# Cyclone detection from IASI data using an object detection model

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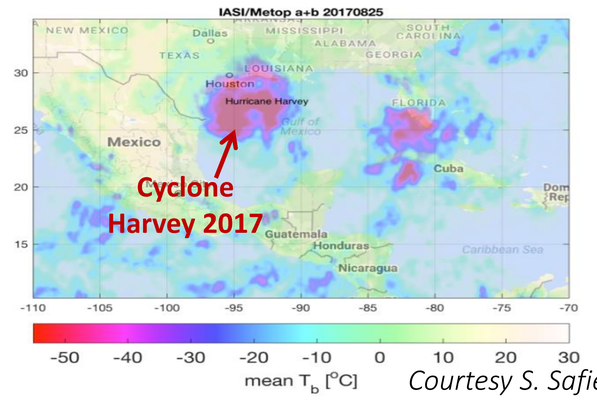
## Introduction

IASI's observations from 2017 show that cyclones can be identified from IASI radiances (right figure). Cyclone detection and surveillance is essential as cyclones can damage human life, agriculture, forestry, and infrastructure.

The objective of this study is to detect cyclones in the North Atlantic Basin using the YOLOv3 model, which is a reference in Deep Learning object detection. Every IASI spectrum will be used, whether it is cloud contaminated or not.

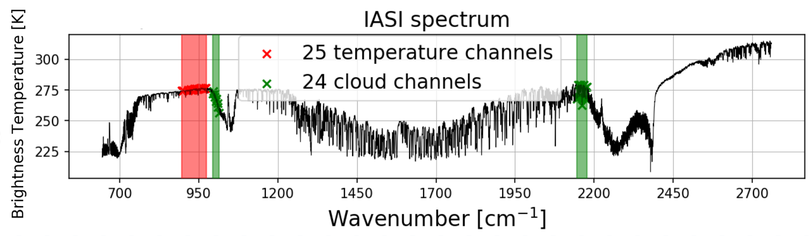



*Courtesy S. Safieddine*

## Building the dataset

### Wavenumber channels selection

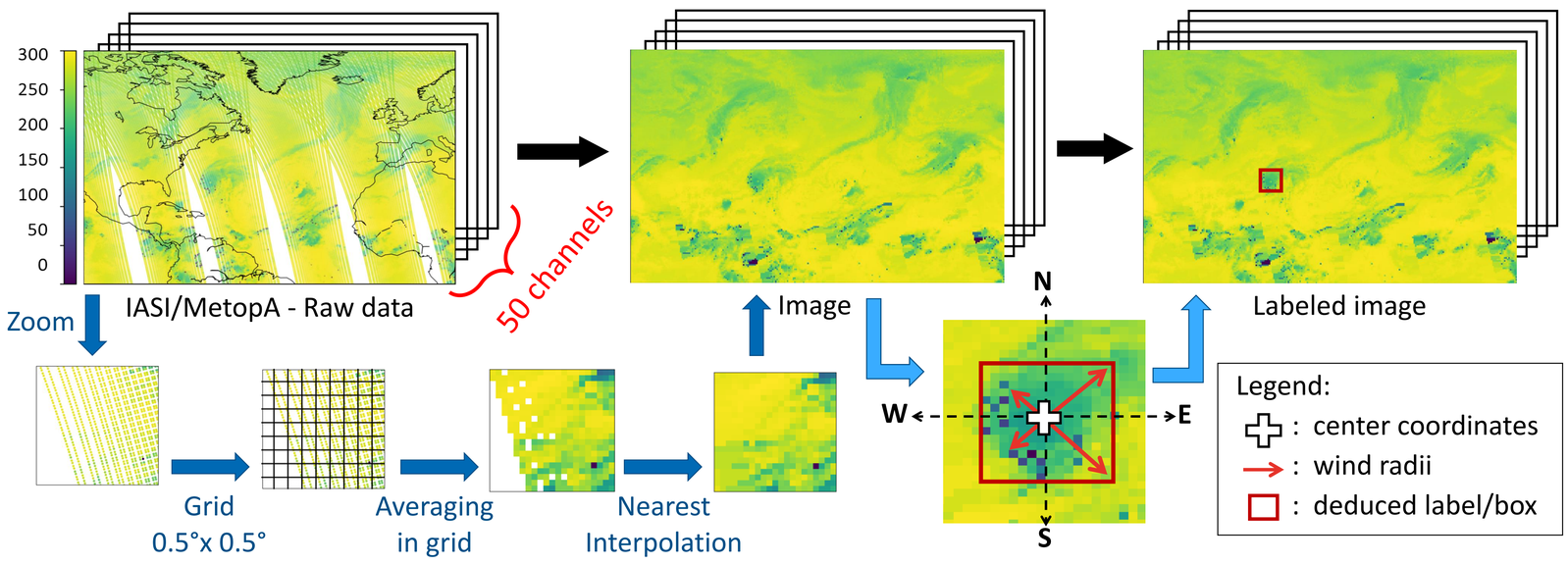
- Reduce computation time and ressource allocation.
- We select 49 wavenumbers related to temperature[a] and clouds[b] + water vapor column (L2 product).




