

Machine vision algorithms on cadaster maps

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Avvialio

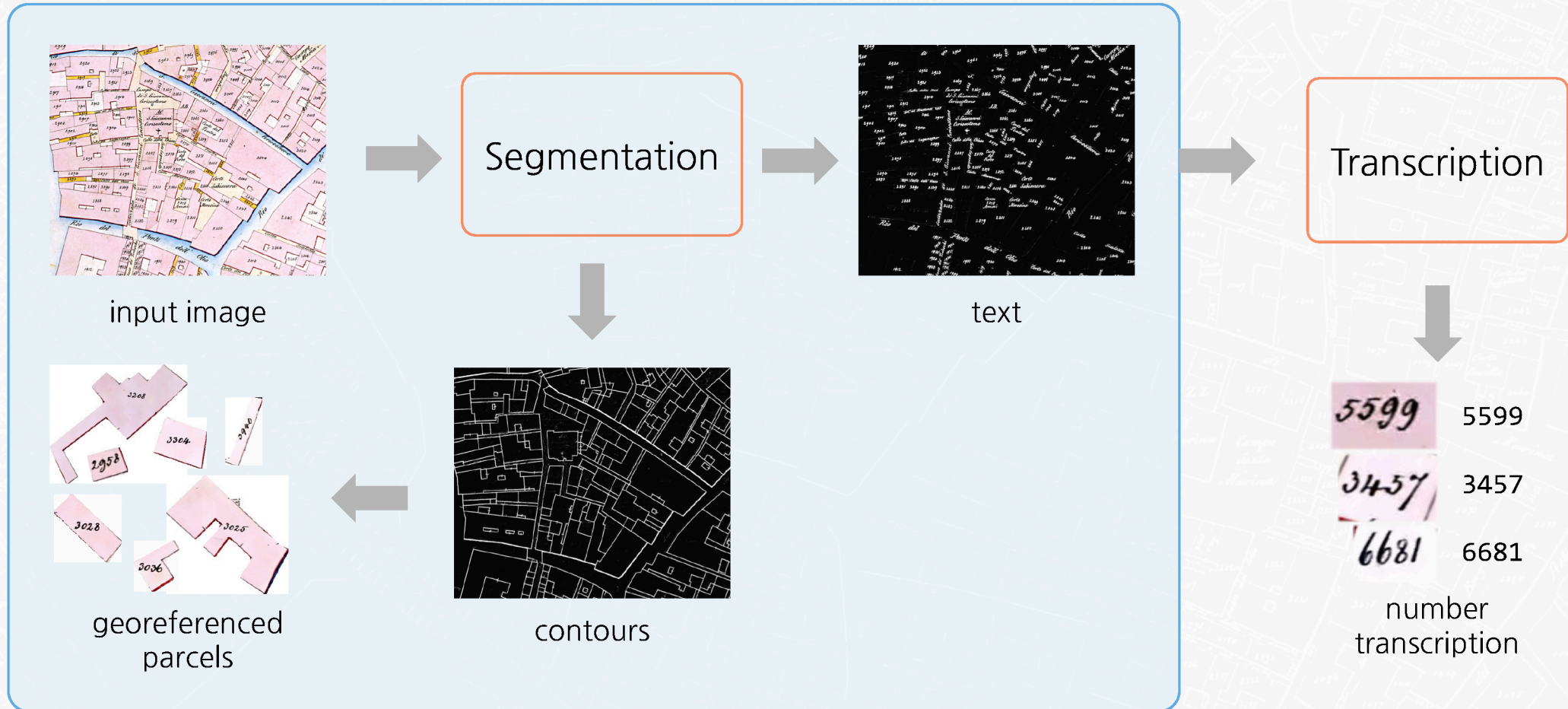
Numeri della Mappa	POSSessori	Denominazione dei Pezzi di terra	QUALITA'	SUPERFICIE	
				Classe	Pertiche Censuarie Gen-tesimi
			Canale di Rialto		
9001	Primani		Bottega d'affitto		
9002	Marcello Marino q. ^{to} Guido	29	C.S. Simile		
9003	Venier Bro. Ferolamo q. ^{to} Pio. Battia	28	C.S. Simile		
9004	Suddetto	27	C.S. Simile		
9005	Marconi Giuseppe q. ^{to} Ant. ^o	26	C.S. Bottega di proprio uso		
9006	Raspi Fran. ^{co} q. ^{to} Pio. Maria	25	C.S. Bottega d'affitto		
9007	Besenti Andrea q. ^{to}	4383	C.S. Simile		
9008	Morosini Ant. ^o di Vincenzo Dolfin Luigi q. ^{to} Dolfin Marcant. q. ^{to} Ferracina Niccolò q. ^{to} Betrogalli Piu. ^o q. ^{to} Berganti Piu. ^o q. ^{to} Dolfin Marianna q. ^{to} Cosepori indivisi	4580	C.S. Simile		
9009	Maruzzi Costantino q. ^{to} Canno	4579	C.S. Simile		
9010	Dolfin Leonardo q. ^{to} Bro.	4578	C.S. Simile		
9011	Venier Ferolamo q. ^{to} Pio. Battia	4577	C.S. Simile		
9012	Eredi del fu Carlo Emilio Canal q. ^{to} Ferolamo. Balbi Canal Mattia Ant. ^o Vedo va del fu Cristoforo Cosepori indivisi	4577	C.S. Simile		
9013	Maruzzi Costantino q. ^{to} Canno	4587	C.S. Simile		
9014	Correr Marcello Maria q. ^{to} Bro.	4586	C.S. Simile		
9015	Labia Fran. ^{co} q. ^{to} Canno Ant. ^o	4585	C.S. Simile		
9016	Venier Bro. Ferolamo q. ^{to} Pio. Battia	4584	C.S. Simile		





