articles filtered out from the WoS query. This is probably due to the smaller flexibility when it comes to the open access restrictions and due to the lack of the scientific category `remote sensing` in the Scopus search engine (the phrase was included in the query string and more manual filtering was needed). It resulted in the fact that from the top 20 articles when ordered by the attribute `Cited by`, 19 results were filtered out as they either did not correspond with the main focus of the thesis on the classification task with object detection and semantic and instance segmentation in the field of remote sensing, or they were found completely insufficient in terms of providing a complex comparison of mentioned architectures.

The 19 filtered articles were the following: [181] with 251 citations, [7] with 73 citations, [166] with 71 citations, [171] with 66 citations, [99] with 53 citations, [50] with 50 citations, [173] with 49 citations, [91] with 39 citations, [79] with 30 citations,

[160] with 28 citations, [26] with 21 citations, [16] with 21 citations, [63] with 19 citations, [207] with 19 citations, [11] with 18 citations, [2] with 17 citations, [54] with 16 citations, [174] with 15 citations, and [209] with 15 citations.

The only article that had a bigger than an insignificant overlap with the goal of this thesis was the ninth result, *Deep learning meets hyperspectral image analysis: A multidisciplinary review* [169]. The aim of this review is to give a general overview of the use of DL in fields of remote sensing and biomedicine and it does so by naming and referencing an impressive amount of papers, but without any abundant architecture list and original experiments. Not even citations of results from original papers can be found in the review.

Using the same query, but restrictive to search only in the title, the abstract, and keywords, the results were (after filtering described below) as follows:

- UAV-Based Structural Damage Mapping: A Review: 5 citations. [94]
- Hyperspectral image classification based on spectral and spatial information using multi-scale ResNet: 1 citation. [183]
- Geographic Object-Based Image Analysis: A Primer and Future Directions: 0 citations. [103]

There were only four results for the more restricted query and one of them - *Spatio-temporal Image Fusion in Remote Sensing* [21] with 15 citations - was filtered out as it dealt with the image fusion and not with the classification. From the rest, the first and third results correspond to articles reviewed already in chapter 2.1.1 and the second one to an article reviewed in the previous section. Therefore, all of them are being skipped in this section.

# 3 Use cases

The best comparison is the one using things readers already know. The best comparison is the one from the real world and praxis.

As the aim of this thesis is to evaluate the performance of different CNN models on different tasks from the field of remote sensing and make an order in *why is an architecture X used on Y*, use cases chosen for experiments should correspond with tasks normal remote sensing researchers could face. This chapter presents research on these chosen use cases (currently - for the purpose of the professional debate - the phrase *use cases* should be actually used in a singular form as there is only one use case so far).

## 3.1 Urban vegetation detection

If we simplify the picture of the world to an absolute minimum, we can say that there are only two classes - urban areas and nature (or also water, if not counting it in the nature class). A big part of the nature section is vegetation. Therefore, it is not a surprise that the vegetation detection, as well as the urban areas detection, constitutes a big part of remote sensing tasks. Even if research does not focus specifically on one of these classes, almost any land cover classification that deals with multi-class continental remote sensing images has one or more classes dedicated to the vegetation, and very probably there will be also a need to recognize urban areas.

One of the most used land cover datasets in Europe is the Coordination of information on the environment (CORINE) land cover (CLC) inventory[5] created by the European Environment Agency (EEA). Its first pan-European land cover dataset was published in 1990 and updates were produced in the year 2000 and every six years after. It contains 44 land cover classes, and some of them are uncommon in other datasets. The class *artificial, non-agricultural vegetated areas* is an example, especially its sub-class *green urban areas.* According to the CLC nomenclature [98], this class is applicable for parks inside settlements, with or without public access, ornamental gardens, mansions' green grounds, botanical and zoological gardens situated inside settlements or in contact-peripheral zone of settlement, city squares with greenery, inner spaces of city blocks, cemeteries with vegetation inside

[5] `https://land.copernicus.eu/pan-european/corine-land-cover`

or directly attached to settlements, vegetated areas that can potentially be used for recreational purpose even if it is not their main utilisation, such as woods inside urban fabric; according to the same source, this class, therefore, includes vegetated areas of parks, lawns, flower beds, bushes, trees, park ponds, lakes, fountains, lanes and paths (paved or non-paved) in parks or other vegetated recreational areas, buildings and service facilities associated to parks and botanical or zoological gardens, small sport grounds and facilities $<$ 25 ha inside city parks.

