Using Deep Learning for Tropical Cyclone Intensity Estimation

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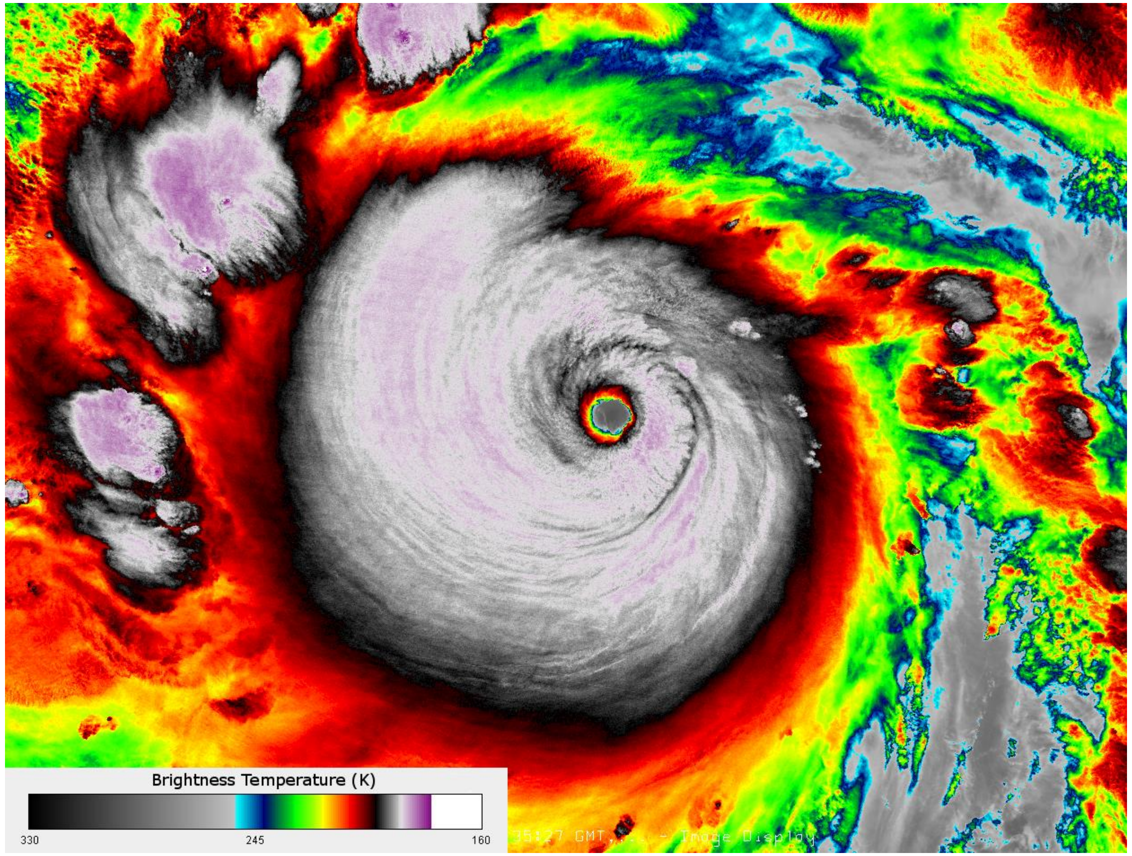
Outline

1. Motivation
2. Overview of current techniques
3. Data/Methodology
4. Results
5. Applications
6. Implications/future work