Method

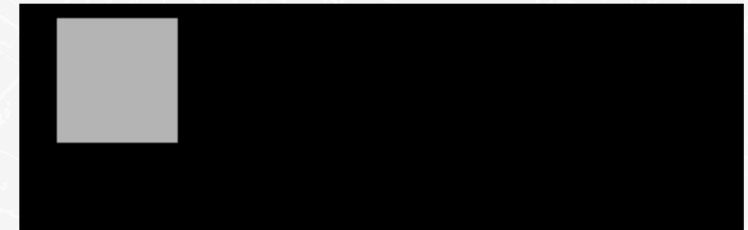
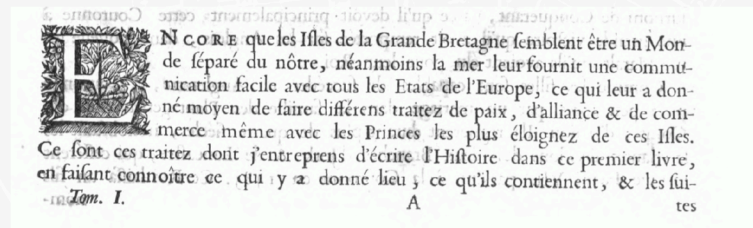
Overview of the system



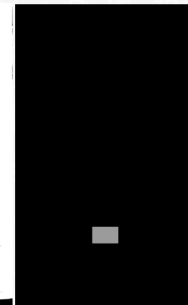
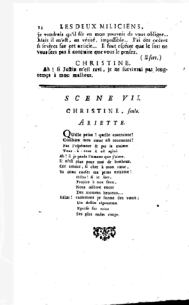
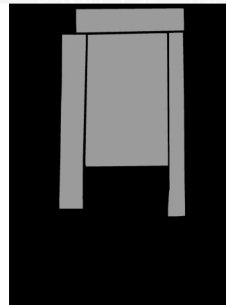
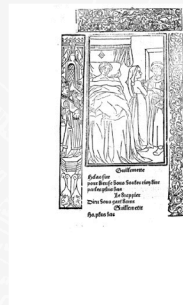
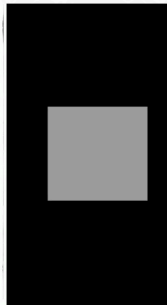
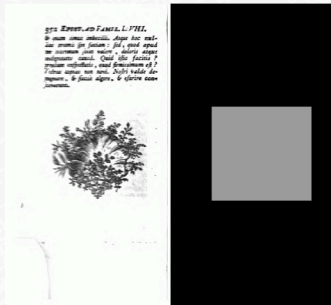
Segmentation

