Deep Learning-Powered Insight from Dark Resources

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THE UNIVERSITY OF
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Outline

- Motivation
- Why Deep Learning?
- Applications
- Analysis

Motivation

- Earth Science Images
  ~70+ million browse images
  -basic metadata

- **Under-exploited**

- Can we use browse imagery
  -to enable discovery of possible new case studies?
  -to perform exploratory analytics?

- **Image Analytics**

- Component of “Dark Data” – NASA AIST Project

Image-based Analytics

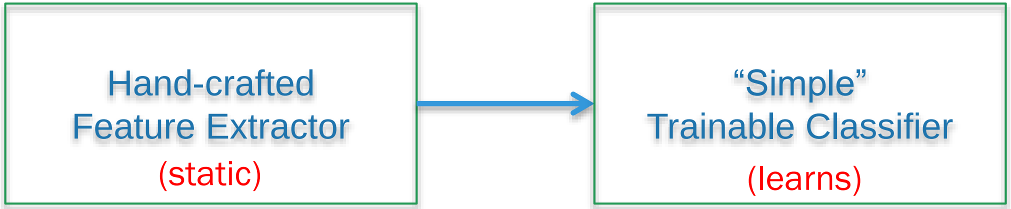
- Goal: Earth science image based tasks:
  - Image Retrieval
  - Image Classification
  - Object Recognition
  - Exploration

- Challenge: “semantic gap”

  Low-level image pixels and high-level semantic concepts perceived by human

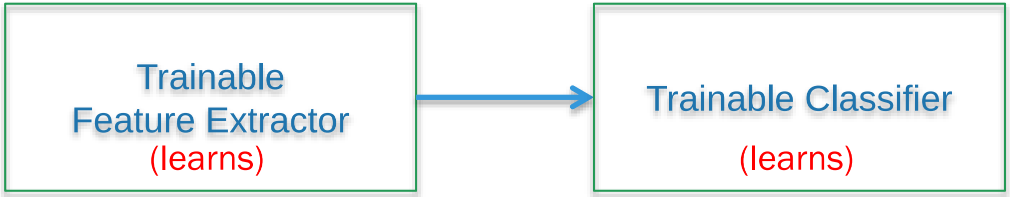
Traditional Image Recognition Approach

- Image features: Color, Texture, Edge histogram, …
- “Shallow” architecture
- **User defines the feature**
- Preliminary study



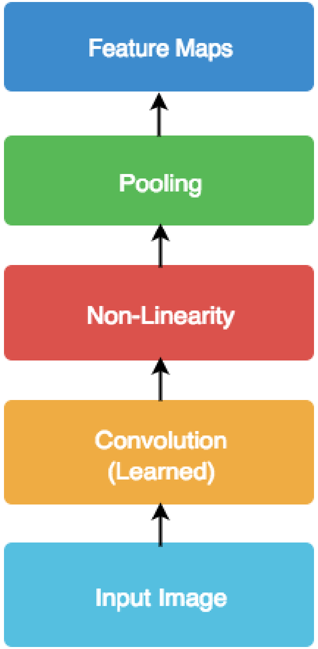
“Deep” Architecture

- Features are key to recognition
- What about learning the features?
- Deep Learning
  - Hierarchical Learning
  - Mimics the human brain that is organized in a deep architecture
  - Processes information through multiple stages of transformation and representation



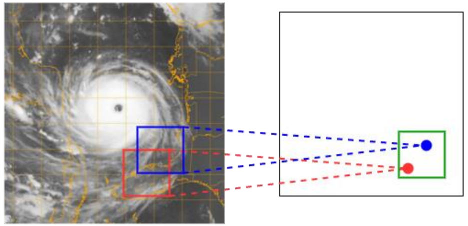
Convolutional Neural Network

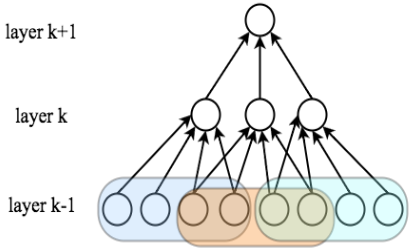
- Convolutional Neural Network (CNN)
  - Deep Learning for supervised image feature learning
    - Nearby pixel values are correlated
  - Supervised
    - Ideal for Image Recognition
  - Feed forward
  - Convolution
    - **Weighted moving sum** (window)
    - Multiple convolutions (Different Filters)
    - Detects multiple motifs at each location
    - Results in a 3D array – each slice: a feature map
- Translation Invariant
- Local correlation
- Global representation
- Little pre-processing
- No/little expert feedback for feature extraction
- Avoids overfitting
- Highly scalable

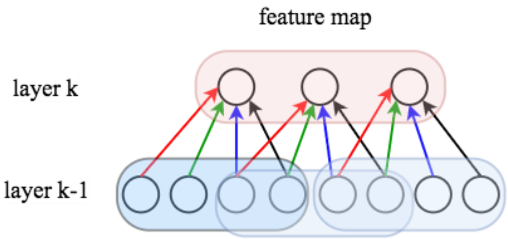


CNN Features

- Local receptive fields
  - Learns particular local part of the input
- Sparse connectivity
  - Local representation (lower layers)
  - Larger overview and abstract (higher layers)
  - Maintains spatial local correlations
- Shared weights
  - Detect exactly same feature at different location
  - Reduce the number of parameters to be learned
- Pre-processing
  - Input with very little pre-processing