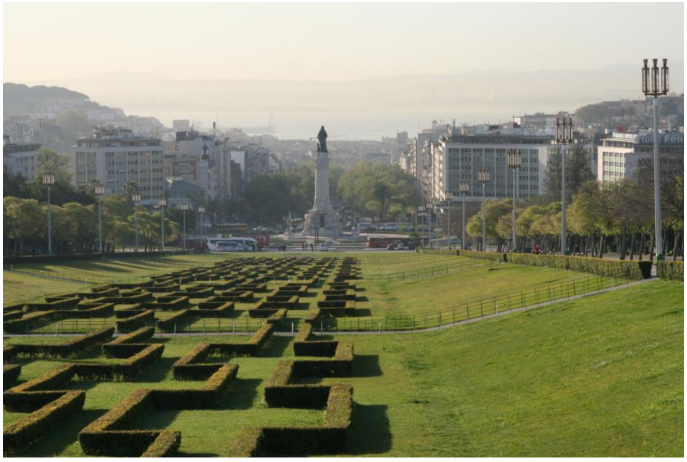

Figure 3.1: CLC green urban areas example, a city park in Lisbon, source: [98]

Figure 3.2: CLC green urban areas example, a vegetated cemetery in Istanbul, source: [98]

This use case will consist of experiments with CNNs conducted on the task of classification of vegetated areas and multi-class classification on urban scenes, but as the CLC is being used in many applications (as of September 2020, a search for *corine* in WoS returns 1006 results and in Scopus 1240 results) but the task of urban vegetation-vegetation outside urban areas automatic differentiation is not widely researched (see section 3.1.1), a special focus will be held also on this problem.

### 3.1.1 Related work

For research on other works dealing with the task of urban green detection or classification from remote sensing data using CNNs, the same academic search engines as in chapter 2 were used - WoS and Scopus. Terms *urban green*, *urban vegetation*, and - although they are not the only aim of this use case, they present a big part of urban greens - *parks* were used in search phrases to maximize the grasp of the research. The research was done in September 2020.

#### Web of Science

The following restrictions were used for the first query in WoS:

- `Query string: urban green convolutional neural network`. To focus only on articles dealing with the urban green classification using CNNs.
- `Search field: All Fields`. Due to the small number of results, a more restricted query did not make sense.
- `Open Access: DOAJ Gold`. To focus only on articles and papers from sources listed on the Directory of Open Access Journals (DOAJ).

Only 7 results were found with this query, and 6 of them were filtered out as not dealing with the selected task. Articles dealing with individual tree detection were also filtered out. The filtered results were [43] with 7 citations, [42] with 2 citations, [182] with 2 citations, [19] with 1 citation, [187] with 0 citations, and [135] with 0 citations.

The only result dealing with the chosen task was *Assessing alternative methods for unsupervised segmentation of urban vegetation in very high-resolution multispectral aerial imagery* [106] with 0 citations, although only a bit as the vegetation is, in the end, urban only because of the chosen area and the difference between urban and rural vegetation is not mentioned. Authors focus on the unsupervised semantic segmentation of a selected urban area, classifying pervious classes water/shadow, soil/ground, shrub/tree, grass, and other. Authors of the article use the National agricultural imagery program (NAIP) dataset with the spatial resolution of

0.6 to 1 meters and 4 bands (blue, green, red, and near infrared with the wavelength of 808 to 882 nanometers) enhanced by the NDVI and enhanced vegetation index (EVI) to augment the vegetation signal, the soil adjusted vegetation index (SAVI) and crust index (CI) to minimize background soil effects, and atmospherically resistant vegetation index (ARVI) and visual atmospheric resistance index (VARI) to reduce atmospheric and topographic effects, resulting in 10 bands. To avoid sham classifications, authors firstly mask out pixels presenting impervious classes, a step in which their approach largely differs from the intended goal of this thesis in this task. They compare k-means clustering [118] (using k-means++ seeding [13] to minimize the eventuality of having a wrong initialization), clustering with a Gaussian mixture model (GMM) [150], and a CNN model based on [205]. The article faces a classical problem of the unsupervised learning evaluation about how to evaluate such methods, but using the Davies-Bouldin index (DBI) [37] and ad-hoc manually labelled data, k-means surprisingly outperforms both GMM and CNN.

The following restrictions were used for the second query in WoS:

- `Query string: urban vegetation convolutional neural network`. To focus only on articles dealing with the urban vegetation classification using CNNs.
- `Search field: All Fields`. Due to the small number of results, a more restricted query did not make sense.
- `Open Access: DOAJ Gold`. To focus only on articles and papers from sources listed on the Directory of Open Access Journals (DOAJ).