Deep learning pixel-wise segmentation

Assign to each pixel a label



Train a neuronal network by showing several examples





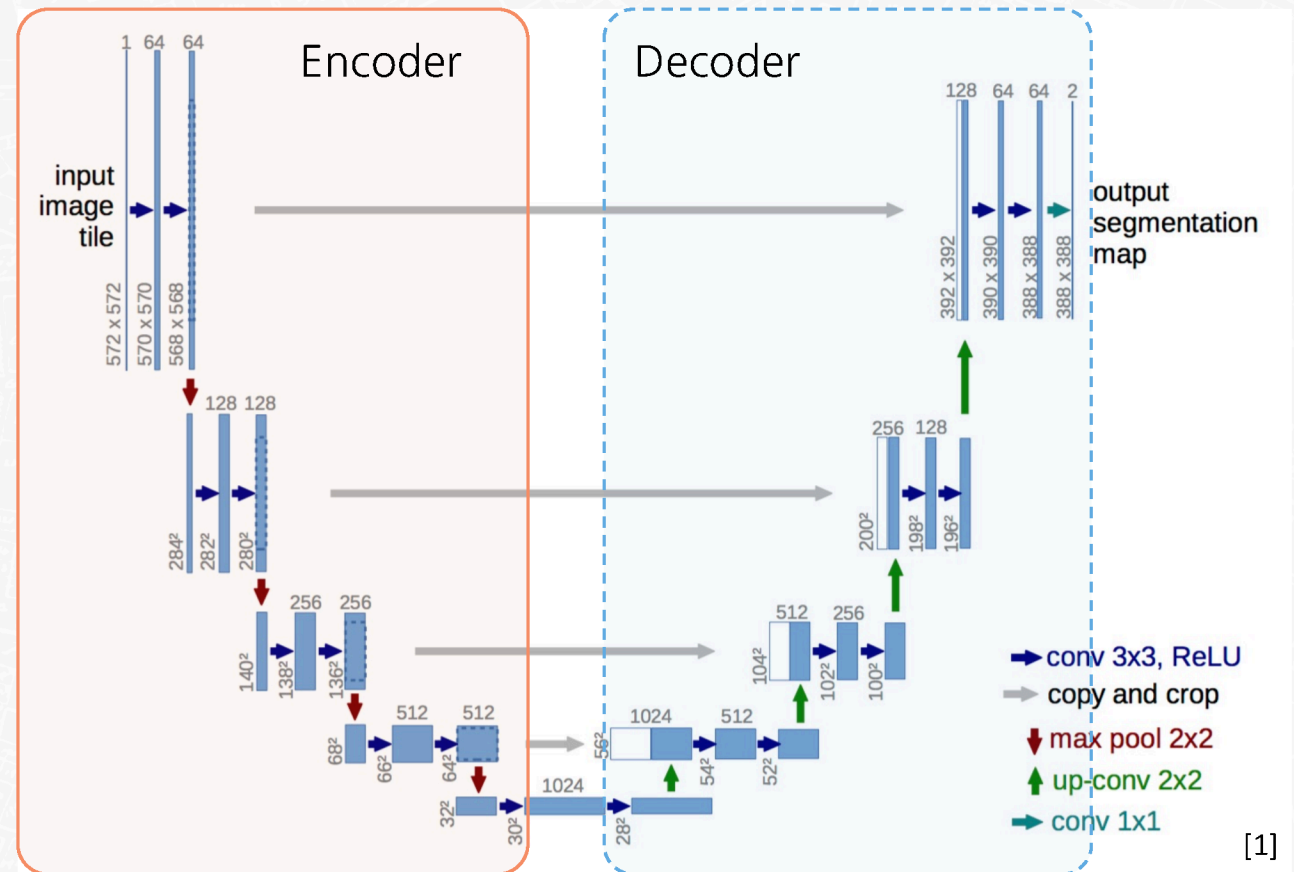
Data annotation
Pixel labelling



Architecture network

- Encoder is a pre-trained convolutional neural network
- Each encoding layer has a corresponding decoding layer