Motivation

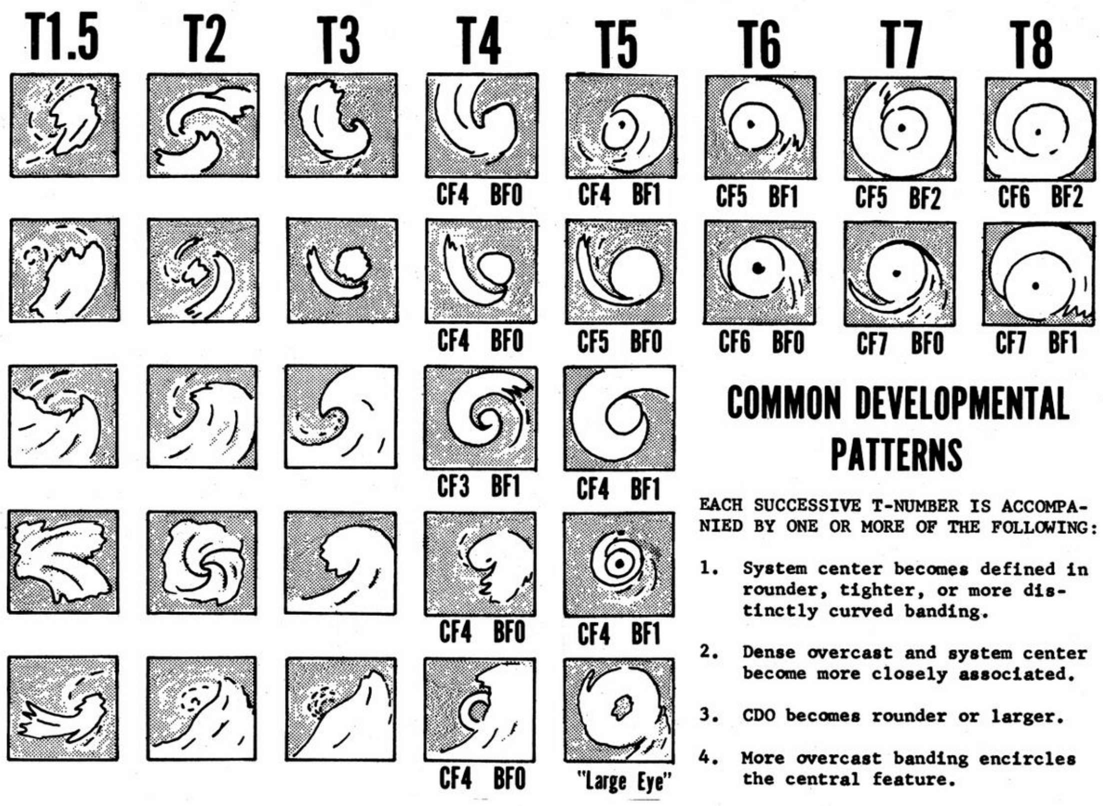
- In situ observations from aircraft are not always available
- Tropical cyclone (TC) warning centers use different variants of satellite-based methods
- 10-20% uncertainty in post analyses when only satellite based estimates are available.
- Can deep learning be used to objectively and



Source: http://rammb.cira.colostate.edu/projects/npp/blog/index.php/uncategorized/rare-super-typhoon-in-the-pacific-ocean/attachment/haiyan_6nov13_1639z_iband5_ann/

Dvorak Technique

- Dvorak technique [1972, 1973, 1975, 1984, 1995]
  - Uses enhanced IR and/or visible satellite imagery
  - Very subjective
  - Dependent on user expertise
- Objective Dvorak technique [1998]
  - Computer based algorithms to recognize patterns
  - Location of the eye must be identified by an expert
- Advanced Dvorak technique [2007]
  - Introduces regression equations



Source: Dvorak, V. F., 1973: A technique for the analysis and forecasting of tropical cyclone intensities from satellite pictures. NOAATech. Memo. NESS 45, Washington, DC, 19 pp.

