

CRATERNET

A Fully Convolutional Neural Network for Lunar Crater
Detection Based on Remotely Sensed Data

Supervised by Yves Cornet

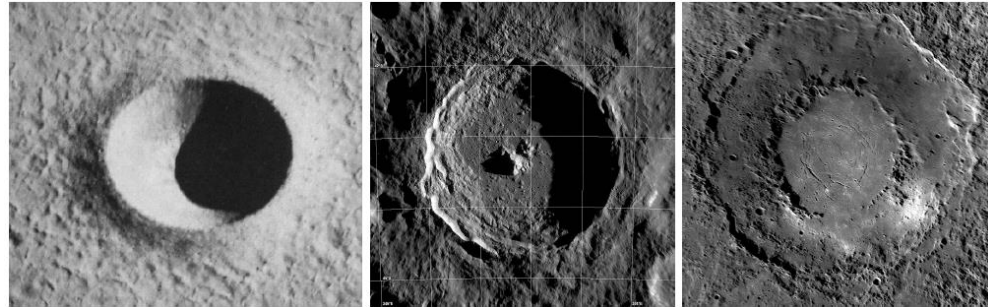
CRATERNET

1. State of the art and Hypothesis
2. Data description
3. Methods and Developments
4. Results
5. Conclusion

Crater Description

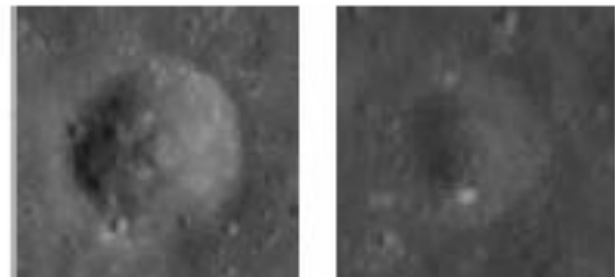
Typology related to aspect:

- Simple craters
- Complex craters
- Giant craters



Crater its-self is complex object :

- Highly variable size
- Overlapping
- Geological composition of the soil
- Illumination conditions
- Niveau de dégradation





Crater Detection Algorithms

Unsupervised :

- Edge detection : Canny, Robert, Sobel, Laplacian, ...
- Shape reconstruction : mostly using Hough transform

→ No need for training data but disappointing results

Supervised :

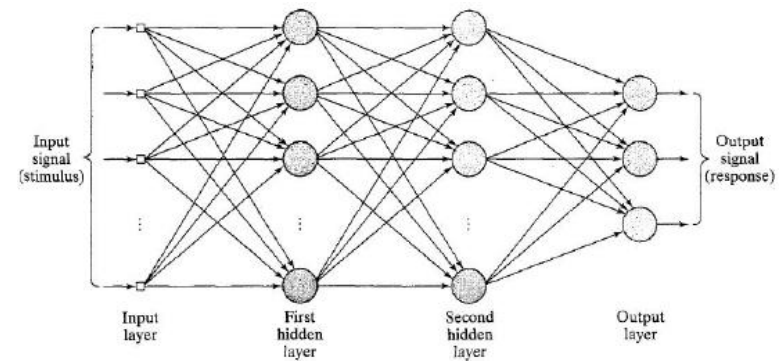
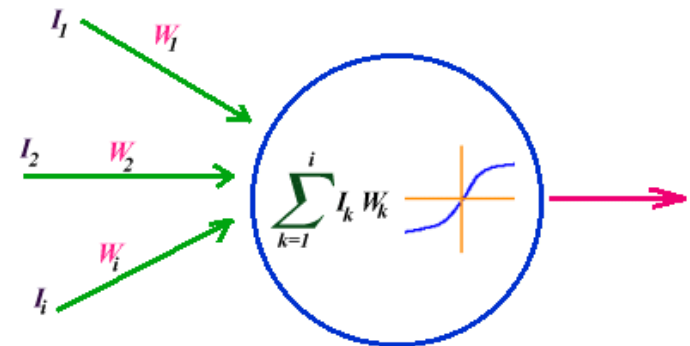
- Candidate search : mathematical morphology
- Post-classification with machine learning : decision tree, boosting, SVM, CNN, ...

→ Sometimes very good results but need for a huge amount of data to train the model

Still no satisfying answer (despite 100+ publications)