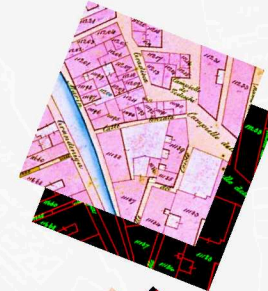
→ U-shaped architecture



[1] O. Ronneberger, P. Fischer, and T. Brox, "U-net: Convolutional networks for biomedical image segmentation", 2015

[2] V. Badrinarayanan, A. Kendall, and R. Cipolla, "Segnet: A deep convolutional encoder-decoder architecture for image segmentation", 2015

Training



Input {image, label}

data augmentation

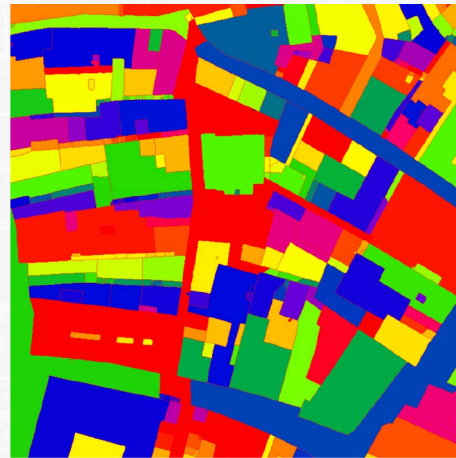
neural network

2-class prediction

Parcel extraction and georeferencing



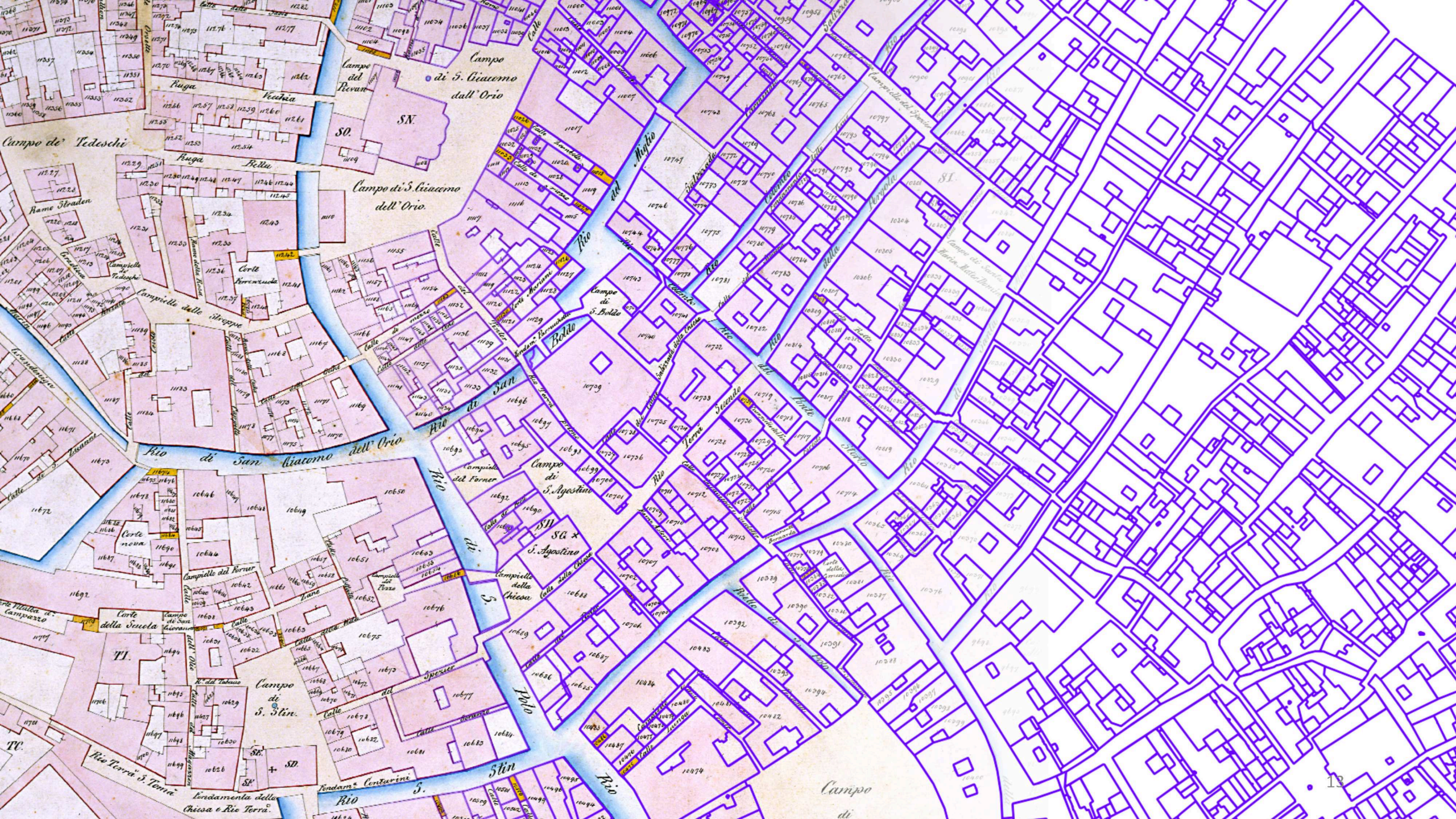
→
watershed