### Raw data to labeled multi-channel images

- Data gridded, averaged and interpolated to obtain images.
- Labeling with HURDAT[c] database which provides cyclone center coordinates and 63 km/h wind radii maximum extent.

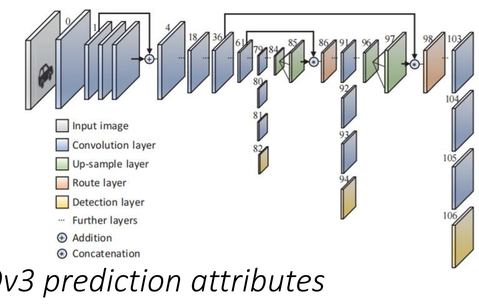
| | |
|---|---|
| Time period | Oct 2007 – Dec 2020 |
| Image shape | 128 x 256 x 50 |
| Number of images | 1675 |
| Number of labels/boxes | 2159 |



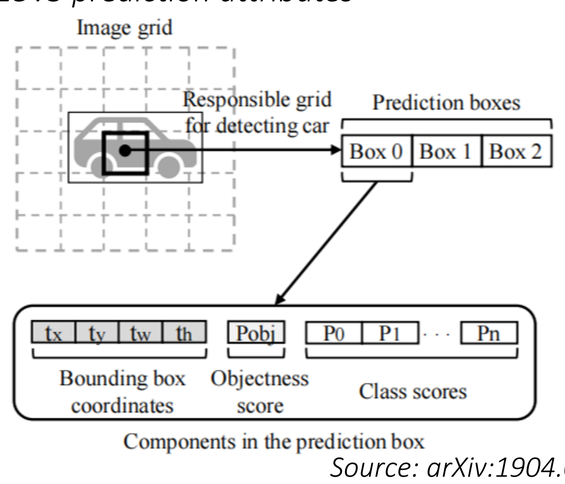

## Model: YOLOv3

YOLOv3[d] (You Only Look Once version 3) is a convolutional neural network for object detection. It takes images as input and returns coordinates of boxes surrounding the objects. It predicts boxes at three different scales (small, medium, large) in order to detect objects of different sizes.

*YOLOv3 architecture*



*YOLOv3 prediction attributes*



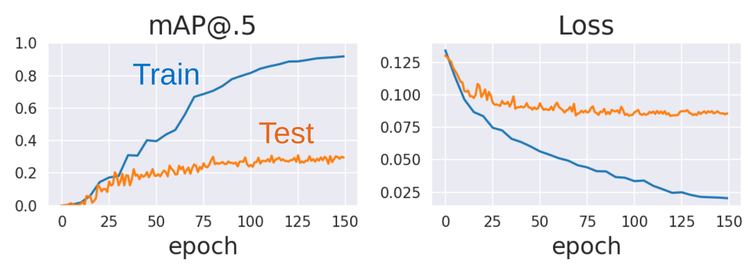

*Source: arXiv:1904.04620*

## Results

As YOLOv3 expects an input of 3 channel images (RGB), we first used only 3 channels, then used an autoencoder in order to use the 50 channels.