Advances in Deep Learning

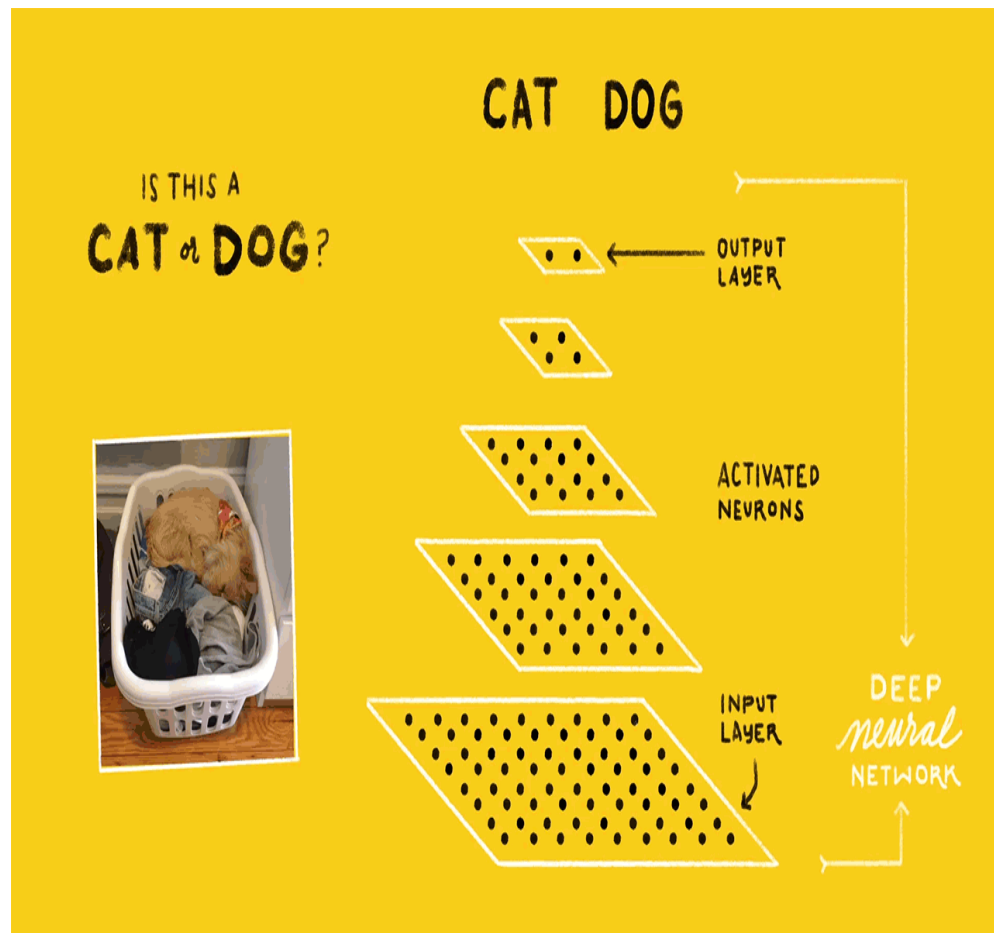
- Rapid and impressive progress
- Based on examples, able to predict unseen elements
- Deep Learning is only a « deeper » way to do machine learning
- Based on neural network



Convolutional networks

- Specific deep learning model broadly employed in image processing, using contextual information (CNN and FCN)
- Learn the image characteristics by training filters arranged in layers

« The first layer detect elementary contours, the second gathers thiese contours in patterns that will then be assembled in parts of objetcs, and so on » Yahn Lecun





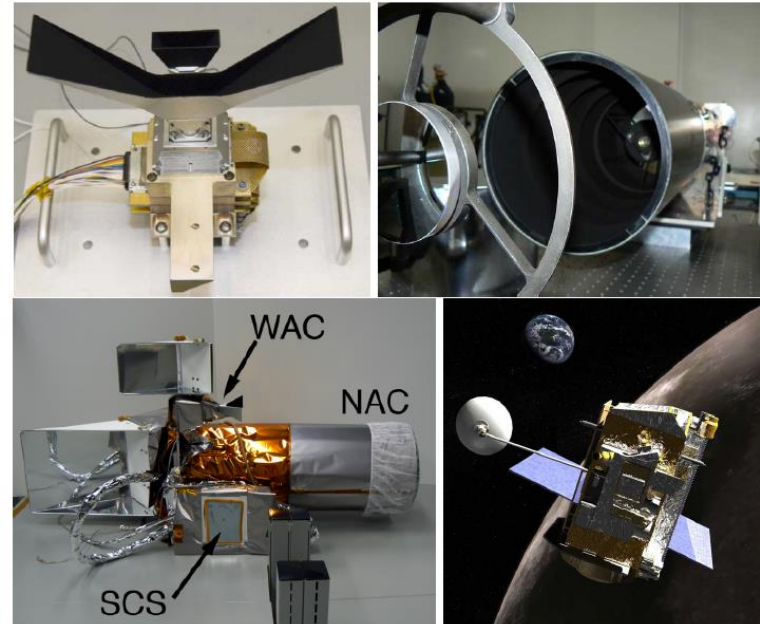
Hypothesis

Attempt to bring to the crater detection problem the advances related to deep learning :

A fully convolutional neural network is an innovative and convincing model for the detection of lunar craters based on remotely sensed data