→
contour
extraction



If the image is georeferenced, the geographical coordinates are directly inferred and the parcels can be exported into a GIS system



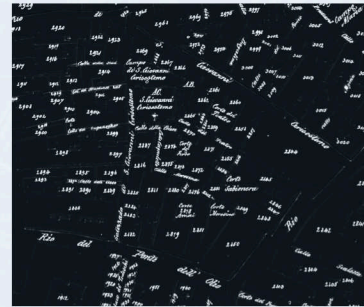
Pipeline



input image



Segmentation



text



Transcription

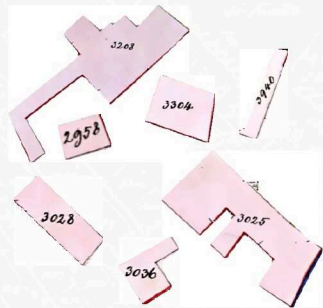


5599	5599
3457	3457
6681	6681

number
transcription



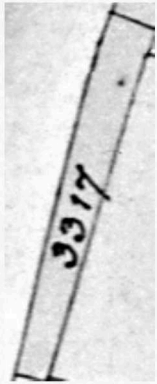
contours



georeferenced
parcels

Text extraction

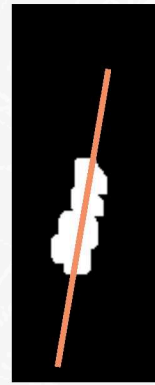
For each parcel, find its corresponding text region