Current Methods

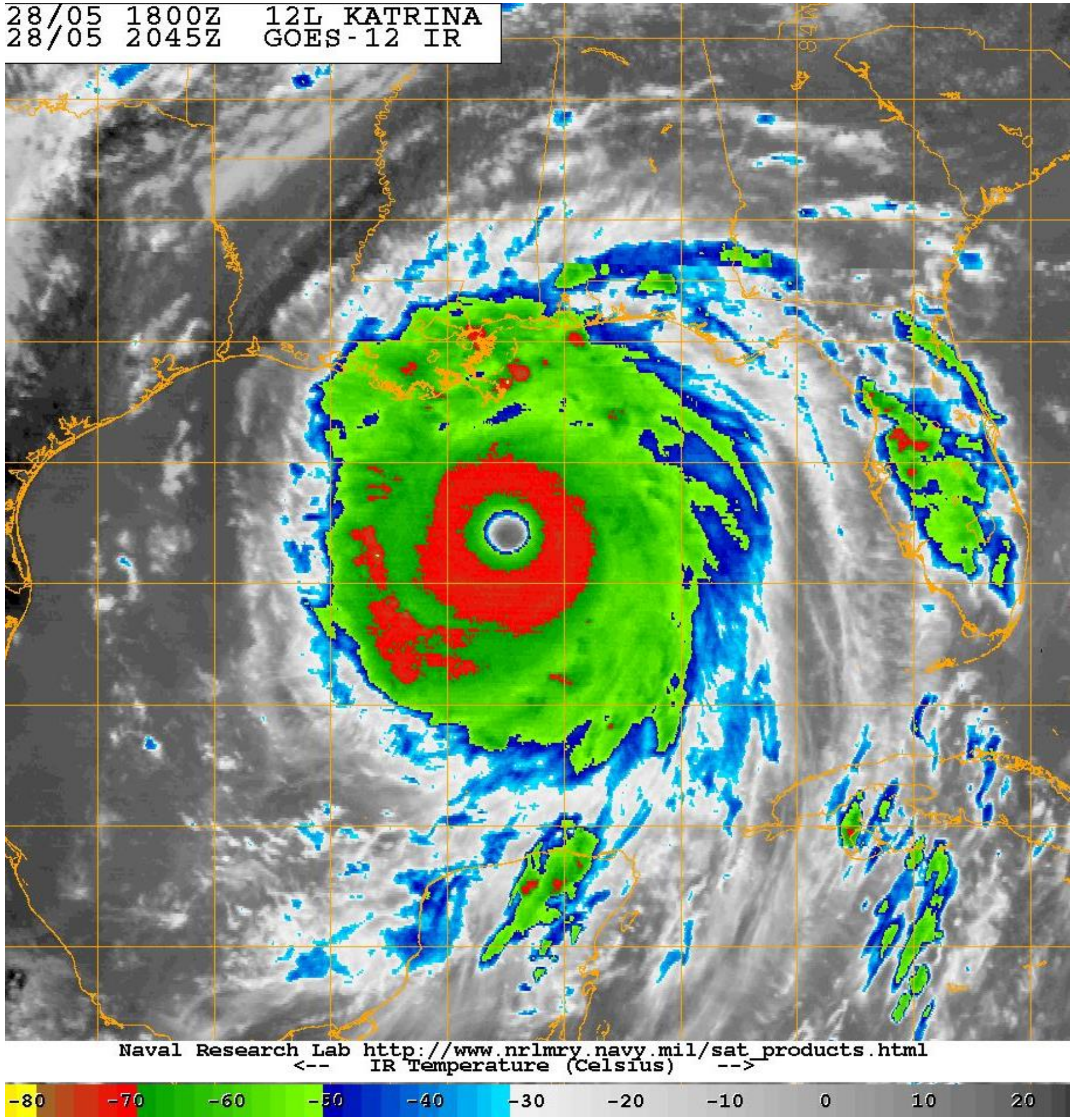
- Subjective
- Don't generalize well
- Inconsistent
- Dependent on user expertise

Deep Learning

- Objective
- Generalize well
- No need for user expertise
- Large amounts of training data

