Using Deep Learning to Extract Cyclone Regions of Interest (ROI)

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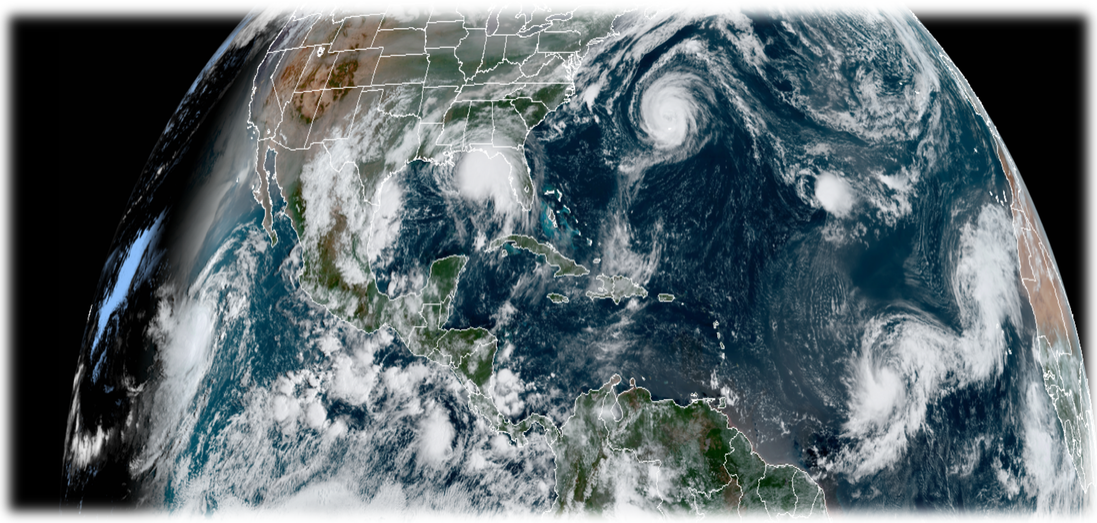
Introduction:

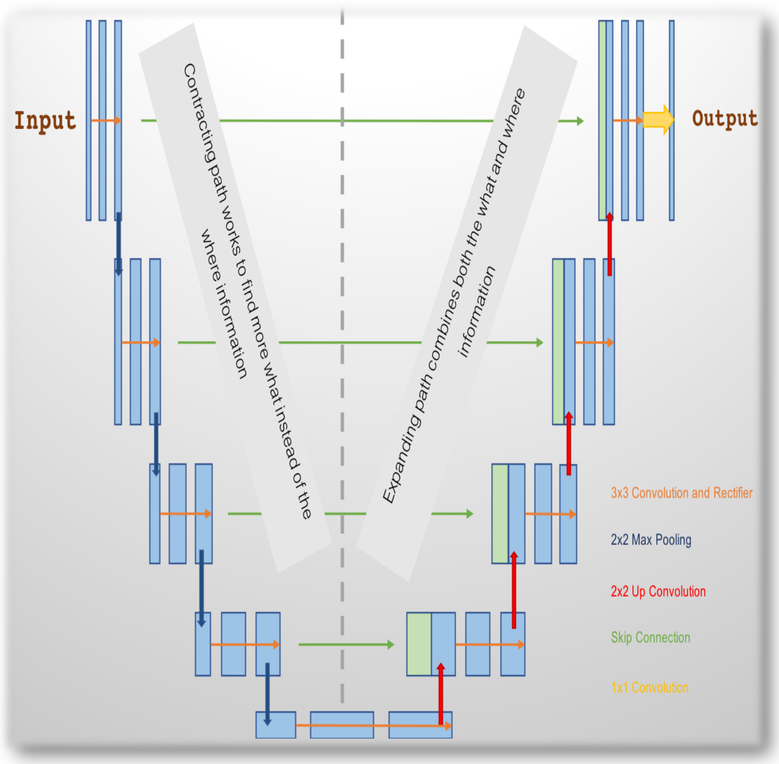
The data problem: keeping up with the quantities of satellite data in real-time applications. How do we extract valuable information from satellite data quickly and is this something that a human would identify or something new to consider? Deep learning is a valuable tool for quick satellite analysis and image segmentation with high success. Using deep learning, we developed four different UNET models that take inputs from the Global Forecasting System (GFS) total precipitable water outputs and Geostationary Operational Environmental Satellites (GOES) water vapor channel and produce labeled ROI within one or a few seconds. This visible GOES image below shows an active tropical region and several tropical cyclones.