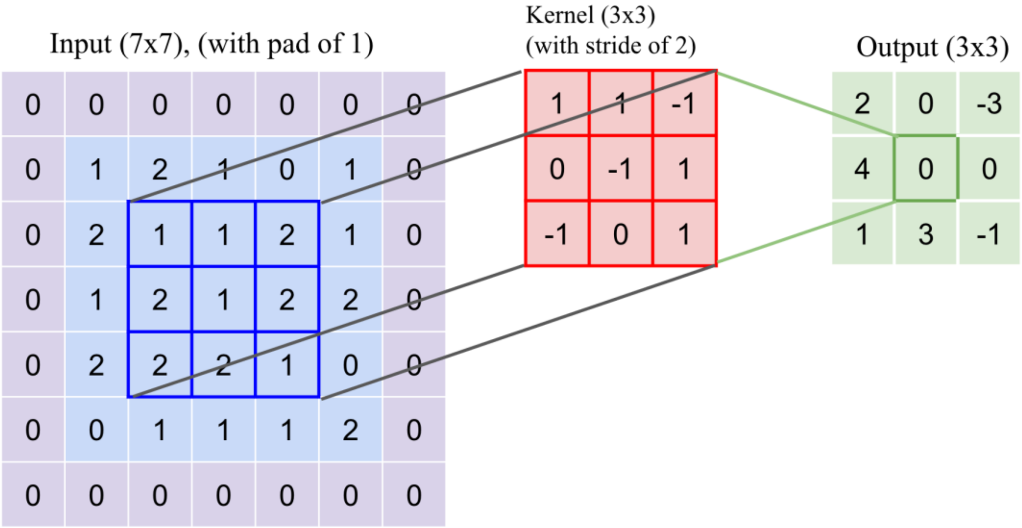


Layers

- Convolutional Layer
- Pooling Layer
- Normalization Layer
- ReLU Layer
- Fully Connected Layer
- Loss Layer

