Faculty of Information Engineering, Computer Science and Statistics Bachelor of Science in Computer Science (L-31)

Academic Year 2021-2022



Internship report

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Deep Learning based approach for Semantic Segmentation of Aerial Images



Application domain



Domain of application: motivation

- Natural disasters more and more frequent and more serious
- Floods make up about 43% of the total of events
- 157 thousand victims and 2.3 billion people affected (1995-2015)
- \$ 1 billion in damages (US in 2020)
- The provision of accurate, timely and understandable information is fundamental in the management of these events







Domain of application: use of UAVs

- UAVs (Unmanned Aerial Vehicles)
 they can quickly access the affected areas
- They can reach areas otherwise unreachable
 by humans
- Quickly deliver low-altitude, high-resolution images







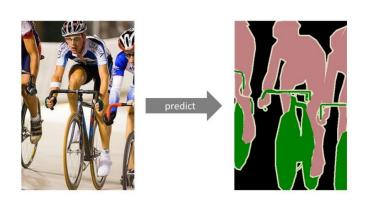
Semantic segmentation



Semantic segmentation: overview

- We can define it as the classification of each pixel of the image in a given class
- There are both traditional methods and methods based on

Deep Learning



Person Bicycle Background







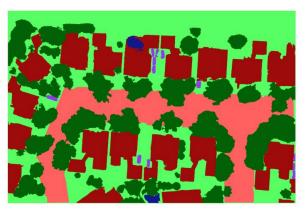
FloodNet dataset



FloodNet: overview

- Published following the FloodNet Challenge of the EARTHVISION 2021 workshop
 Captured between 30 August and 4 September 2017 in Texas (USA) immediately after the disaster caused by Hurricane Harvey with a DJI Mavic Pro
- 2343 images captured at an altitude of 200 feet and with a resolution of 1.5 cm per pixel
- 9 Classes: Flooded Building, Non-Flooded Building, Flooded Road, Non-flooded Road, Water, Tree, Vehicle, Pool, Lawn







FloodNet: main difficulties and solutions

Presence of errors in the masks

Data cleaning

Data cleaning

Data augmentation offline

Objects of different scale

Context-based architecture

Intrinsic difficulty of some classes

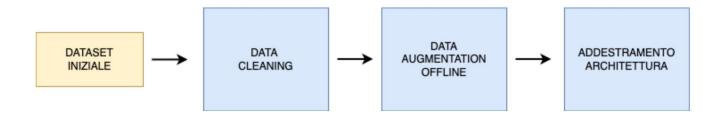
Context-based architecture

Proposed approach



Proposed approach

- Based on three main parts:
 - Data cleaning
 - Offline data augmentation
 - Context-based architecture

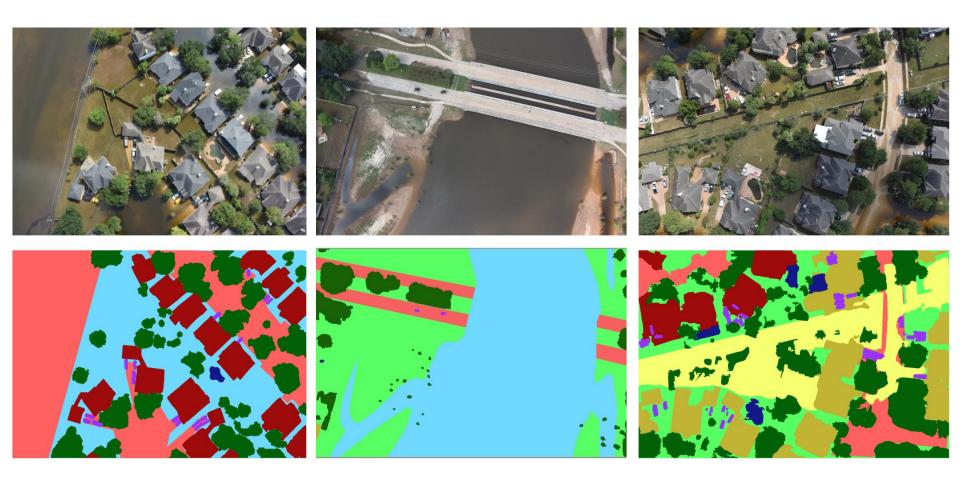




Proposed approach: Data cleaning

- Cleaning and correction phase of the
- dataset Manual scanning of all images and their corresponding ones masks
- 182 masks found with errors
- Three main types of errors found:
 - incorrect classification of pixels non-occurrence of objects in the masks presence
 of inconsistency and confusion