Lunar Reconnaissance Orbiter Camera

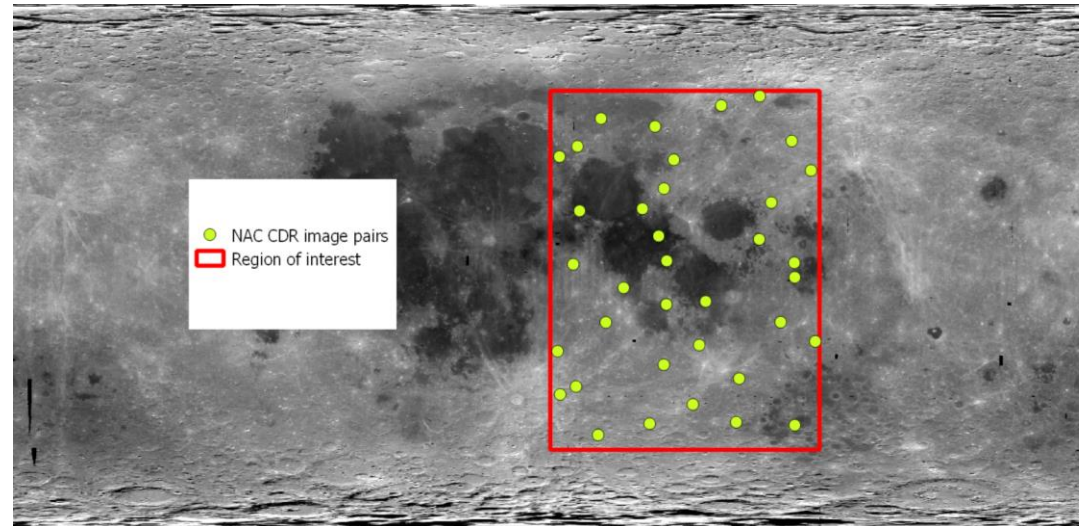
- LRO - NASA (2009)
- 1 des 7 acquisition devices
- Composed of 3 cameras
 - 1 with a large FOV (100m/pixel), called WAC (swath of 60 km)
 - 2 with a thin FOV (50cm/pixel), with small overlap, called NAC left or right (swath of 2x2.5km)
- Data available via NASA's archives





Description of the area of interest

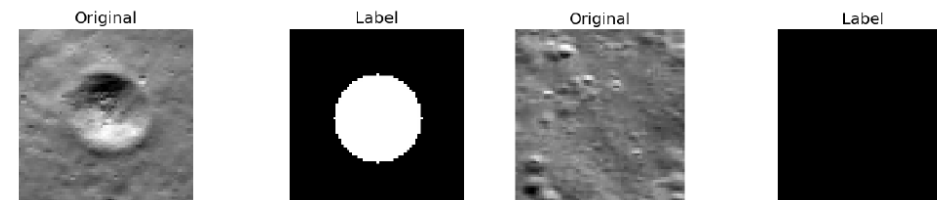
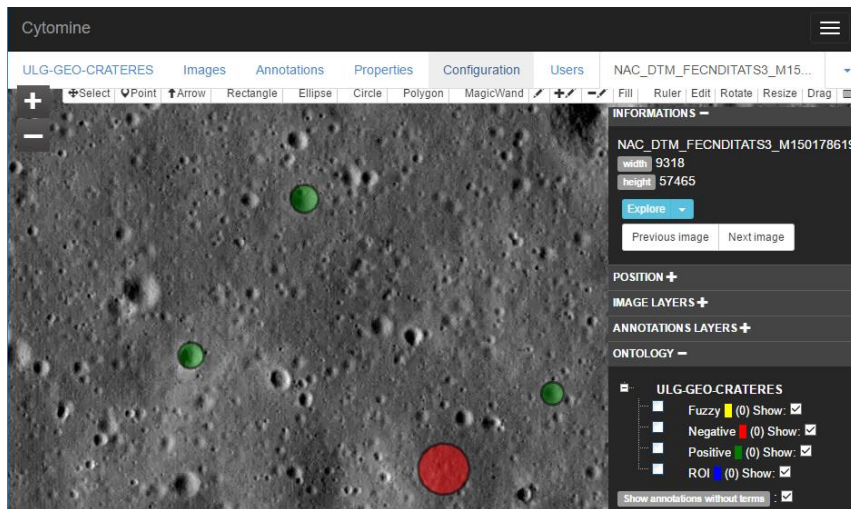
- Representative dataset of all possible situations on the Moon
- Choice of 72 NAC images by random systematic sampling covering 120 degrees of latitude and numerous illumination conditions
- In parallel to these images, we have orthorectified images produced by stereophotogrammetry (Arizona State University)





Description du dataset

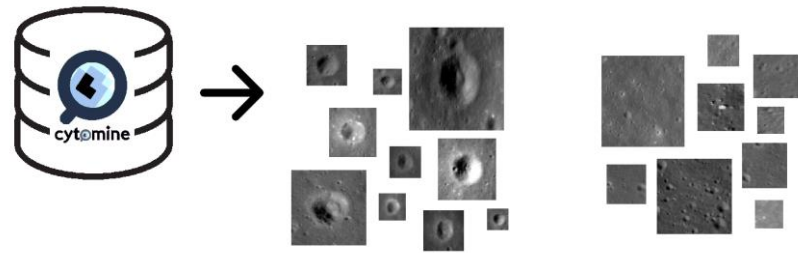
- Deep learning requires training data
- No sub-kilometric dataset exists for the Moon
- Use of the Cytomine web-application to efficiently annotate our images
- Possibility to interact directly with Cytomine via a Python Client
- In total, **11 223** annotations have been manually created, available on my GitHub