Data

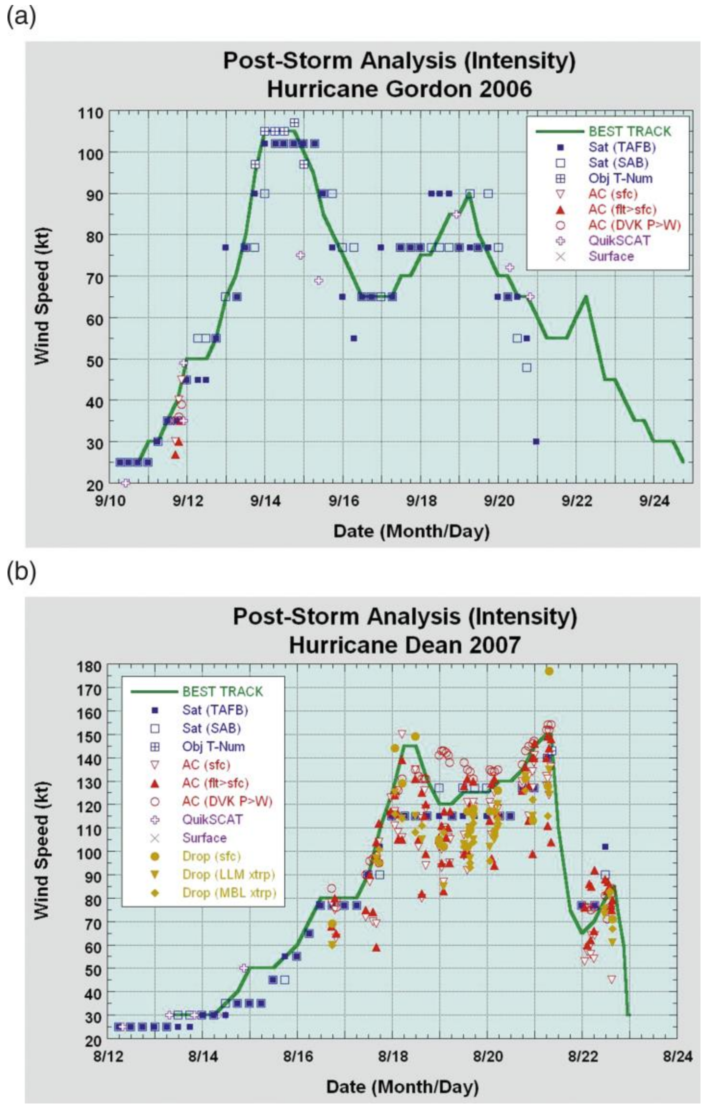
- US Naval Research Laboratory (NRL)
  - 2000 to 2016
  - ~30 minute interval
  - Pacific and Atlantic
  - Multiple geostationary satellites
    - GOES, Himawari, MTSAT, etc…
  - ~45,000 images



Source: https://www.nrlmry.navy.mil/tcdat/tc05/ATL/12L.KATRINA/ir/geo/1km/

Truth data

- Best tracks (HURDAT, HURDAT2)
  - Post-storm analysis of intensity, central pressure, location and size
  - 6 hour intervals
- Specially subsetted portion of the HURDAT2 dataset [Landsea and Franklin 2013]
  - Restricted to time periods that had airborne recon data
  - One hour intervals



Source: Atlantic Hurricane Database Uncertainty and Presentation of a New Database Format, Landsea, C.W. and J.L. Franklin, Monthly Weather Review 2013 141:10, 3576-3592

