

CONTEXT

- Urban expansion leads to more buried wastewater networks, often poorly documented.
- Very high resolution aerial images may be used to identify and pinpoint the aerial elements of these networks
- Deep Learning, Convolutional Neural Network
- Challenge: detect small objects i.e manhole covers (80 cm); in low contrast settings and cluttered backgrounds

Objective: An automatic recognition and localization method for manhole covers.



Figure 1: Extract of the 5cm resolution image used for validation.

REFERENCES

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- [3] Xuchun Li, Lei Wang, and E. Sung. A study of adaboost with svm based weak learners. In *Proceedings. 2005 IEEE International Joint Conference on Neural Networks, 2005.*, volume 1, pages 196–201 vol. 1, July 2005.
- [4] M. Everingham, C. K. I. Van Gool, L. and Williams, J. Winn, and A. Zisserman. The pascal visual object classes (voc) challenge. *International Journal of Computer Vision*, 88(19):303–338, 2010.
- [5] O. Bartoli, N. Chahinian, A. Allard, J.-S. Bailly, K. Chancibault, F. Rodriguez, C. Salles, M.-G. Toumoud, and C. Delenne. Manhole cover detection using a geometrical filter on very high resolution aerial and satellite images. In *Join Urban Remote Sensing Event*, Lausanne, Switzerland, 30 March - 1 April 2015.

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MATERIALS AND METHODS

The method is developed and applied on two towns located in the south of France: Gigean and Prades-Le-Lez.

Data:

2 RGB Images, 5cm/pixel:
 - Training dataset: 605 manhole covers from Prades Le Lez
 - Validation dataset: 101 manhole covers from Gigean
 The thumbnails are 40*40 pixels size (Figure 2)
 Classification into 2 categories: "Manhole covers" and "others"
 Data augmentation with the Keras library [1]