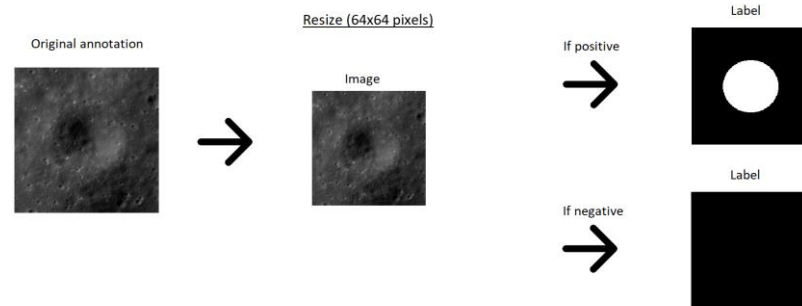
github.com/QuentinGlaude/CraterNet

Data importation

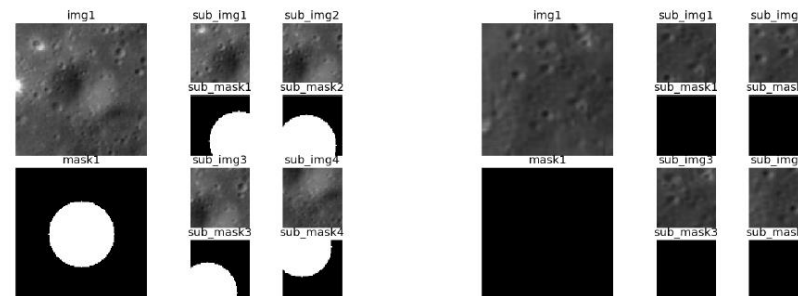
- Using the Python Client

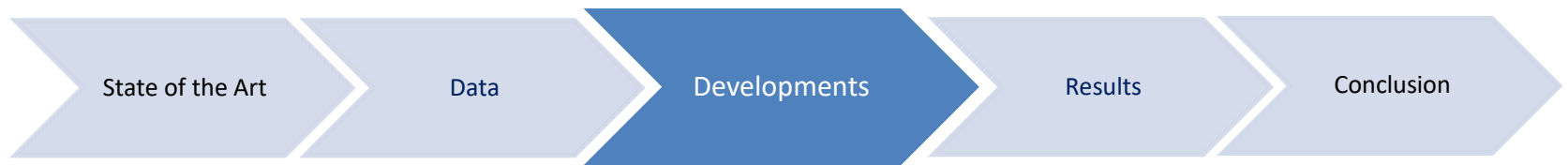


- Creation of the image label



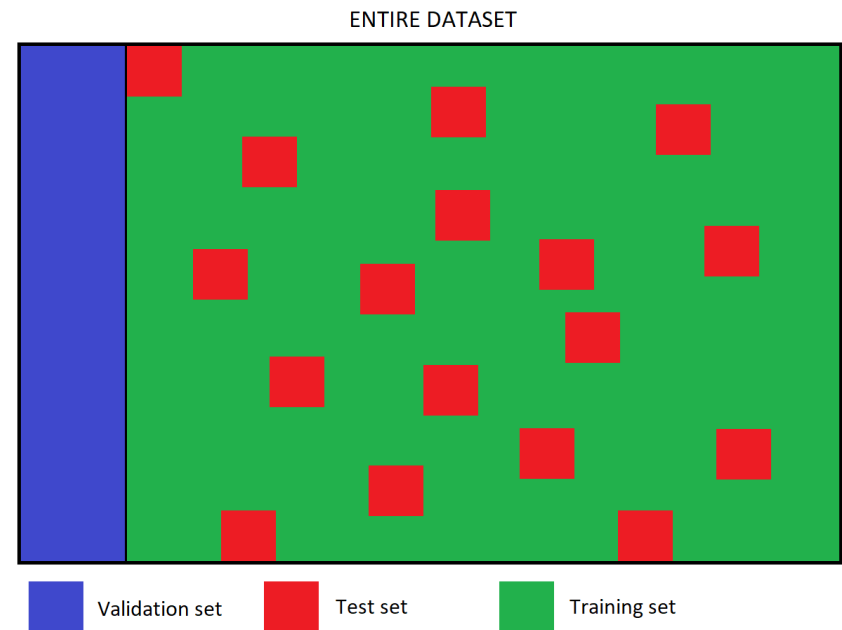
- Creation of a set of random patches





Learning Set / Test Set / Validation Set

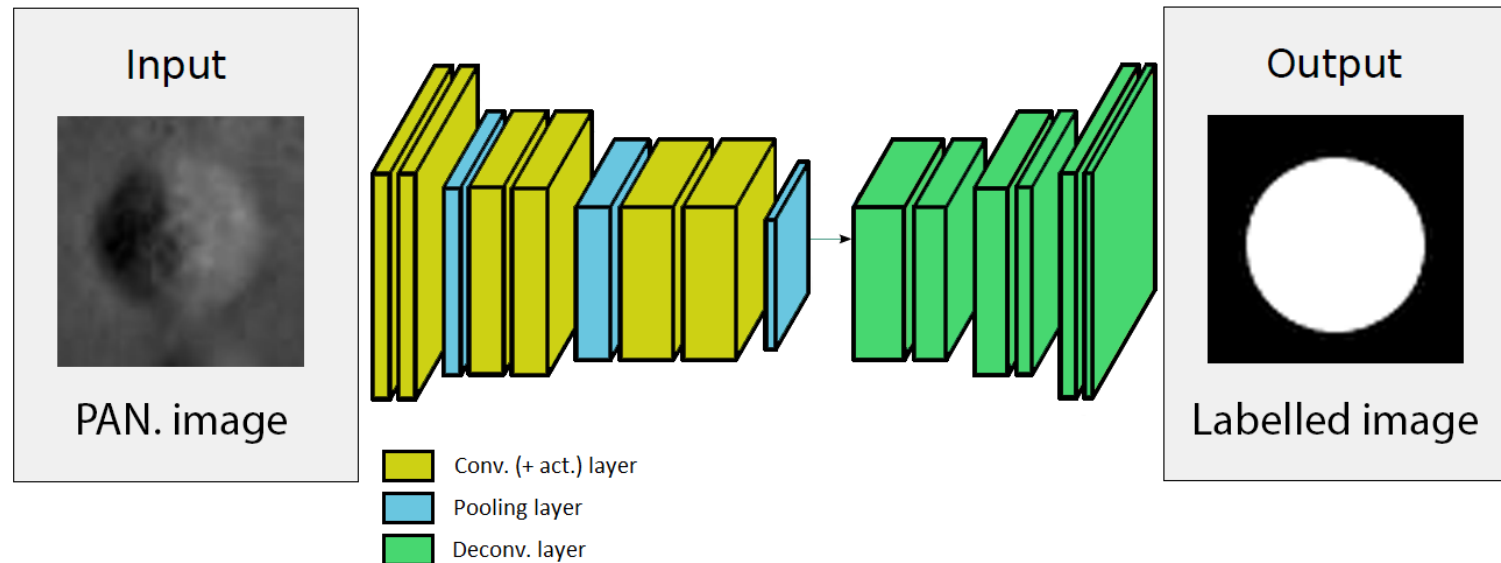