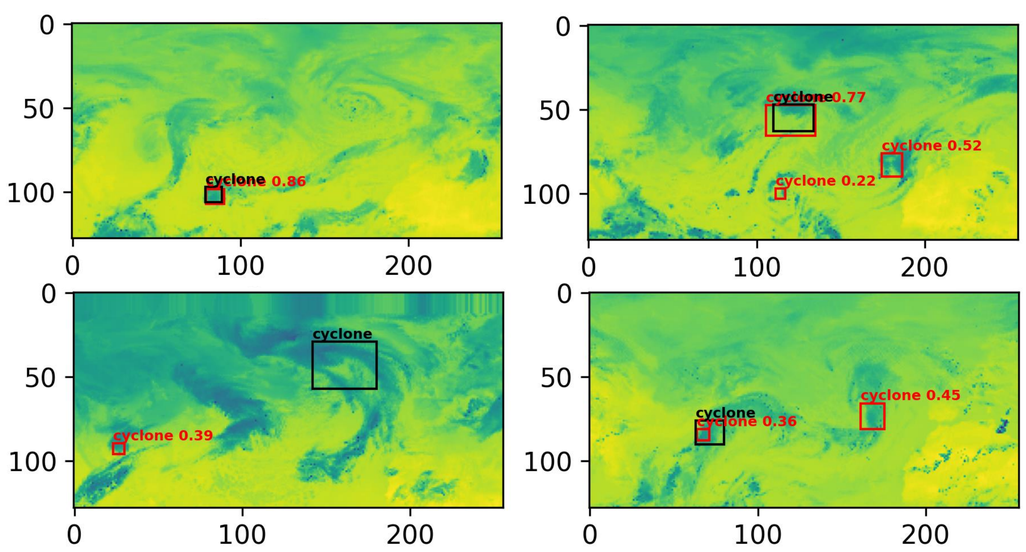
### Images with 3 channels

- One channel corresponds to temperature, one to clouds and water vapor column.
- The model is overfitting . Several methods improved results: the use of weights pretrained on COCO[e] dataset, hyperparameters optimization and data augmentation (horizontal/vertical flip). Other methods that did not improved results: dropout, L2 regularization tuning.




***Best results obtained:***
*mAP@.5 = 0.31*

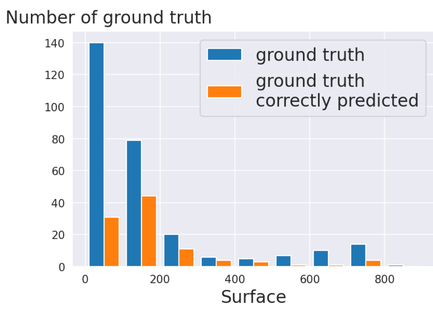
*mAP@.5 = mean Average Precision at threshold 0.5*



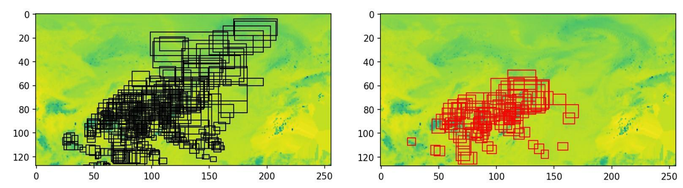

*Examples of predictions by YOLOv3 in test.* ***Black****: ground truth label,* ***Red****: prediction and objectness score*

### Predictions analysis

The model have some difficulties in predicting large and small boxes, with small boxes being particularly present in the dataset. Also the north-east area seems to be challenging, as no boxes are being predicted in this part of the map.




*Distribution of labels surface in test dataset*

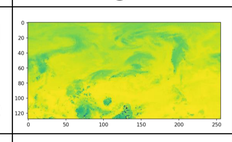
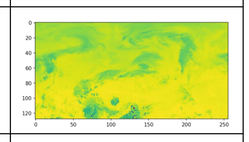
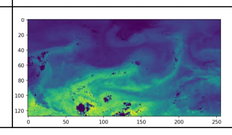
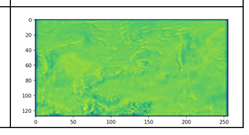


***Black****: labels in test dataset*
***Red****: labels correctly predicted by YOLOv3 in test*

### Images with 50 channels

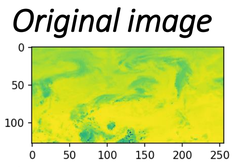
We use an autoencoder to compress information contained in the 50 channels into 3 channels (latent space), then use it as input. We find good reconstruction for each channel except the water vapor channel. It did not improve results compared to 3 channels: an explanation could be that the information in the 50 channels might be redundant.

We could try to use explainable AI in order to find which channels contributed the most to the prediction.

| | Original | Reconstructed |
|---|---|---|
| One channel related to temperature |  |  |
| Water vapor product |  |  |

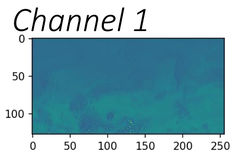
*Reconstructed image by the autoencoder*

***Original image***

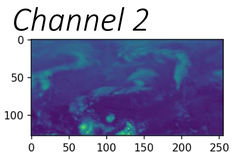


***Latent space***

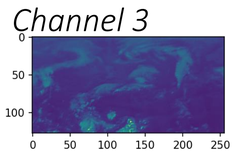
*Channel 1*



*Channel 2*



*Channel 3*



## References & Acknowledgements

(a) Sarah Safieddine and al., Artificial Neural Networks to Retrieve Land and Sea Skin Temperature from IASI, 2020.
(b) Simon Whitburn, personal communication.
(c) Database from the National Oceanic and Atmospheric Administration that gathers re-analyzed information about tracks of tropical and subtropical cyclones in the Atlantic Basin since 1851 till 2020. Freely available here: https://www.nhc.noaa.gov/data/#hurdat
(d) « You Only Look Once »: Joseph Redmon and Ali Farhadi, YOLOv3: An Incremental Improvement, 2018.
(e) Common Object in Context: large-scale object detection, segmentation, and captioning dataset (https://cocodataset.org/#home).

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