The top results from the query, when ordered by the attribute `Cited by` and filtered as will be described below, were the following:

- Classification and Segmentation of Satellite Orthoimagery Using Convolutional Neural Networks: 129 citations. [105]
- Learnable Gated Convolutional Neural Network for Semantic Segmentation in Remote-Sensing Images: 3 citations. [66]
- Dual and Single Polarized SAR Image Classification Using Compact Convolutional Neural Networks: 3 citations. [4]

- Assessing alternative methods for unsupervised segmentation of urban vegetation in very high-resolution multispectral aerial imagery: 0 citations. [106]

Only 9 results were found with this query and 5 of them were filtered out as not dealing with the selected task. The filtered results were [72] with 12 citations, [201] with 4 citations, [19] with 1 citation, [15] with 0 citations, and [194] with 0 citations. [106] with 0 citations was reviewed already previously in this section, therefore it is being skipped now.

*Classification and Segmentation of Satellite Orthoimagery Using Convolutional Neural Networks* deals with a multi-class classification of an urban scene. The five differentiated classes are vegetation, ground, road, building, and water; no difference between urban and rural vegetation is mentioned in the paper. The used dataset consists of multi-band images enhanced by the DSM; the choose of spectral bands was done using two wrapper feature selection methods [96], sequential forward selection (SFS) and sequential backward selection (SBS). Authors experiment with two CNN architectures, a one-layered one and four one-layered ones used in parallel to boost the multiscale feature learning, as proposed in [47]; even with such shallow CNNs, authors claim to outperform other ML methods, and although results of other methods are taken from different tasks and datasets, the performance of CNNs is still very high (reaching overall accuracy of 94.49 % for the parallel approach). The biggest problem in this study was the detection of buildings in shadows as these were often misclassified as vegetation.

*Learnable Gated Convolutional Neural Network for Semantic Segmentation in Remote-Sensing Images* deals with two tasks of urban detection. The first one is a binary building-nonbuilding Massachusetts dataset [133] consisting of RGB images with a spatial resolution of 1 meter. The second one is a Potsdam dataset[6] with six classes impervious, building, low vegetation, tree, car, and clutter consisting of RGB bands enhanced by the infrared band, DSM, and normalized digital surface model (NDSM) with a spatial resolution of 5 centimetres; however, the infrared band and surface models were not used for experiments, as well as the clutter class. All data were augmented with rotation, mirroring and resizing before the model training. As for the model, authors present their own architecture called learnable-gated convolutional neural network (L-GCNN) using a gate function with learnable parameters

[6] `http://www2.isprs.org/commissions/comm3/wg4/2d-sem-label-potsdam.html`

for multiscale feature fusion, implementing this parameterized gate module (PGM) also into different encoder levels. Authors achieve very good results, outperforming other researched architectures especially for artificial objects with large variations in visual appearance and size, on the other hand, authors admit that the architecture will very probably not perform well for small training datasets.

*Dual and Single Polarized SAR Image Classification Using Compact Convolutional Neural Networks* deals with the task of a single-polarized and dual-polarized synthetic aperture radar SAR image classification. Authors propose a small, compact CNN architecture consisting of single hidden CNN and MLP layers; these parameters give the model few advantages over deep architectures, as its operational performance in work with small data, its speed reduction, and the fact that it does not need any initial feature extraction stage. The first benchmark dataset is a single-polarized SAR image from the area of Po delta with a spatial resolution of 3 meters and including classes urban fabric, arable land, forest, inland waters, maritime wetlands, and marine waters. The second benchmark dataset is a dual-polarized SAR image from the city of Dresden with a spatial resolution of 4 meters and including classes urban fabric, industrial zones, arable land, pastures, forest, and inland waters. In the work with both datasets, the proposed architecture outperformed other mentioned architectures in the most of the experiments (possibly due to the fact that they were not suitable for small datasets and images were upsampled for them) and the architecture was found to perform better when the channels were enhanced with hue, saturation, and intensity (HSI) colour model and for a sliding window of size $21 \times 21$ to $27 \times 27$.

The following restrictions were used for the last query in WoS:

- `Query string: parks convolutional neural network`. To focus only on articles dealing with the parks classification using CNNs.
- `Search field: All Fields`. Due to the small number of results, a more restricted query did not make sense.
- `Open Access: DOAJ Gold`. To focus only on articles and papers from sources listed on the Directory of Open Access Journals (DOAJ).