parcel
localization



text
probabilities



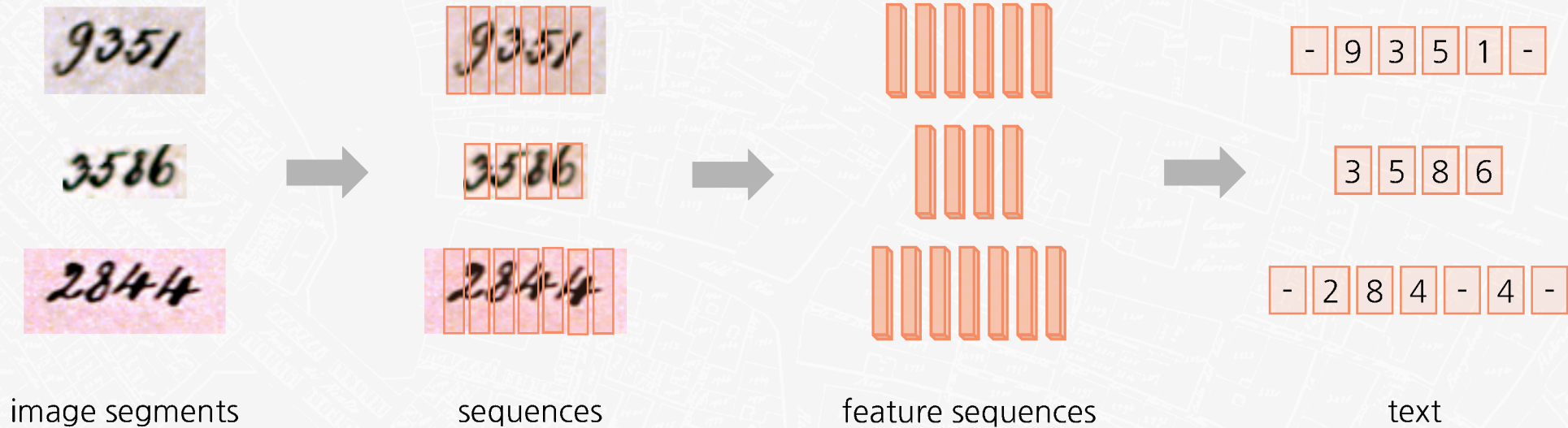
orientation
finding



rotation and
cropping

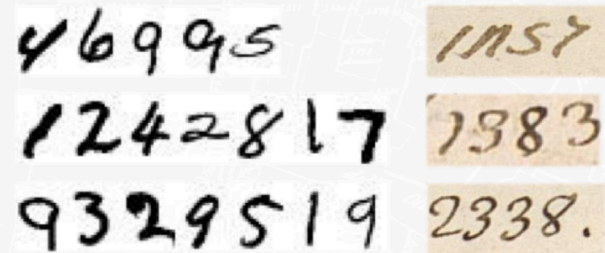
Transcription

Convert image segments into features sequences that will be mapped into text



Training data

- Synthetic data generated from MNIST dataset (100K)
- Handwritten numbers extracted from venetian archives (~ 30K)

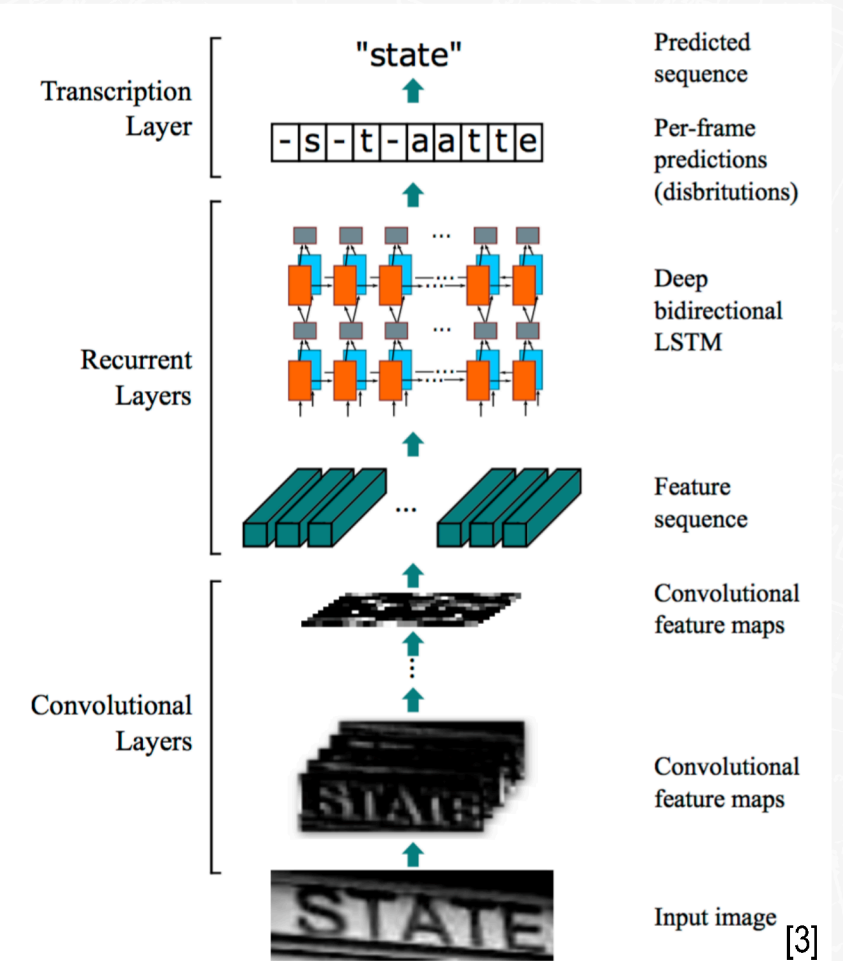


46995	1157
1242817	1383
9329519	2338.