- Train the model with the learning set
- Optimize with the test set
- Assess with the validation set



Description of the model's architecture

Implementation via the TensorFlow library (GoogleBrain) GPU processing using CUDNN (Nvidia)

- Input layer
- Convolution layer
- Activation layer
- Pooling layer
- Deconvolution layer
- Output layer

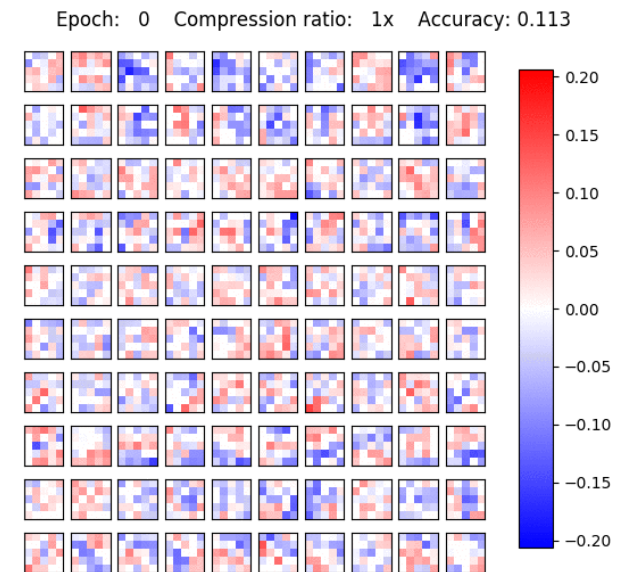
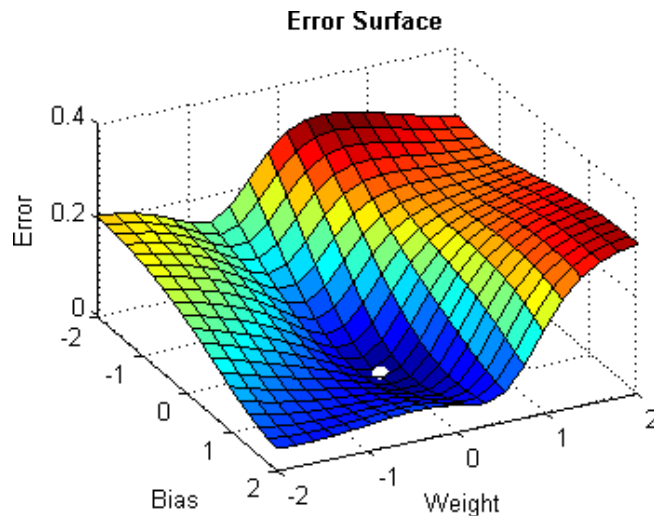