From the top twenty results obtained with the described query, all were filtered out as not dealing with the selected task. The found results were [110] with 17 citations, [78] with 11 citations, [14] with 9 citations, [41] with 8 citations, [139] with 8 citations, [90] with 7 citations, [140] with 3 citations, [46] with 2 citations, [87] with 2 citations, [58] with 1 citation, [56] with 1 citation, [187] with 0 citations, [83] with 0 citations, [148] with 0 citations, [111] with 0 citations, [95] with 0 citations, [147] with 0 citations, [168] with 0 citations, [33] with 0 citations, and [120] with 0 citations.

**Scopus**

The following restrictions were used for the first query in Scopus:

- `Query string: urban green "convolutional neural network"`. To focus only on articles dealing with the urban green classification using CNNs.
- `Search field: All fields`. Due to the small number of results, a more restricted query did not make sense.
- `Access type: Open Access`. To focus only on articles in *Scopus Gold Open Access*. It includes fully open journals, hybrid journals (authors pay a fee to make an article open access), open archives and articles with free promotional access.

From the top twenty results obtained with the described query, all were filtered out as not dealing with the selected task. The found results were [128] with 204 citations, [124] with 207 citations, [188] with 176 citations, [203] with 134 citations, [165] with 115 citations (the difference in the number of citations with chapter 2 is due to a different timestamp of the query), [149] with 114 citations, [122] with 112 citations, [5] with 103 citations, [97] with 91 citations, [163] with 86 citations, [166] with 84 citations (the difference in the number of citations with chapter 2 is due to a different timestamp of the query), [40] with 81 citations, [51] with 72 citations, [36] with 60 citations, [59] with 59 citations, [76] with 55 citations, [213] with 54 citations, [189] with 52 citations, [60] with 49 citations, and [20] with 46 citations.

Using the same query, but restrictive to search only in the topic (searching the title, the abstract, and keywords), five results were obtained and all of them were filtered out as not dealing with the selected task. The found results were [43] with 11 citations, [29] with 2 citations, [19] with 1 citation, [187] with 0 citations, and [71] with 0 citations.

The following restrictions were used for the next query in Scopus:

- `Query string: urban vegetation "convolutional neural network"`. To focus only on articles dealing with the urban vegetation classification using CNNs.
- `Search field: All fields`. Due to the small number of results, a more restricted query did not make sense.
- `Access type: Open Access`. To focus only on articles in *Scopus Gold Open Access*. It includes fully open journals, hybrid journals (authors pay a fee to make an article open access), open archives and articles with free promotional access.

From the top twenty results obtained with the described query, nineteen were filtered out as not dealing with the selected task. The filtered results were [126] with 247 citations, [131] with 183 citations, [138] with 163 citations, [18] with 144 citations, [211] with 123 citations, [165] with 121 citations, [9] with 98 citations, [166] with 86 citations, [61], [100] with 71 citations, [108] with 65 citations, [76] with 55 citations, [212] with 49 citations, [65] with 45 citations, [197] with 42 citations, [198] with 39 citations, [167] with 36 citations, [39] with 34 citations, and [162] with 34 citations.

The only article not filtered out was [105] with 154 citations. This article was presented already in the previous section; therefore, it is being skipped now.

Using the same query, but restrictive to search only in the topic (searching the title, the abstract, and keywords), ten results were obtained and six of them were filtered out as not dealing with the selected task. The rest, when ordered by the attribute `Cited by`, were the following:

- Advanced multi-sensor optical remote sensing for urban land use and land cover classification: Outcome of the 2018 IEEE GRSS data fusion contest: 19 citations. [191]
- Learnable Gated Convolutional Neural Network for Semantic Segmentation in Remote-Sensing Images: 3 citations. [66]
- Assessing alternative methods for unsupervised segmentation of urban vegetation in very high-resolution multispectral aerial imagery: 0 citations. [106]
- Land Use Land Cover Classification from Satellite Imagery using mUnet: A Modified Unet Architecture: 0 citations. [57]

The filtered results were [201] with 5 citations, [73] with 3 citations, [19] with 1 citation, [30] with 0 citations, [15] with 0 citations, and [151] with 0 citations. As both the second and the third results were presented already in the previous section, they are being skipped now.