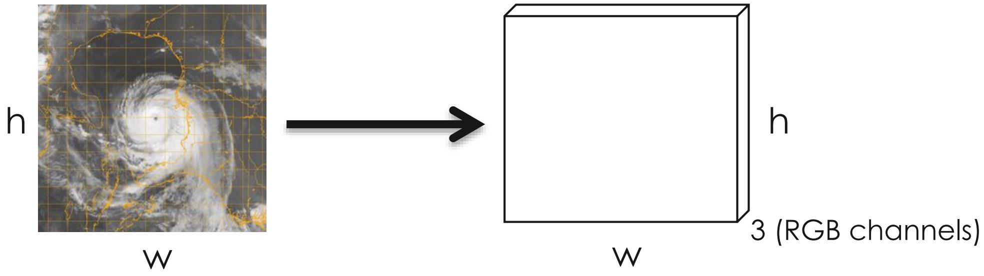
Convolutional layer

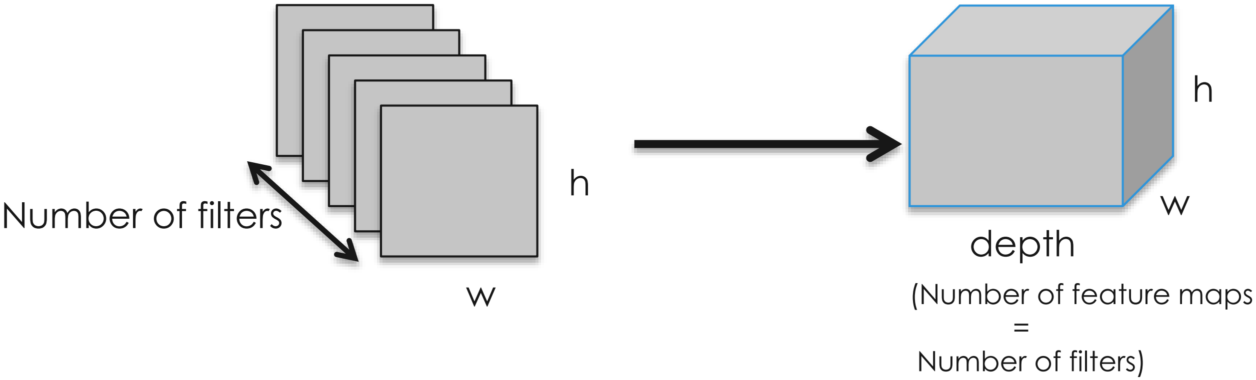
- Convolution



Convolutional Layer

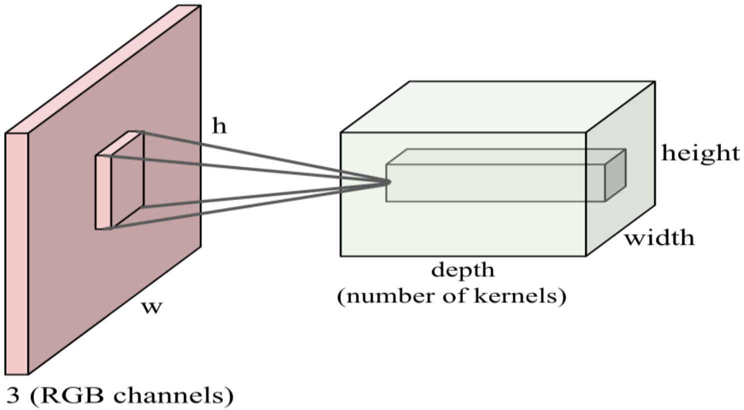
3D Representation





Convolutional Layer

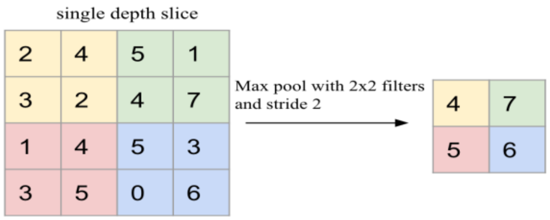
- Depth (d)
  - Number of filters
  - Different depth slices activates different features
  - Stacked feature maps from all filters gives 3D output volume



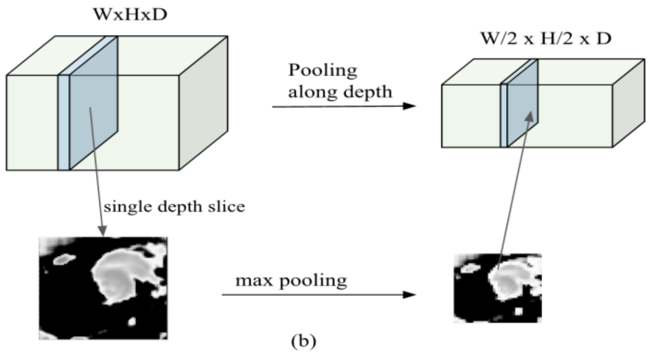
Convolutional input volume (red) and output volume (green)

Pooling Layer

- Reduces number of parameter through down sampling
- Max-pooling
  - Selects maximum activated pixel in pooling region
  - Simple
  - Computationally Efficient
  - Preserves translation invariance



(a)



(b)

Fully Connected Layer

- Similar to regular neural network
- Transition from series of convolutional and pooling layers
- Produces single output vector (w=h=1 output volume)

Hyperparameters

- Number of convolutional filters
- Size of convolutional filters
- Size of pooling filters
- Stride
- Padding
- Local size for normalization
- Dropout ratio
- Weight decay
- Learning rate
- Momentum

Applications

- *Improving Forecast Operations*
- *Searching for Events*
- *Image signature identification for Transverse bands*
- *Enabling New Science*
  - *Dust Climatology*

Application:
Improving Forecast Operations

Collaboration with Dan Cecil, NASA/MSFC

Tropical Cyclone Intensity Estimation

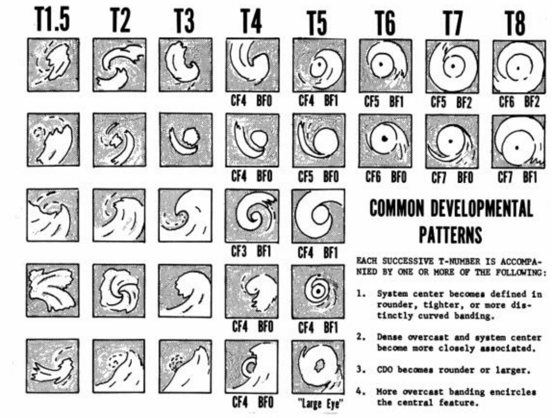
- Hurricane Intensity: based on Maximum Sustained Wind (MSW).
- Saffir-Simpson Hurricane Wind Scale (SSHWS)

Category	**Symbol**	**Wind speeds**	**Description**
Five	H5	$\geq$ 137 knots, $\geq$ 157 mph, $\geq$ 252 km/h	Catastrophic damage will occur
Four	H4	113–136 knots, 130–156 mph, 209–251 km/h	Catastrophic damage will occur
Three	H3	96–112 knots, 111–129 mph, 178–208 km/h	Devastating damage will occur
Two	H2	83–95 knots, 96–110 mph, 154–177 km/h	Extremely dangerous winds will cause extensive damage
One	H1	64–82 knots, 74–95 mph, 119–153 km/h	Very dangerous winds will produce some damage
Tropical storm	TS	34–63 knots	Can produce significant damage
Tropical depression	TD	20–33 knots	Gale force or stronger winds
No Category	NC	$\leq$ 20 knots	-

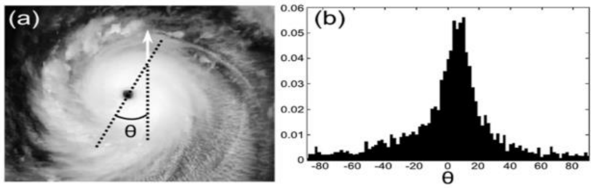
Intensity Estimation Techniques

- The Dvorak technique
  - Vernon Dvorak (1970s)
  - Satellite-based method
  - Cloud system measurements
  - Development patterns corresponds to T-number