Entraînement du modèle

- Ajustement des poids par minimisation d'une fonction de coût
- Cette fonction = entropie croisée

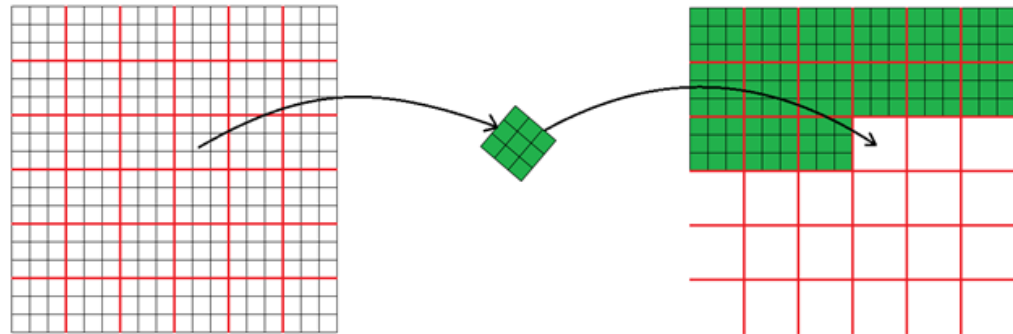
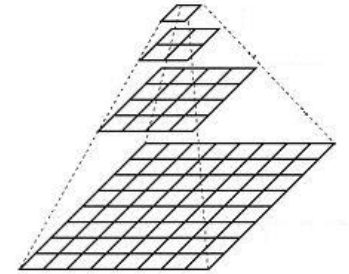
$$H_y(\hat{y}) = - \sum_i (y_i * \log \hat{y}_i + (1 - y_i) * \log (1 - \hat{y}_i))$$

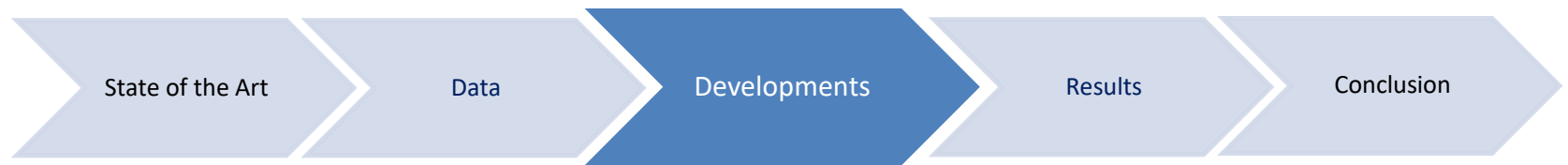
- Minimisation par descente de gradient



Analysing a scene

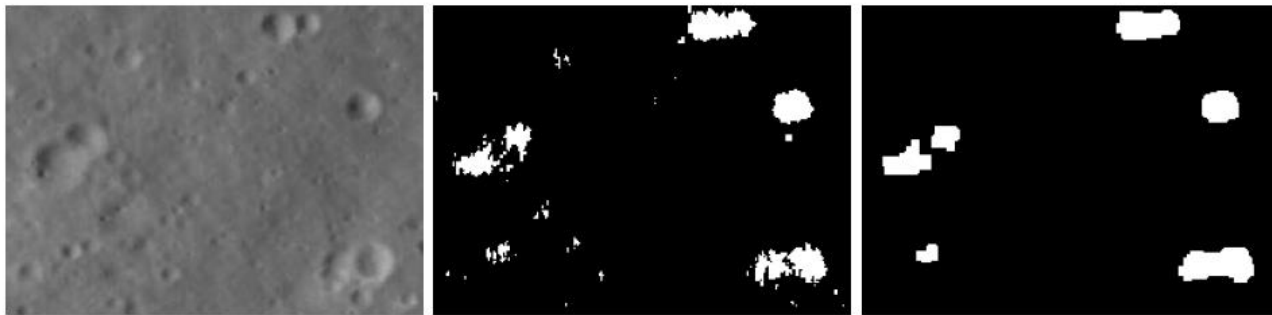
- Model pable de detect crater of a specific size
- Creation of a resolution pyramid and application of the model to each floor
- Technical limitations push us to implement an efficient image tiling system





Analysing a scene

- Post process by mathematical morphology to clean the segmented image



Object extraction

- Object extraction by connected-component labelling algorithms
- Computation of centroid and radius for each component



Framework for an objective evaluation of performances

- Willingness to define an evaluation methodology to enable comparisons between methods