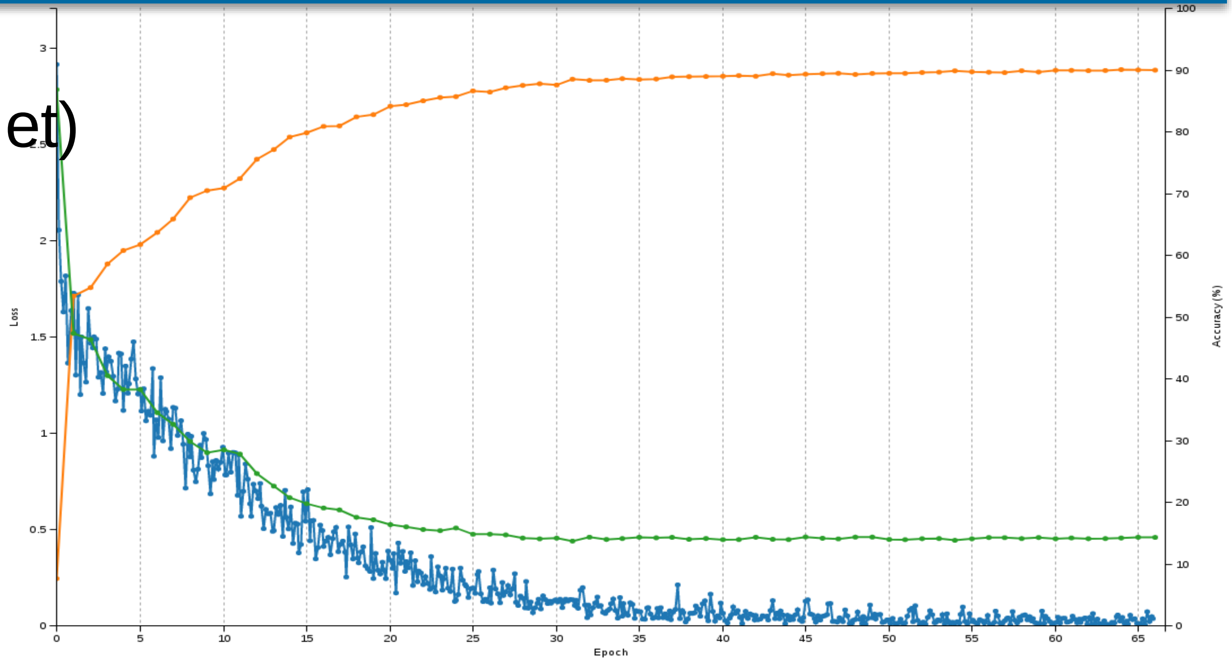
Methodology

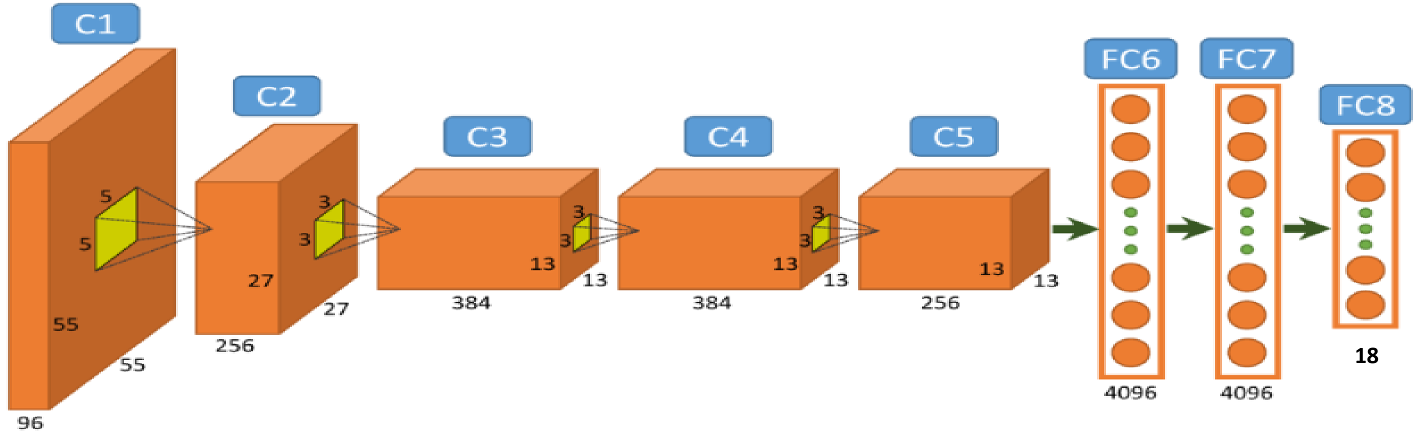
- Classes based on maximum sustained wind speed
  - 5 kts intervals
- Remove images where more than 20% of the pixels are black
- Split data into train/test/validation sets
- Augment images before training
  - Rotate, zoom