*Advanced multi-sensor optical remote sensing for urban land use and land cover classification: Outcome of the 2018 IEEE GRSS data fusion contest* presents outcomes of the 2018 Institute of electrical and electronics engineers (IEEE) Geoscience and remote sensing society (GRSS) data fusion contest. The competition offered three data sources - a light detection and ranging (LiDAR) point cloud, orthorectified and radiometrically calibrated 48-band (380–1050 nm) hyper-spectral data with a meter spatial resolution, and very-high-resolution colour imagery - and their 50-centimetre spatial resolution ground truth reference data and consisted of three land use classification challenges - from the hyper-spectral data, from the point cloud, and a data fusion one with the usage of at least two of available datasets. Data came from the area of Central Houston and comprise of twenty urban and non-urban classes, the vegetation ones consisting of healthy grass, stressed grass, artificial turf, evergreen trees, and deciduous trees. Two architectures from the competition are described in the paper - the winning one and the second one. As LiDAR data are not in the focus of this thesis, we will focus only on the hyperspectral classification task. Winners applied a two-branch FCN, where the first branch worked as a spatial feature extractor for the first three principal components of the image and the second one took the entire image; as a preprocessing step, authors had resampled the data to 50-centimetre spatial resolution using the nearest neighbour method to correspond with the ground truth and normalized them to a range of [0, 1]. The team found that a combination with LiDAR data later helped the classification a lot. The second team used a very complex architecture combining a shallow fully connected ANN as a classifier for joint basic natural features such as grass, trees, and water and a deep CNN for more complex ones, and then parsing all outputs together; the initial resampling into 50-centimetre spatial resolution was done using an order-3 spline. It is a very interesting approach, but has to be done with some knowledge of data used for the training and intended for the application. No difference between urban and rural vegetation is mentioned in the paper.

*Land Use Land Cover Classification from Satellite Imagery using mUnet: A Modified Unet Architecture* deals with the land cover classification over the city of Karachi. Authors propose their own architecture based on U-Net [158] called modified U-Net (mUnet). mUnet has four less convolutional layers than U-Net and therefore has, although it uses filters of size $5 \times 5$ with padding instead of $3 \times 3$ used in U-Net, only two thirds of trainable parameters of original U-Net. This makes the modified architecture faster and lighter, while it still, according to the presented results, outperforms the original one in the task of classification of four classes - open, vegetation, water, and habitation. No difference between urban and rural vegetation is mentioned in the paper.

The following restrictions were used for the next query in Scopus:

- `Query string: parks "convolutional neural network"`. To focus only on articles dealing with the urban vegetation classification using CNNs.
- `Search field: All fields`. Due to the small number of results, a more restricted query did not make sense.
- `Access type: Open Access`. To focus only on articles in *Scopus Gold Open Access*. It includes fully open journals, hybrid journals (authors pay a fee to make an article open access), open archives and articles with free promotional access.

From the top twenty results obtained with the described query, nineteen were filtered out as not dealing with the selected task. The filtered results were [6] with 754 citations, [141] with 674 citations, [101] with 518 citations, [10] with 441 citations, [202] with 386 citations, [32] with 336 citations, [25] with 333 citations, [128] with 308 citations, [172] with 304 citations, [181] with 283 citations, [200] with 263 citations, [104] with 259 citations, [123] with 255 citations, [44] with 254 citations, [52] with 253 citations, [114] with 228 citations, [45] with 227 citations, [206] with 223 citations, and [93] with 223 citations.

The only article not filtered out was *Deep convolutional neural networks for hyperspectral image classification* [81] with 485 citations deals with the classification of hyperspectral imagery over three datasets, only one containing an urban area. It is a dataset covering the area of Pavia consisting of 103 bands with a spatial resolution of 1.3 meters and of classes asphalt, meadows, gravel, trees, sheets, bare soil, bitumen, bricks, and shadows. The entire data are normalized to a range of [-1, 1] as during the pre-processing step. 200 pixels are extracted from each class, serving as the training data, and many more serve as testing data. Authors work with a simple CNN architecture in the form of five layers: An input layer, a convolutional one, a max-pooling layer, a fully-connected one, and the output layer. They still managed to outperform SVM with a radial basis function (RBF) kernel [23].

Using the same query, but restrictive to search only in the topic (searching the title, the abstract, and keywords), nineteen results from the top twenty were again filtered out as not dealing with the selected task. The filtered results were [145] with 35 citations, [164] with 12 citations, [132] with 8 citations, [90] with 8 citations, [49] with 4 citations, [46] with 3 citations, [58] with 1 citation, [193] with 1 citation, [144] with 1 citation, [121] with 0 citations, [38] with 0 citations, [27] with 0 citations, [95] with 0 citations, [143] with 0 citations, [86] with 0 citations, [35] with 0 citations, [147] with 0 citations, [85] with 0 citations, and [137] with 0 citations.