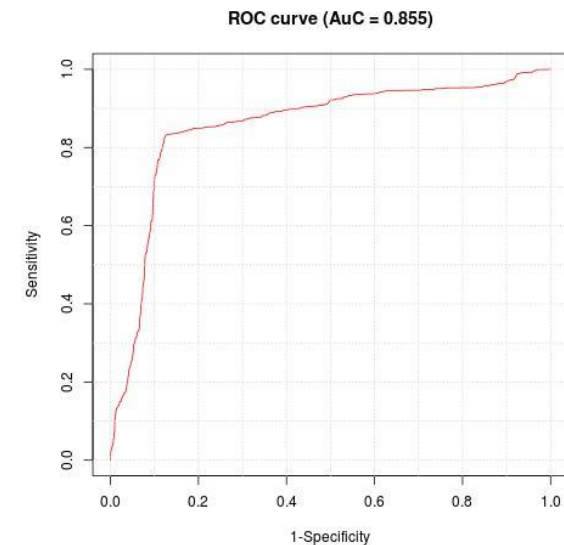
- Error matrix:

		Predicted	
		0	1
Ground Truth	0	TN	FP
	1	FN	TP

- Possibility to extract metrics

- Recall (or sensitivity)
- Precision
- Specificity
- Accuracy
- F1-score
- Intersection over Union

- And build classical ROC curve

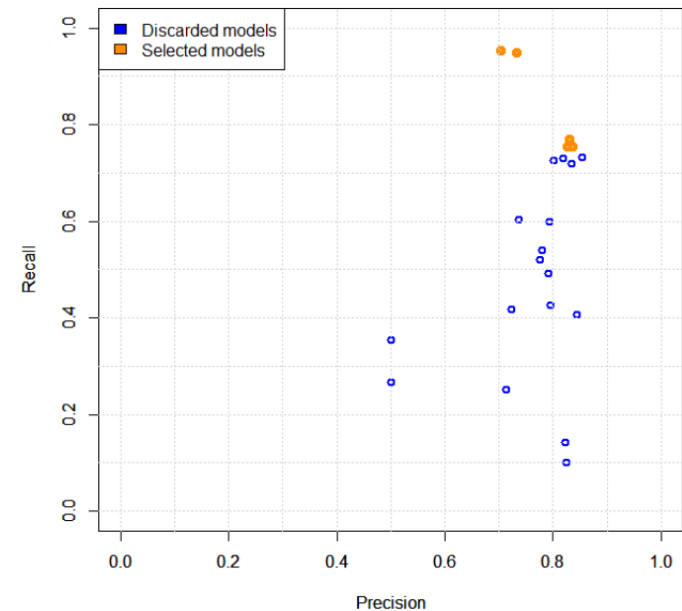


Results (raw)

- Long to produce
- Gradual elimination of non-convincing models
- Important correlation between the sub-dataset
- Important correlation between the metrics

R	Train	Test	Valid
Train		0.947	0.948
Test			0.913
Valid			

R	Precision	Recall	F1-Score	Accuracy	IoU
Precision		0.313	0.397	0.788	0.411
Recall			0.903	0.695	0.920
F1-Score				0.747	0.990
Accuracy					0.776
IoU					



State of the Art

Data

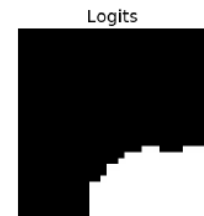
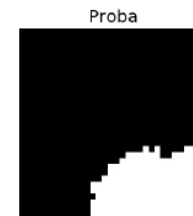
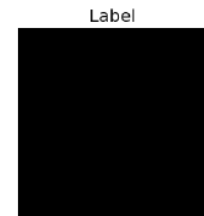
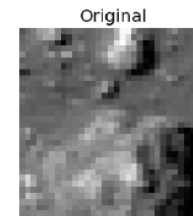
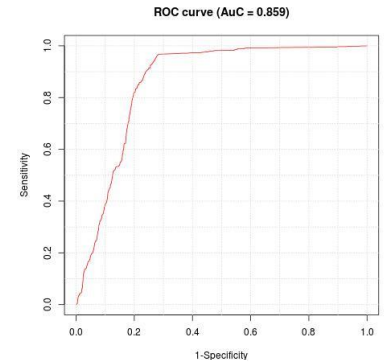
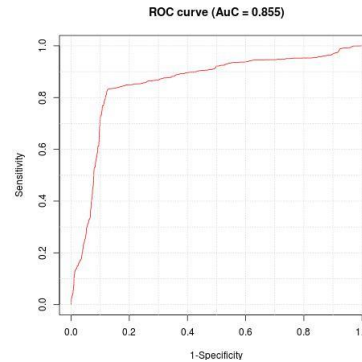
Developments