Class (kts)	Train Set	Val. Set	Test Set	Total
0-49	12053	4017	6886	22956
50-54	1318	439	751	2508
55-59	1459	486	833	2778
60-64	1116	372	636	2124
65-69	1163	387	664	2214
70-74	674	225	385	1284
75-79	794	265	453	1512
80-84	552	184	314	1050
85-89	650	216	370	1236
90-94	747	249	426	1422
95-99	458	152	260	870
100-104	688	229	391	1308
105-109	253	84	143	480
110-114	442	147	251	840
115-119	706	235	403	1344
120-124	268	89	153	510
125-129	360	120	204	684
130+	987	329	562	1878
Totals	24,688	8225	14085	46998

Architecture and Training

- Caffe reference network (CaffeNet)
  - Transfer learning
    - Trained on ImageNet
  - 5 convolutional layers
  - 3 fully connected layers
- Caffe
- NVIDIA Tesla P100
- ~90% validation accuracy





Adapted from: Hu et al. 2015 Transferring Deep Convolutional Neural Networks for the Scene Classification of High-Resolution Remote Sensing Imagery. *Remote Sensing*, *7*(11)

Preliminary Results

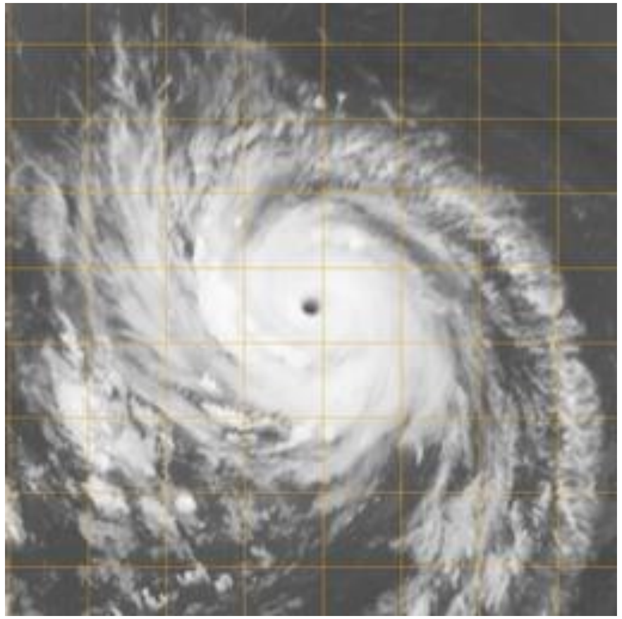
- Our model
  - Top-1 accuracy: **86.4%**
  - Achieved RMSE of **10.00*kt***
  - Atlantic and Pacific
- North Atlantic
  - Piñeros et al. (2011): **14.7*kt***
  - Ritchie et al. (2012): **12.9*kt***
- North Pacific
  - Ritchie et al. (2014): **14.3*kt***