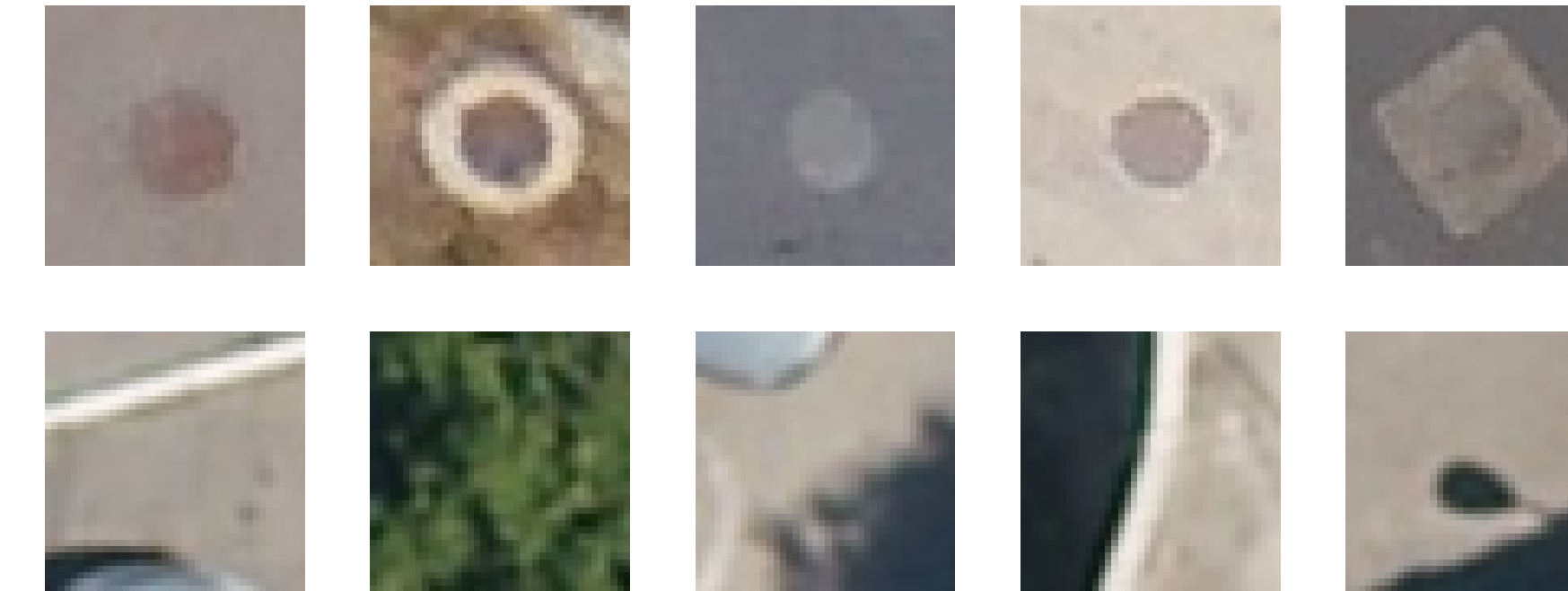
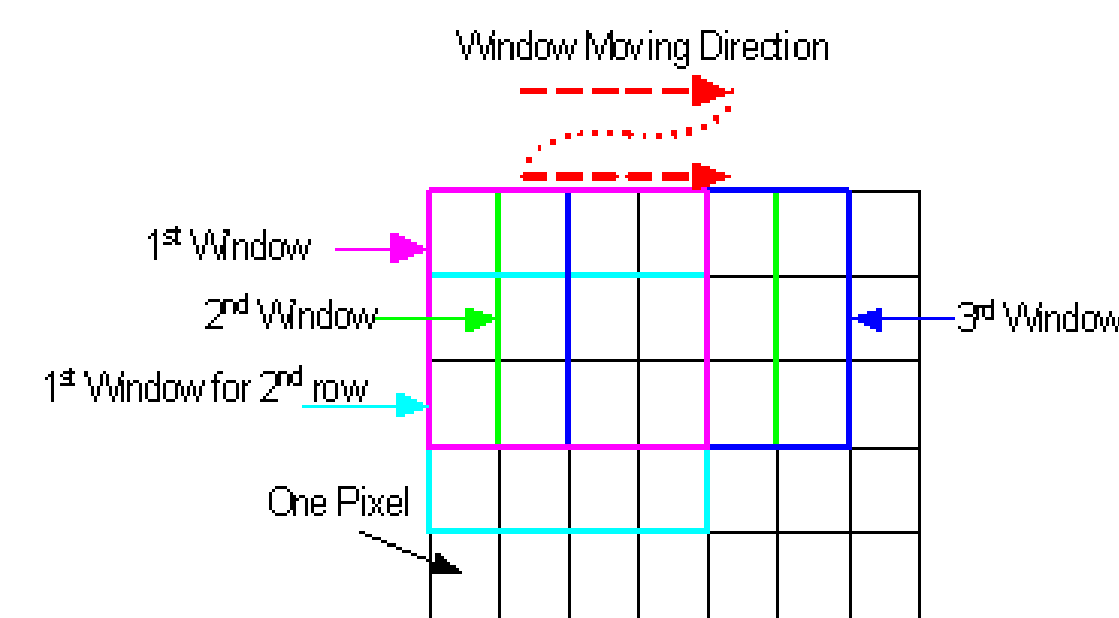


Figure 2: Example of thumbnails: up, manhole covers, down, others.

Method:

Convolutional Neural Network

Customized Alexnet [2] (Figure 3)
 Extract thumbnails from images using a sliding window:



Boosting the network:

After application on Prades-Le-Lez:
 Add all false positives to the other objects' category and train the network again. [3]

Cleaning the database:

Remove all the thumbnails that have a dominant feature that is not related to manhole covers from training database.

Classification:

A thumbnail is retained if the probability of representing a manhole is greater than 90%.

Validation:

Comparison with ground truth data [4]:

$$a_0 = \frac{\text{area}(B_p \cap B_{gt})}{\text{area}(B_p \cup B_{gt})}$$

B_p = Bounding box detected by the network

B_{gt} = Ground truth bounding box

True detection if $a_0 > 50\%$

Application:

Four networks tested:

1. Original Alexnet network
2. Fifth iteration boosted network
3. Fifth iteration boosted network with cleaned database
4. Customized network with cleaned database