+ data augmentation

Architecture network : CRNN

1. Convolutional neural network (CNN)
2. Recurrent neural network (RNN) with bidirectional Long Short-Term Memory (LSTM)
3. Mapping of separated time step labels to sequence label with connectionist temporal classification (CTC)



[3] B. Shi et al. "An end-to-end trainable neural network for image-based sequence recognition and its application to scene text recognition," 2017

[4] A. Graves, et al. "Connectionist temporal classification: labelling unsegmented sequence data with recurrent neural networks," 2016

Results

Parcel extraction results

IoU threshold	0.7	0.8	0.9
Parcel recall	0.90 (1062)	0.79 (941)	0.51 (605)
Parcel precision	0.50	0.44	0.28
Extracted parcels	2121		
Ground truth	1185		

$$recall = \frac{\text{true positives}}{\text{total ground truth}} \in [0, 1]$$

$$precision = \frac{\text{true positives}}{\text{total retrieved}} \in [0, 1]$$

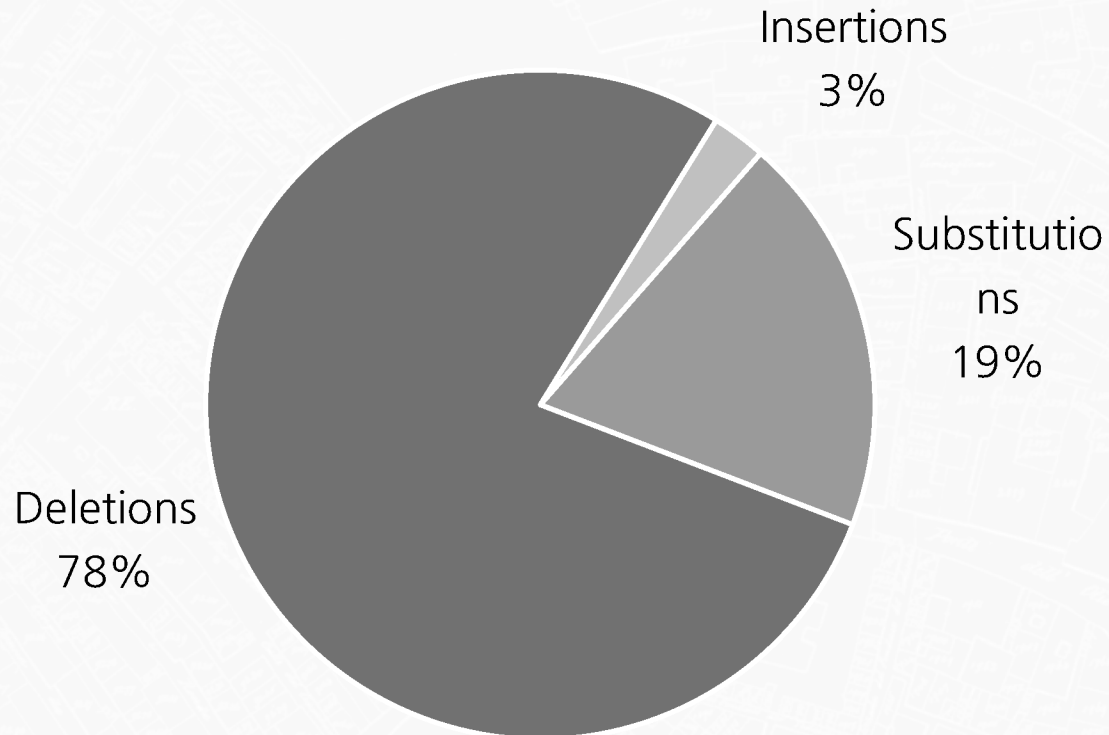
Label extraction and transcription results