- Deviation-angle variation technique (DAVT)
  - Piñeros et al.
  - Variance for quantification of cyclones
  - Calculates using center (eye) pixel
  - Directional gradient statistical analysis of the brightness of images



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

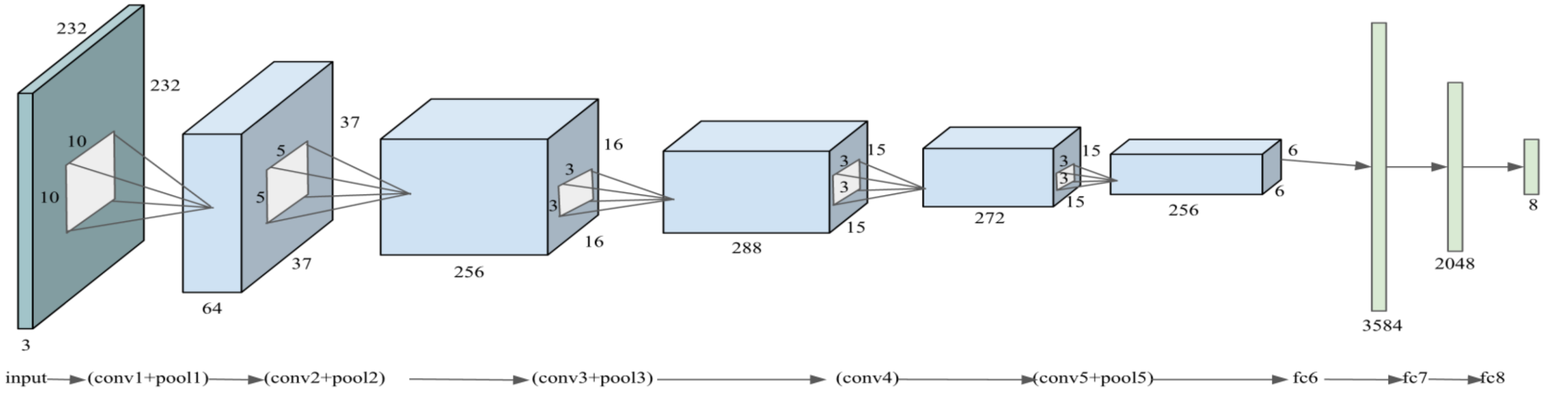


Source: Elizabeth A. Ritchie, Kimberly M. Wood, Oscar G. Rodriguez-Herrera, Miguel F. Pineros, and J. Scott Tyo. Satellite-derived tropical cyclone intensity in the north pacific ocean using the deviation-angle variance technique, 2014.

Problems

- Lack of generalizability
- Inconsistency
- Subjective
- Complexity
- Significant pre-processing

Architecture



Configurations

Layer	Shape	Output Size	Parameter Shape	Learned Parameters
Input	3@232x232			
conv1	64@10x10, s=3, p=0	75x75	(64, 3, 10, 10)	19,264
pool1	3x3, s=2, p=0	37x37		
conv2	256@5x5, s=1, p=0	33x33	(256, 64, 5, 5)	409,856
pool2	3x3, s=2, p=0	16x16		
conv3	288@3x3, s=1, p=1	16x16	(288, 256, 3, 3)	663,840
pool3	2x2, s=1, p=0	15x15		
conv4	272@3x3, s=1, p=1	15x15	(272, 288, 3, 3)	705,296
conv5	256@3x3, s=1, p=0	13x13	(256, 272, 3, 3)	528,984
pool5	3x3, s=2, p=0	6x6		
fc6	3584		(3584, 9216)	27,872,768
fc7	2048		(2048, 3584)	7,342,080
fc8	8		(8, 2048)	16,392
				37,558,480

- 8 layers deep
- 5 convolutional layers
- 3 fully connected layers
- ~37.5 million parameters learned

Dataset

- Image data
  - US Naval Research Laboratory (http://www.nrlmry.navy.mil/tcdat)
  - 1998 to 2014
  - 15 minute interval
  - 98 cyclones (68 Atlantic and 30 Pacific)

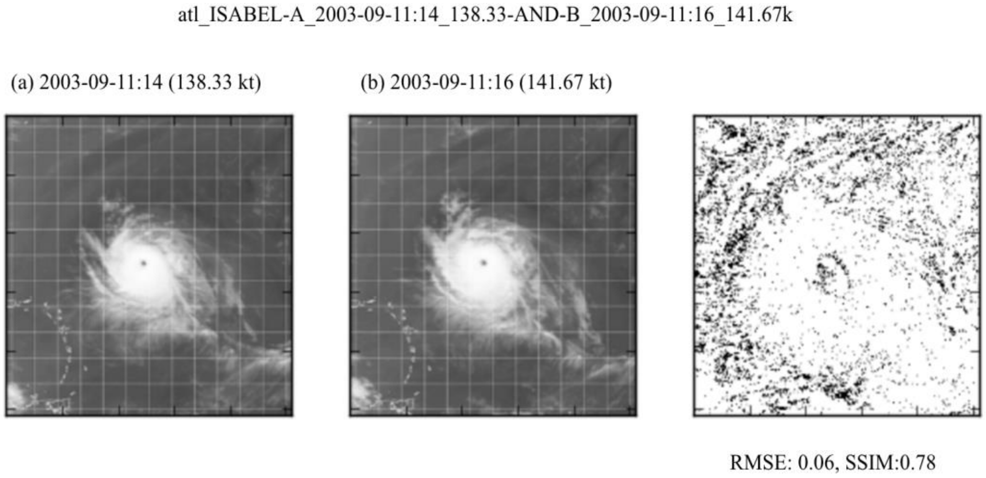
- Wind speed data
  - National Hurricane Center (http://www.nhc.noaa.gov) (Best track data: HURDAT and HURDAT2)
  - Hurricane Research Division (http://www.aoml.noaa.gov/hrd/hurdat/Data_Storm.html)
  - 6 hour interval