The only article not filtered out was [106]. This article was presented already in the previous section; therefore, it is being skipped now.

# 4 Conclusion

The goal of this professional debate was to sketch future directions of the planned doctoral thesis and present its research part.

The first part of the debate was dedicated to the research on the current situation when it comes to CNNs usage for classification in the field of remote sensing. This research showed that although there is plenty of articles whose authors like to claim that their models outperform everything else that had ever appeared in the field, such claims very often miss sufficient comparisons with other approaches and architectures to prove them. This research is followed by a study of reviews covering the intended task. It was found that the amount of complex and really systematic reviews dealing with the CNN-based classification in the area of remote sensing is sadly pitiable. This chapter tells us that such research is needed and could serve for future applications of CNNs in the field as a valuable guide for researchers' approach choose and could stir up the common approach of experiments with the newest architectures without any knowledge about their real performance on satellite and aerial images.

The second part of the debate presents one of the use cases chosen to serve as test applications of various CNN architectures. It is a combination of a common task of urban scenery land use classification and the task of differentiation between urban and rural vegetation, a task so far uncovered in the field. For the future doctoral thesis, at least three use cases are intended to be presented, the second one being most probably the detection of horizontal traffic signs.

The ambition of this debate and later the thesis is not to enrich the field of deep learning - such efforts are currently filling seats of research centres all over the world. The ambition of this debate and later the thesis is to finally create a sufficient scientific mycelium on which researchers in the field can rely on and build their future studies on.

# List of abbreviations

| | |
|---|---|
| AI | Artificial intelligence |
| ANN | Artificial neural network |
| ARVI | Atmospherically resistant vegetation index |
| CD-CNN | Contextual deep convolutional neural network |
| CI | Crust index |
| CLC | CORINE land cover |
| CNN | Convolutional neural network |
| CNN-PPF | Convolutional neural network using pixel-pair features |
| CORINE | Coordination of information on the environment |
| CRF | Conditional random fields |
| CRNN | Convolutional recurrent neural network |
| DBI | Davies-Bouldin index |
| DL | Deep learning |
| DOAJ | Directory of Open Access Journals |
| DSM | Digital surface model |
| EEA | European Environment Agency |
| EO | Earth observation |
| EVI | Enhanced vegetation index |
| FCN | Fully convolutional network |
| FPN | Feature pyramid network |
| GEOBIA | Geographic object-based image analysis |
| GEOCNN | Geographic object-based convolutional neural network |

| | |
|---|---|
| GMM | Gaussian mixture model |
| GRSS | Geoscience and remote sensing society |
| HSI | Hue, saturation, intensity |
| IEEE | Institute of electrical and electronics engineers |
| KNN | K-nearest neighbour |
| L-GCNN | Learnable-gated convolutional neural network |
| LapSVM | Laplacian support vector machine |
| LiDAR | Light detection and ranging |
| ML | Machine learning |
| MLP | Multi-layer perceptron |
| MS-COCO | Microsoft-Common Objects in Context |
| mUnet | Modified U-Net |
| NAIP | National agricultural imagery program |
| NDSM | Normalized digital surface model |
| NDVI | Normalized differential vegetation index |
| OBIA | Object-based image analysis |
| PCA | Principal component analysis |
| PGM | Parameterized gate module |
| PL-SSDL | Semi-supervised deep learning using pseudo labels |
| PSPNet | Pyramid scene parsing network |
| R-CNN | Region-based convolutional neural network |
| $R^2$CNN | Rotational region convolutional neural network |
| RBF | Radial basis function |

| | |
|---|---|
| ResNet | Residual network |
| RNN | Recurrent neural network |
| RRPN | Rotation region proposal network |
| RF | Random forest |
| SAR | Synthetic aperture radar |
| SAVI | Soil adjusted vegetation index |
| SDA | Stacked denoising autoencoder |
| SBS | Sequential backward selection |
| SFS | Sequential forward selection |
| SS-LapSVM | Spatio-spectral Laplacian support vector machine |
| SSD | Single shot multi-box detector |
| SVM | Support vector machine |
| TSVM | Transductive support vector machine |
| VARI | Visual atmospheric resistance index |
| WoS | Web of Science |

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