	Accuracy (%)
Top-1	86.4
Top-2	93.06

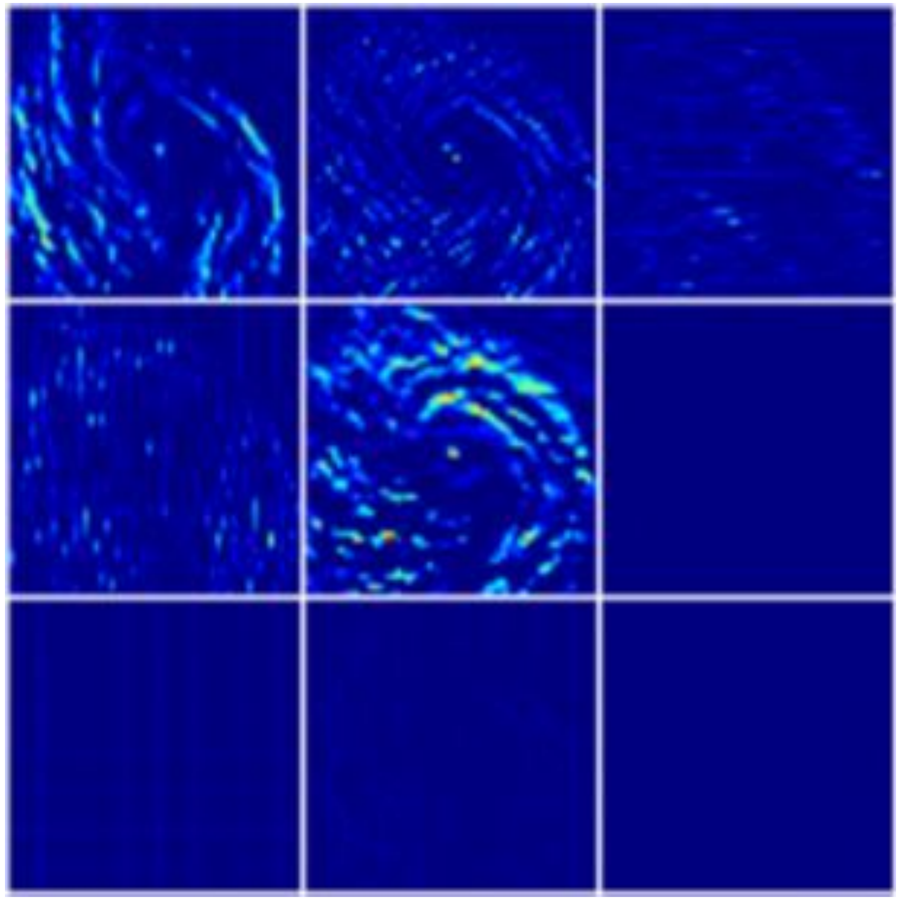
Class (kts)	RMSE (kts)	MAE (kts)
0-49	3.84	0.4
50-54	12.62	6.03
55-59	14.3	6.61
60-64	14.06	6.26
65-69	11.78	4.47
70-74	15.7	6.91
75-79	14.2	5.68
80-84	12.19	4.57
85-89	15.87	5.8
90-94	12.03	4.71
95-99	14.07	4.73
100-104	12.65	4.53
105-109	14.21	6.52
110-114	13.43	4.21
115-119	13.54	3.64
120-124	19.89	7.16
125-129	11.76	3.62
130+	10.48	2.94
Total:	10.00	2.88