Cyclones

Region/Basin	Year	Cyclones
Atlantic	1998	Mitch
	2003	Isabel
	2004	Ivan
	2005	Emily, Katrina, Rita, Wilma
	2007	Dean, Felix
	2010	Alex, Bonnie, Colin, Danielle, Earl, Fiona, Five, Gaston, Igor, Julia, Karl, Lisa, Matthew, Nilcole, Otto, Paula, Richard, Shary, Tomas, Two
	2011	Arlene, Bret, Cindy, Don, Emily, Franklin, Gert, Harvey, Irene, Jose, Katia, Lee, Maria, Nate, Ophelia, Philippe, Rina, Sean, Ten
	2012	Alberto, Beryl, Chris, Debby, Ernesto, Florence, Gordon, Helene, Isaac, Joyce, Kirk, Leslie, Michael, Nadine, Oscar, Patty, Rafael, Sandy, Tony
	2014	Edouard
Pacific	2002	Elida, Fausto, Hernan, Kenna
	2005	Jova, Kenneth
	2006	Bud, Daniel, Ioke, John, Lane
	2007	Flossie
	2008	Hernan, Norbert
	2009	Felicia, Guillermo, Jimena, Rick
	2010	Celia, Darby
	2011	Adrian, Dora, Eugene, Hilary, Jova, Kenneth
	2012	Bud, Emilia, Miriam, Paul

Data Augmentation

- Interpolate to increase even more
- NRL images for every 2 hour – wind speed interpolation
- Image transformation
  - Original
  - 90 degree rotation
  - 180 degree rotation
  - 270 degree rotation
  - Other..



Example image difference: 2hr interval, wind speed interpolation

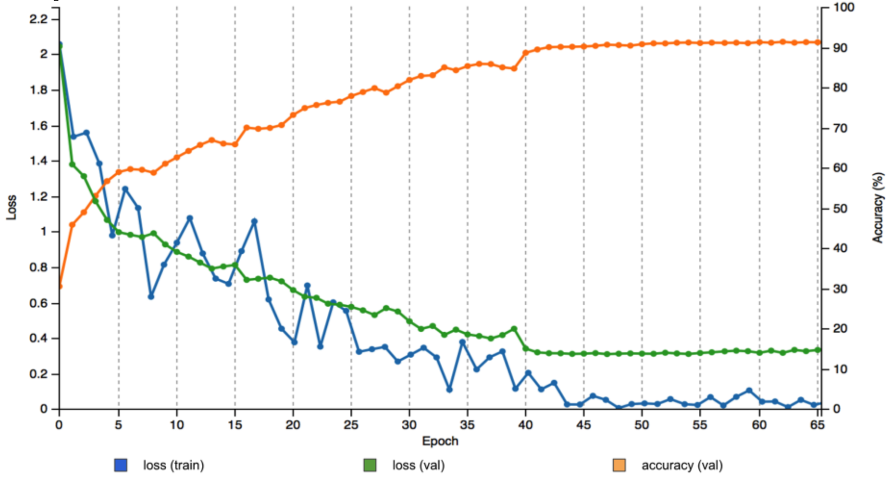
Training/Test/Validation split

- (Training + Validation) 70% - 30% (Test)
- (Training) 75% - 25% (Validation)