Results

Conclusion

Raw results

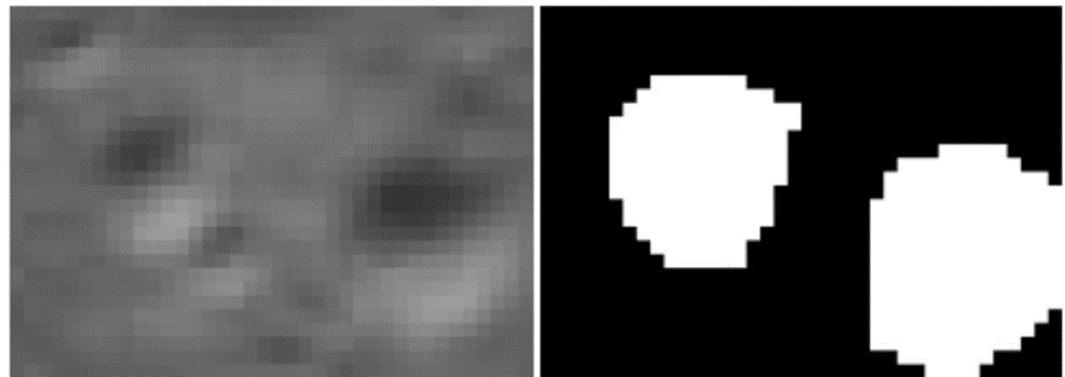
- Performances varying according to the model
(maximize sensitivity of specificity)
- Bad classification of some topographic elements



Accuracy ~ 90%

F1-Score ~ 0.8

IoU ~ 0.7





Stratification according to the latitude

- Stratifying the validation set shows that the model is more prone to detect craters near the lunar equator

Stratification according to the data source

- Stratifying the validation set shows that the model is more prone to detect craters on the NAC images than on the orthorectified images
- Detecting craters on another data source gives poor results



Conclusion

- Developpement of a deeplearning model to detect craters
- Contribution to the scientific community by providing an exhaustive set of crater/non-crater annotations available on my GitHub
- The model has some advantages but comparison with litterature is ill-suited

Ressources

NAC images : goo.gl/7j8CjM

Ortho-rectified images : goo.gl/qivZYt

My GitHub with all data and codes : github.com/QuentinGlaude/CraterNet

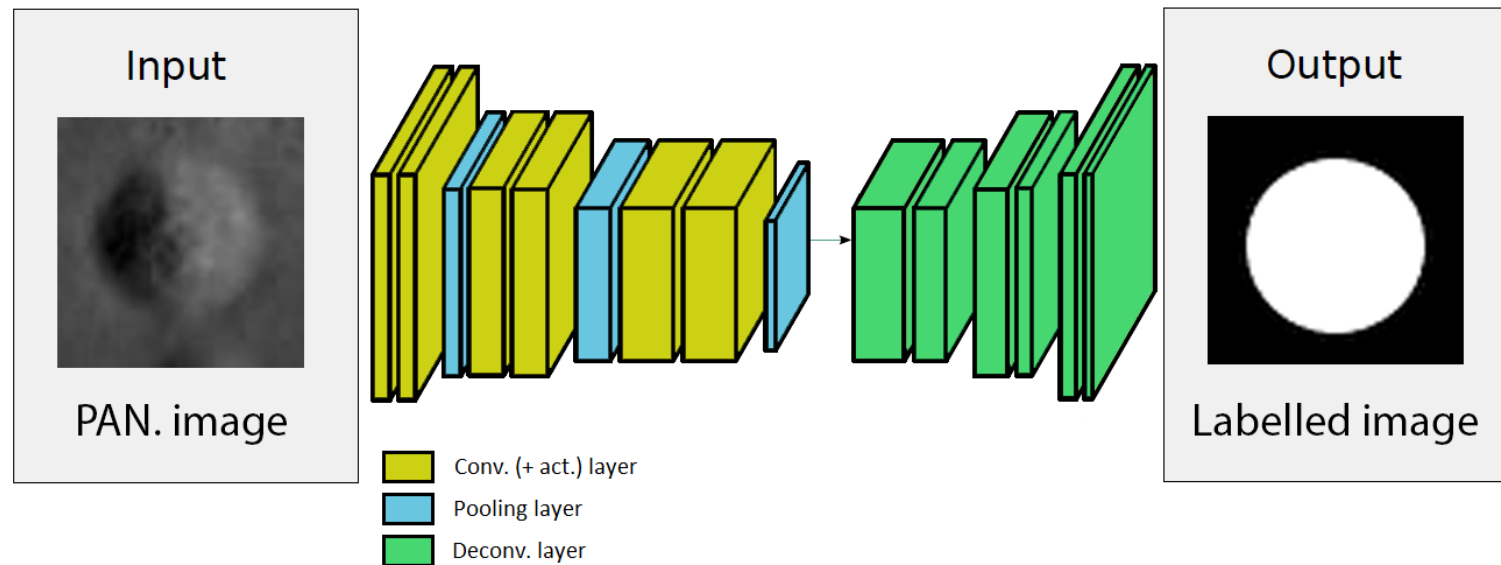
Cytomine Project : cytomine.be

Poster :

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(Quentin Glaude, session Geomatics)



More info/discussion about resources, GPU processing, Cytomine and other stuff !!