Activations

Input Image



Conv1 Activations



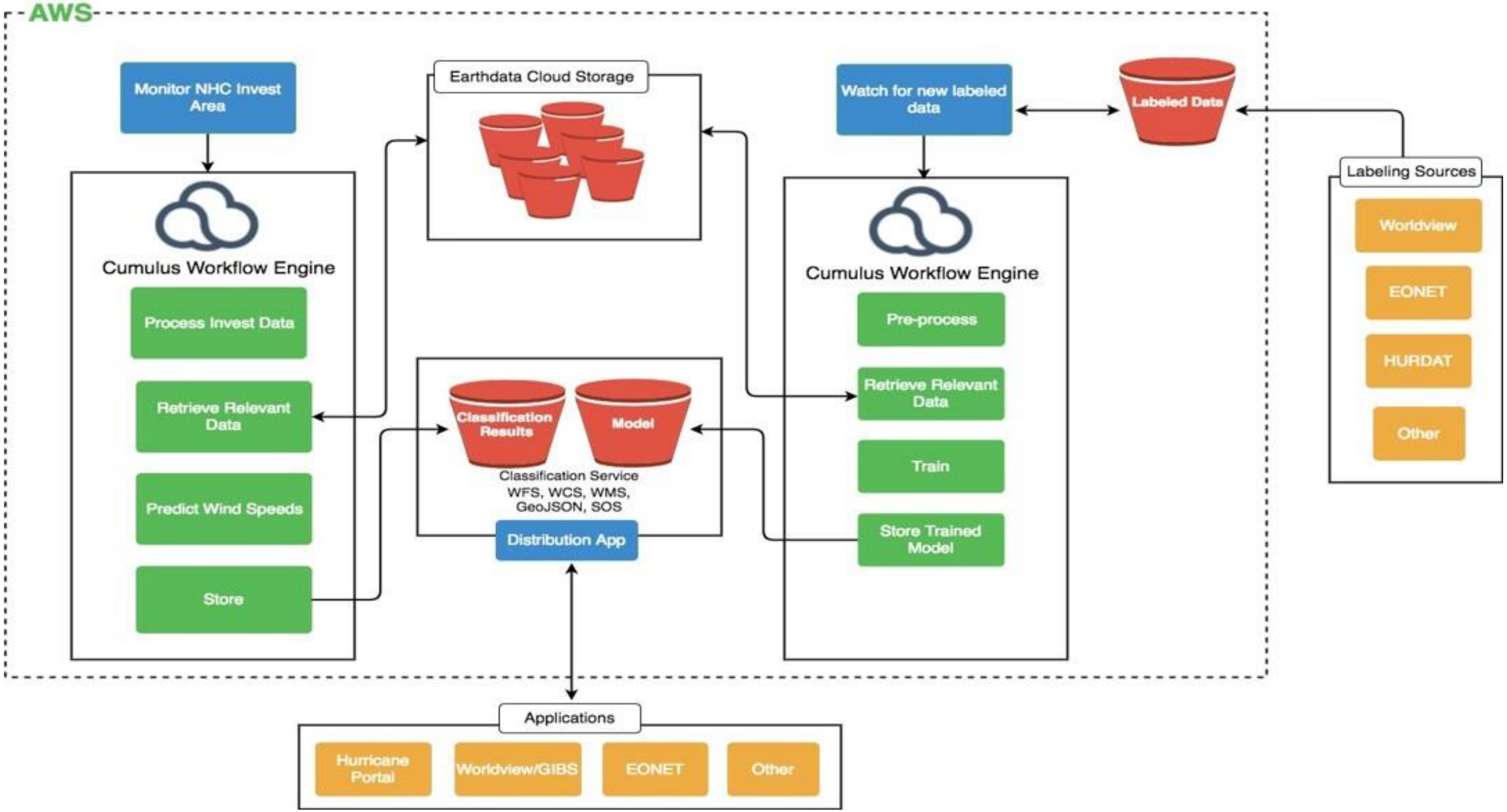
Ongoing Research

- Training a network where storms are unique to test/training set
- Include data from other sources
  - Microwave imagery
- Evaluate performance with different network architectures
  - Modality Hallucination

Intensity Estimation Service

- Develop a near real-time tropical cyclone intensity estimation service
  - Monitor NHC invest areas
  - Download images from invest area
  - Predict intensity (wind speed)
  - Store estimations in DB
  - Information can be retrieved through API
- Work with endusers to develop a website that will display past and present storm information along with estimated wind speed information and relevant overlays
- Utilize standards-based services (WFS, SOS, WCS, WMS, GeoJSON)
  - integration with AWIPS/N-AWIPS

System Concept



Key Take Aways

- Deep learning can be used as a tool for TC intensity estimation
  - 86.4% top-1 accuracy
    - Performance should increase with more training data
  - Network appears to utilize storm shape and patterns, similar to current operational techniques
- Build a web-service to distribute storm data in near real time

Acknowledgements

- Dan Cecil (NASA MSFC)
- Derrick Herndon (CIMSS UW-Madison)

Thank you

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