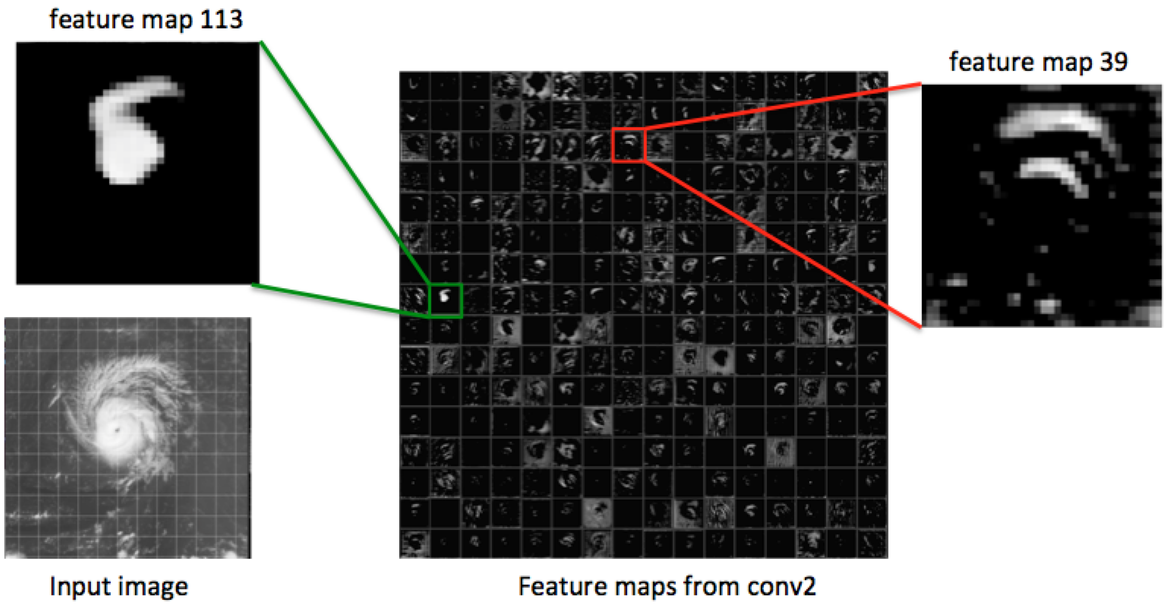
Hurricane Category	Train	Validation	Test	Total
H1	3314	1104	1816	6234
H2	1860	620	994	3474
H3	1848	616	992	3456
H4	1886	628	1032	3546
H5	603	201	306	1110
NC	126	42	54	222
TD	6363	2121	3576	12060
TS	9863	3288	5575	18726
Total	**25863**	**8620**	**14345**	**48828**

Training

- Preprocessing
  - Resize to 232 x 232 for input
  - Subtract image mean from training images
- GRID K520 4GB GPU
- Stopped at 90% validation accuracy
- 65 epochs in 8 hours
- Caffe framework



Visualization



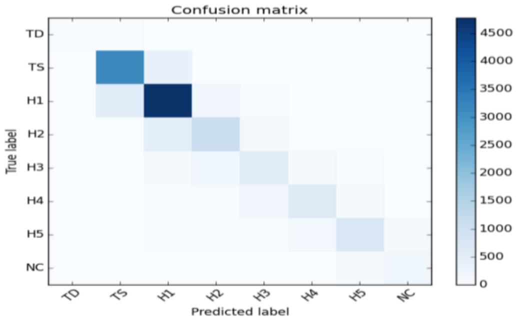
Feature maps from second convolution

Performance

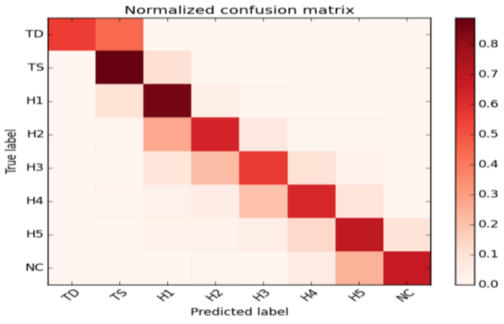
- Model with around 90% of validation accuracy
- 14,345 test images (Atlantic + Pacific)
- Measures
  - Confusion Matrix
  - Classification Report
  - Accuracy
  - RMS Intensity Error

Confusion Matrix

		Predicted Category								
		NC	**TD**	**TS**	**H1**	**H2**	**H3**	**H4**	**H5**	**Total**
Actual Category	**NC**	32	20	2	0	0	0	0	0	**54**
	TD	9	3174	393	0	0	0	0	0	**3576**
	TS	1	488	4838	208	25	10	3	2	**5575**
	H1	0	16	423	1235	115	20	7	0	**1816**
	H2	0	0	70	193	614	98	19	0	**994**
	H3	0	0	35	37	156	657	106	1	**992**
	H4	0	0	14	4	24	117	816	57	**1032**
	H5	0	0	0	0	1	14	86	205	**306**
	Total	**42**	**3698**	**5775**	**1677**	**935**	**916**	**1037**	**265**	**14345**



(a)



(b)

Classification Report

Category	Precision	Recall	F1-score	Support
NC	0.76	0.59	0.67	54
TD	0.86	0.89	0.87	3576
TS	0.84	0.87	0.85	5575
H1	0.74	0.68	0.71	1816
H2	0.66	0.62	0.64	994
H3	0.72	0.66	0.69	992
H4	0.79	0.79	0.79	1032
H5	0.77	0.67	0.72	306
avg/total	**0.80**	**0.81**	**0.80**	**14345**