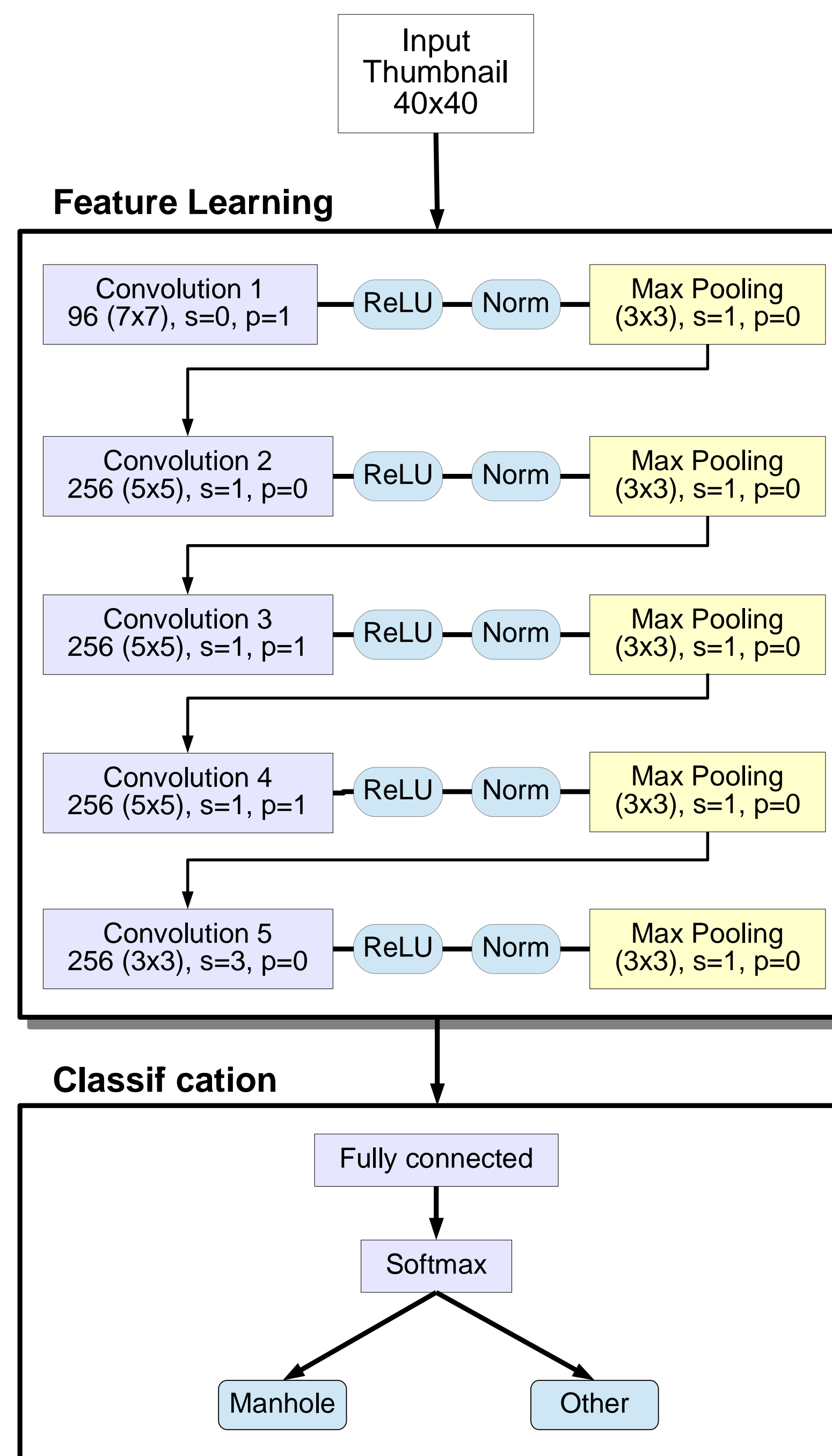


Figure 3: Customized AlexNet architecture

The results are assessed in terms of precision and recall:

$$\text{Precision} = \frac{TP}{TP + FP}, \quad \text{Recall} = \frac{TP}{TP + FN}$$