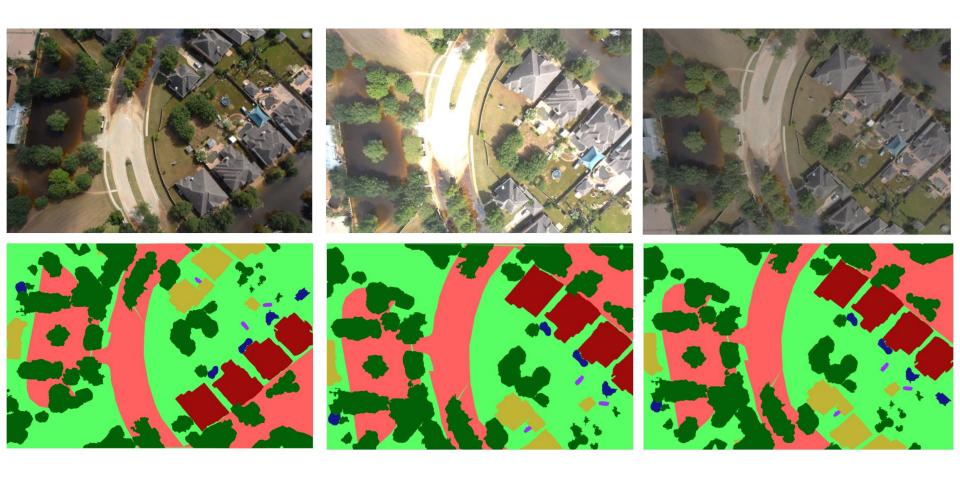




Proposed approach: Offline data augmentation

- Purpose: to specifically increase the number of images to cope with the imbalance of the classes
- 4 types of transformation: Rotation, Horizontal Flip, Vertical Flip and variation of brightness and contrast
- From each of the **140 selected images**, three other images were produced with the corresponding mask **(+420 images)**

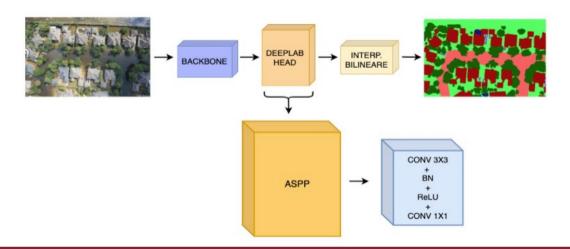






Proposed approach: Architecture

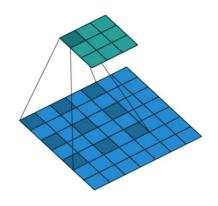
- Inspired by **DeepLabV3**, architecture proposed in 2017
- Consisting of 3 parts:
 - Backbone
 - DeepLabHead (ASPP)
 - Bilinear interpolation

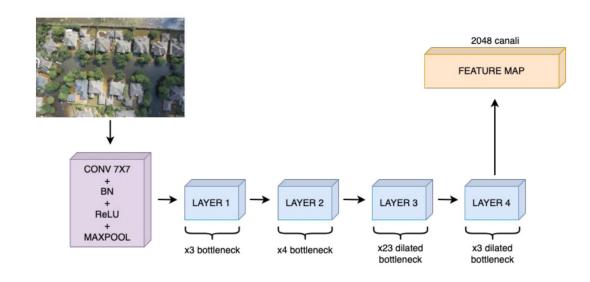




Backbone

- Responsible for **feature extraction**
- Convolutional network consisting of approximately 101 layers (inspired to ResNet101)
- Uses dilated convolutions

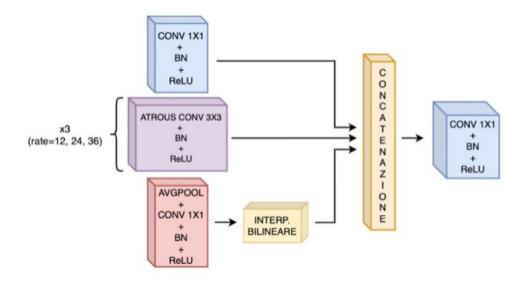






DeepLabHead and ASPP

- Mainly composed of ASPP (Atrous Spatial Pyramid Pooling)
- Inspired by SPP (Spatial Pyramid Pooling)
- The main idea is to capture **contexts at different scales** using different convolutions **in parallel**





Hardware resources



Hardware limitations

- Hardware resources have been a major **obstacle** to work
- The Google Colab platform was used
- Very limited availability: 3/5 hours a day







Experiments and Results



Experiments

- Hyperparameters in common between all experiments:
 - Adam
 - Batch size = 2
 - Learning Rate = 0.01 (except for the last experiment)
 - Split dataset: 60% for training, 20% for validation and 20% for testing
- 1 ^ exp: baseline (600 * 800)

Classe	mIoU								
H		3				7	•	9	
0.0018	0.087	0.0002	0.28	0.14	0.339	0.006	0.0	0.309	0.129

• 2 ^ exp: + Data augmentation online (600 * 800)

Classe	Classe	Classe	Classe	Classe	Classe	Classe	Classe	Classe	mIoU
Classe 1	2	3	4	5	6	7	8	9	
0.0003	0.12	0.001	0.27		0.38		0.03		0.175



Experiments

• 3 ^ exp: + Data cleaning (750 * 1000)

Classe	mIoU								
1	2	3	4	5	6	7	8	9	
0.14	0.47	0.06	0.48	0.46	0.55	0.34	0.26	0.81	0.402

• 4 ^ exp: + Data augmentation offline (750 * 1000)

Clas	sse Class	se Classe	e Classe	Classe	Classe	Classe	Classe	Classe	mIoU
1	2	3	4	5	6	7	8	9	
0.32	0.51	0.24	0.55	0.55	0.6	0.4	0.44	0.84	0.5

• 5th exp: + Dynamic learning rate

Classe	mIoU								
1	2	3	4	5	6	7	8	9	
0.41	0.60	0.32	0.6	0.57	0.65	0.49	0.52	0.86	0.564



Results and comparison with other works of the State of the Art

Comparison:

- their version of the dataset has 857 more images (+ 36%)
- Continuous availability of computational resources

Modello	Classe	mIoU								
	1	2	3	4	5	6	7	8	9	
ENet	0.069	0.473	0.124	0.484	0.489	0.683	0.322	0.424	0.762	0.426
DeepLabV3+	0.327	0.728	0.52	0.7	0.75	0.77	0.42	0.47	0.84	0.61
Approccio proposto	0.41	0.60	0.32	0.6	0.57	0.65	0.49	0.52	0.86	0.564

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Thanks for your attention!



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