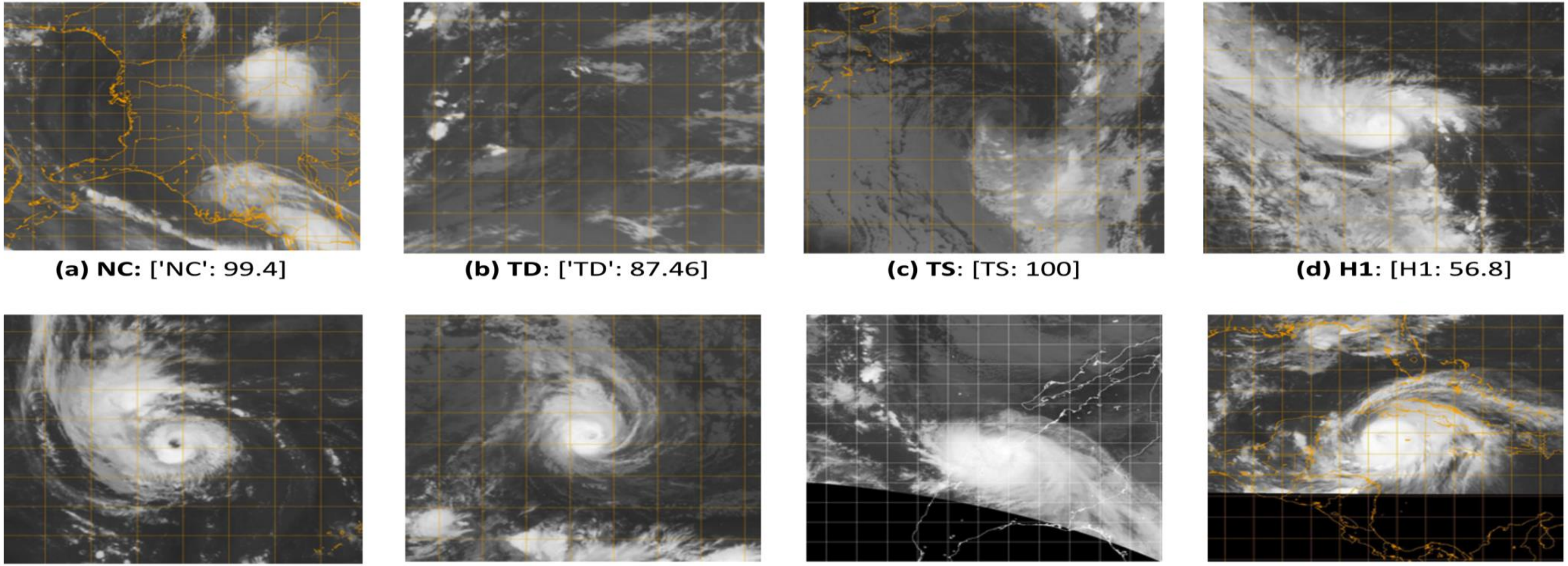
RMS Intensity Errors

- Our model
  - Across Atlantic and Pacific
  - Achieved RMSE of 9.19*kt*
- 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*

Category	RMSE	MAE
NC	10.14	6.19
TD	6.59	2.18
TS	7.68	2.71
H1	12.17	6.59
H2	12.43	6.82
H3	12.44	6.31
H4	10.50	4.09
H5	10.08	5.32
Total Average	**9.19**	**3.77**

Correct Predictions

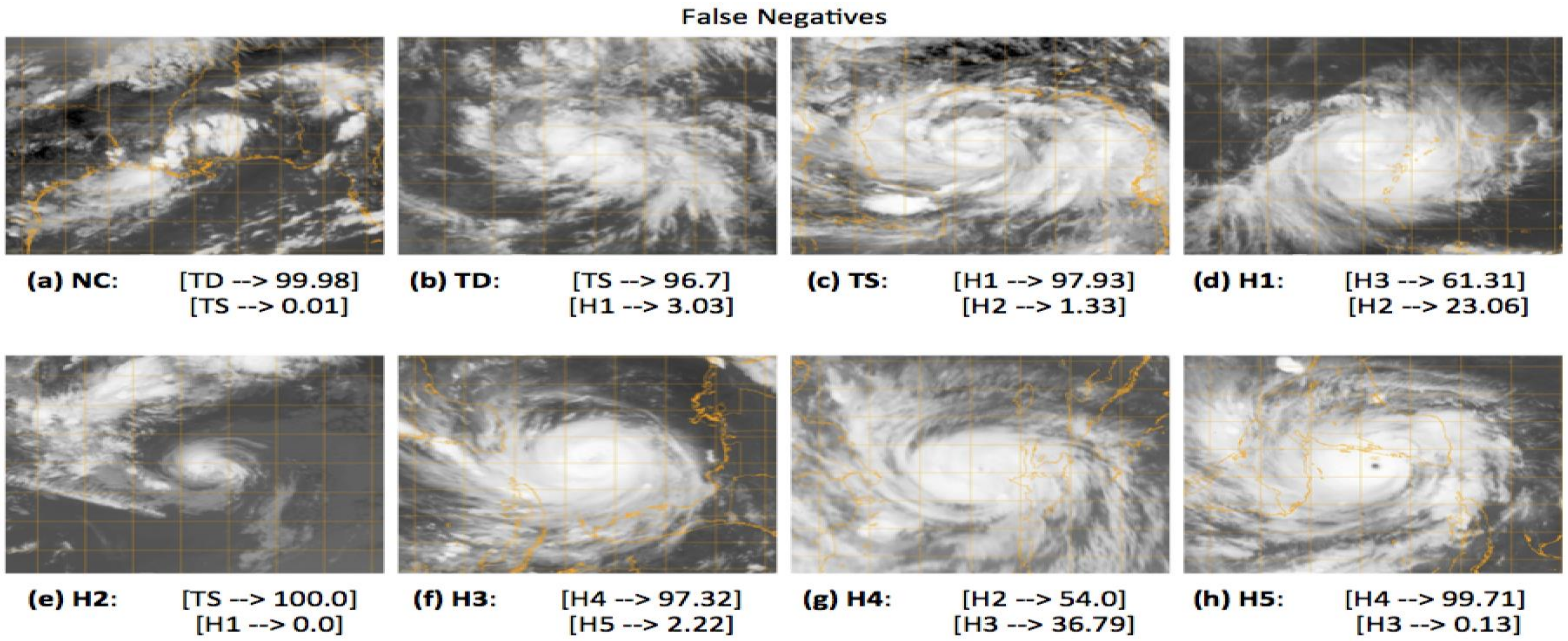
True Positives



(a) **NC:** ['NC': 99.4] (b) **TD**: ['TD': 87.46] (c) **TS**: [TS: 100] (d) **H1**: [H1: 56.8]