TP = Number of correctly classified manhole covers

FP = Number of thumbnails wrongly classified

FN = Number of undetected manhole covers

RESULTS



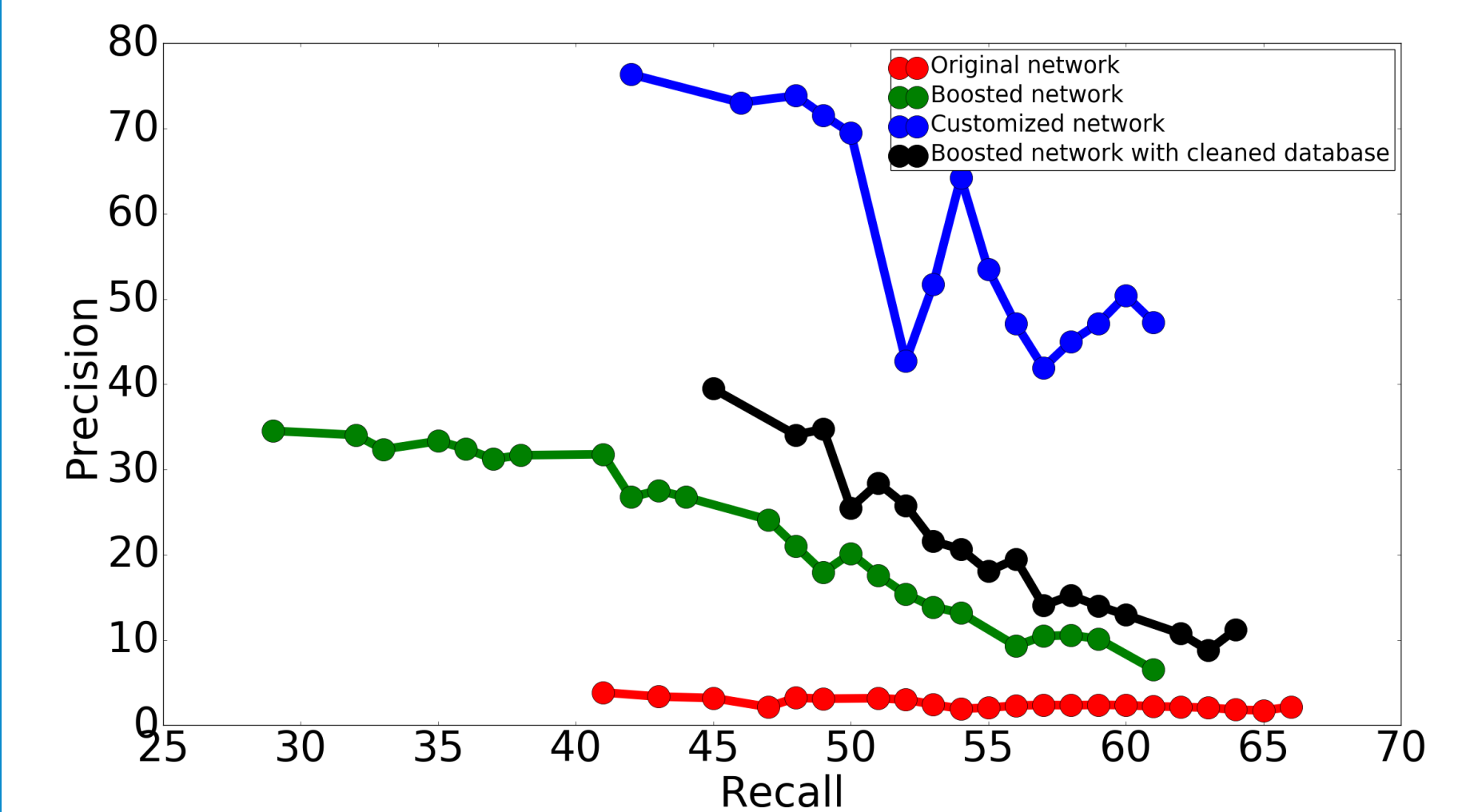
Figure 4: Sample of the results obtained with the customized network and the cleaned database.

Green square: correctly detected manhole covers

Red square: false detection

Blue square: undetected manhole covers

Customized network yields better results as shown by the ROC curves:



CONCLUSION AND PERSPECTIVES

An automated procedure was put forward to identify and localize manhole covers using aerial RGB images.

Preliminary results: recall is higher than 50% for an average precision of 60%.

Perspectives:

- Combine a circular filter [5] and convolutional neural network to reduce false positives.
- Add a third category - inlet gates - to the classification in order to optimize the learning phase and extract more precise features.