Label locating	Inter : 0.8
Recall	0.86 (633)
Precision	0.37
Extracted labels	1693
Ground truth (labels)	736

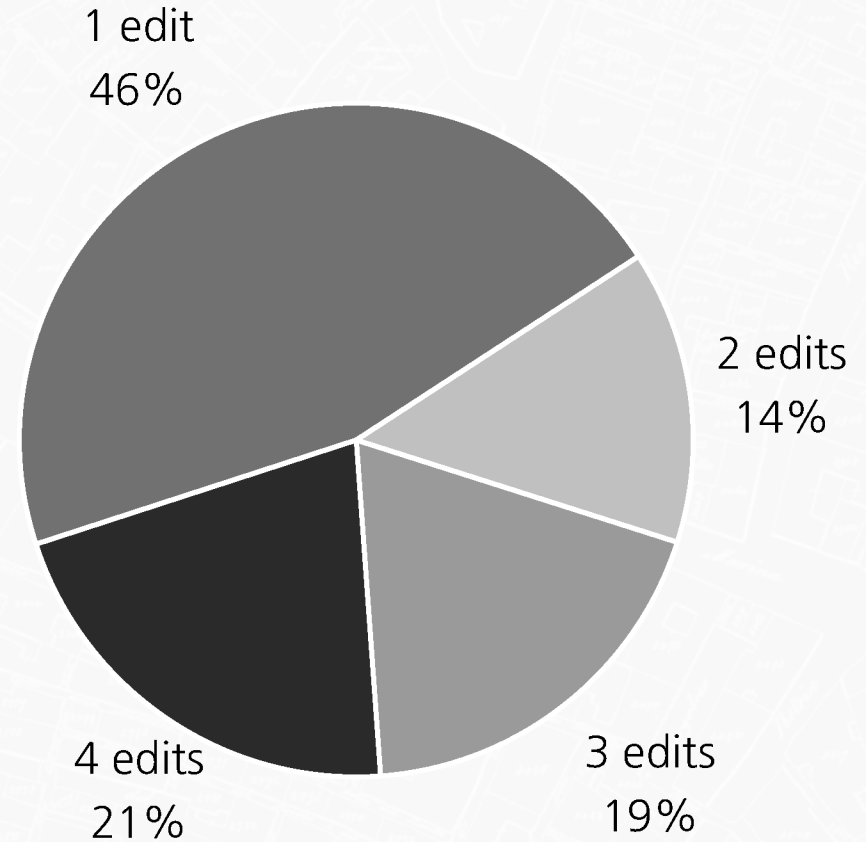
Label transcription	Inter : 0.8
Recall (correctly transcribed)	0.83 (608)
Precision	0.36
Character Error Rate (CER)	0.14
Ground truth (labels)	736

Label transcription: what are the errors ?

Type of errors



Edit distance





Conclusion

The system automatically extracts the parcels and their labels with high confidence level and opens new perspectives for spatial analysis in social, economic and urban structures.

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References

1. RONNEBERGER, Olaf, FISCHER, Philipp, et BROX, Thomas. U-net: Convolutional networks for biomedical image segmentation. In : *International Conference on Medical Image Computing and Computer-Assisted Intervention*. Springer, Cham, 2015. p. 234-241.
2. BADRINARAYANAN, Vijay, KENDALL, Alex, et CIPOLLA, Roberto. Segnet: A deep convolutional encoder-decoder architecture for image segmentation. *arXiv preprint arXiv:1511.00561*, 2015.
3. SHI, Baoguang, BAI, Xiang, et YAO, Cong. An end-to-end trainable neural network for image-based sequence recognition and its application to scene text recognition. *IEEE transactions on pattern analysis and machine intelligence*, 2016.
4. GRAVES, Alex, FERNÁNDEZ, Santiago, GOMEZ, Faustino, *et al.* Connectionist temporal classification: labelling unsegmented sequence data with recurrent neural networks. In : *Proceedings of the 23rd international conference on Machine learning*. ACM, 2006. p. 369-376.