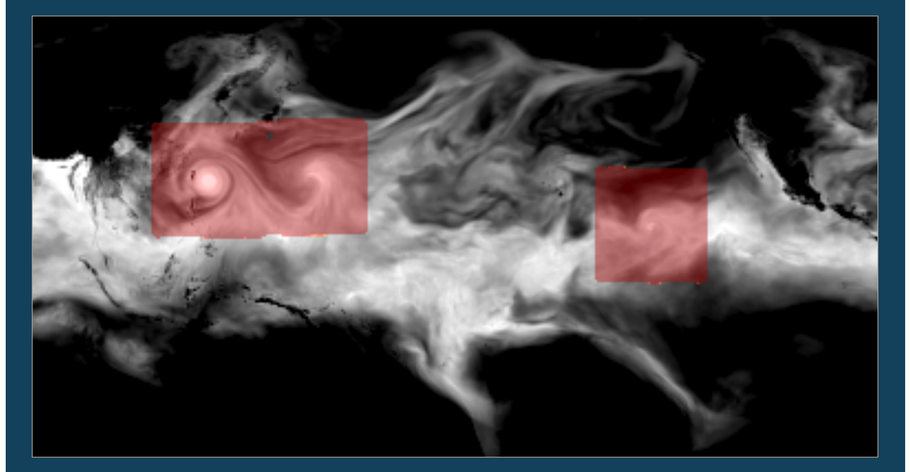
U-Net models preserve both large and small scale features, which is good for spatial weather data. The figure below is the general layout for U-Net models. All four U-Net models took three channel inputs which were images labeled at time=0, time-3, and time-6 hours. This gave the models a sense of rotation and time without using a specific time-based model. Labels were created from the International Best Track Archive for Climate Stewardship (IBTrACS) and the Bonfanti Heuristics Model. Square regions of either 25x25 (IBTrACS-GFS and IBTrACS-GOES), 30x30 (Heuristic-GFS), or 60x60 (Heuristic-GOES) pixels labeled truth cyclone regions on an input image. The IBTrACS U-Net models identify tropical cyclones and the heuristic models identify both tropical and extratropical cyclones. The U-Net models output one segmented cyclone image.

Conclusions:

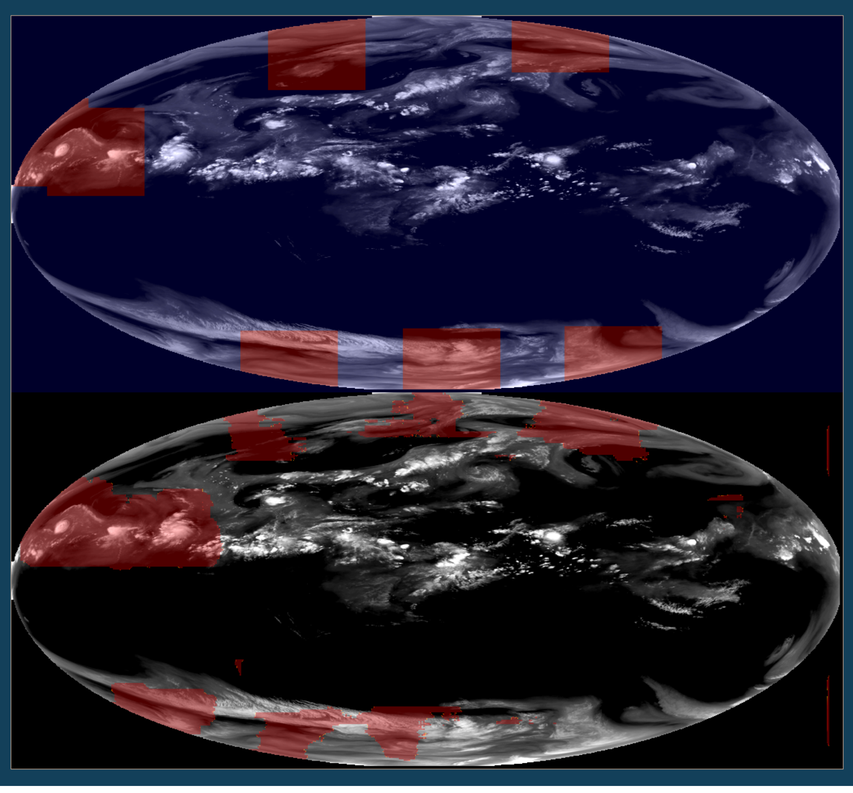
U-Nets are good tools for fast cyclone detection. Four unique U-Net models were developed to identify either tropical or both tropical and extratropical cyclone ROI from either GFS or GOES imagery sources. U-Nets performed nearly 3 times faster than heuristic methods for inference stage in identifying cyclone ROI. Missed detection by UNET or by the a priori truth labels hurt the performance scores. However, when UNETs identify ROI with high significant weather potentials, it is beneficial to real-time alerts, data assimilation, and other meteorological applications, then the public benefits.



Model & Metrics:



Above is a IBTrACS-GFS result, below is a result comparing the Heuristic-GOES result (below-black) to truth label (top-blue). Models were evaluated with Intersection over Union (IoU) metrics. A weighted Tversky Coefficient and Dice Coefficient were utilized, where 1 equals a perfect intersection match between the U-Net and truth label. U-Net models sometimes identify hurricanes before the truth label and sometimes labeled extratropical cyclones that the heuristics labels missed. This shows that the U-Nets could have earlier detection potential and therefore, an IoU of 1 is not the ideal target. Training labels impact how the model is trained. Numerical results will only be as good as the labels provided. If a label is a false positive, the model could falsely identify cyclones. If a label is a false negative event, the model could miss labeling cyclones.



UNET Model Results

Model Labels	Model Input	Accuracy	Dice Coefficient	Tversky Coefficient	Optimizer	Dropout or Noise	Training Years	Validation Year(s)	Testing Year(s)	Input Image Size
IBTrACS	GFS	0.991	0.763	0.750	rms 0.00008	noise 0.2	2010-2014	2009, 2016	2008, 2015	720x361
Heuristic	GFS	0.807	0.58	0.649	rms 0.00001	dropout 0.1	2011-2015	2017	2010	720x361
IBTrACS	GOES	0.996	0.689	0.680	rms 0.0001	noise 0.1	2010-2014	2009, 2016	2008, 2015	1024X560
Heuristic	GOES	0.901	0.511	0.558	rms 0.00001	dropout 0.1	2011-2015	2017	2010	1024X560

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