(e) **H2**: [H2: 78.54] (f) **H3**: [H3: 95.73] (g) **H4:** [H4: 86.04] (h) **H5**: [H5: 58.26]

Incorrect Predictions



Application:
Searching for Events

Searching for Events

- Labeled Data
  - MODIS Rapid Response
    - Experts manually labeled ~850 images
    - 4 classes:
      - Hurricane, Dust, Smoke/Haze, Other
    - Final Dataset
      - images transformation
        - » (flip, transpose, rotate, random patch)
      - Total ~5000 images
      - 70% for training and validation

- Test Data
    - 30% of Labeled data
    - Unseen by CNN trained model

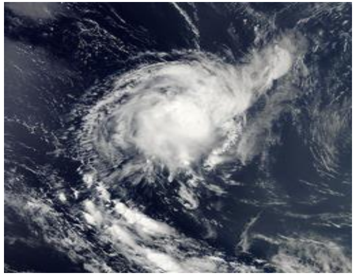
  - Global Browse Image Service (GIBS)
    - MODIS_Aqua_CorrectedReflectance_TrueColor tiles for 2012 - classified against trained model

Searching for Events - Results

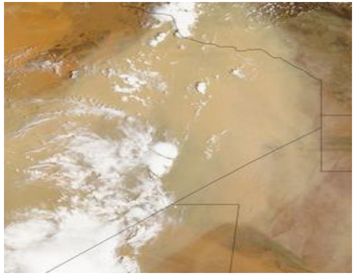
True/Pred	Dust	Hurricane	Smoke	Other
Dust	**287**	8	32	33
Hurricane	0	**379**	1	10
Smoke	12	12	**443**	9
Other	33	9	23	**211**

Confusion Matrix

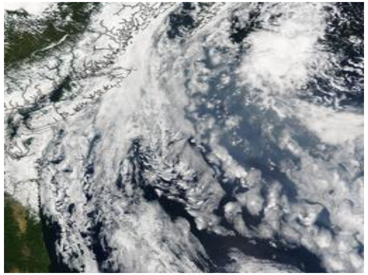
Overall Accuracy = **87.88**%



Hurricane – True Positive

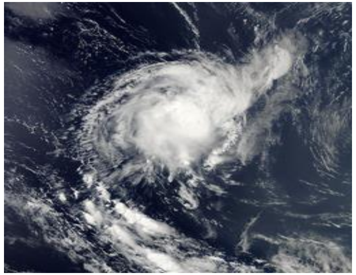


Dust – True Positive

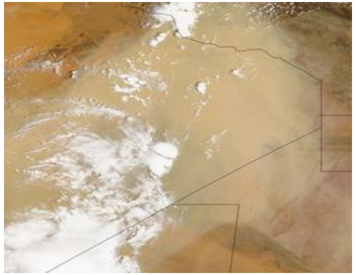


Smoke– True Positive

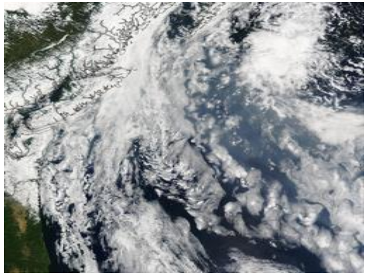
Searching for Events - Results



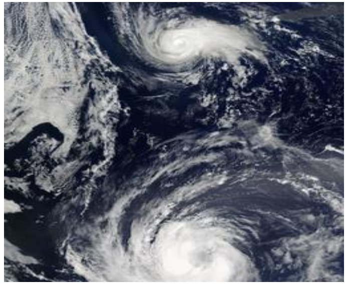
Hurricane – True Positive



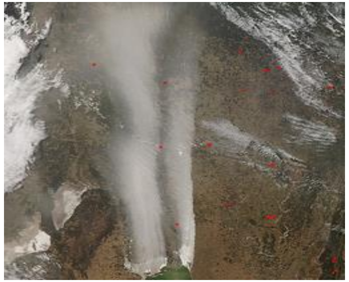
Dust – True Positive



Smoke– True Positive



Hurricane – False Negative



Dust – False Positive

Smoke– False Positive

Application:

Image signature identification for Transverse bands

Image signature identification for Transverse bands

- Found in association with multiple types of phenomena.
  - Hurricanes, Jet-Streaks, Mesoscale Convective Systems (MCS)
- Associated with differing levels of aviation turbulence

- Problem:
  - Identify transverse cirrus bands in MODIS True Color imagery.
  - Relatively small scale features (1-10 km wide).

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Methodology

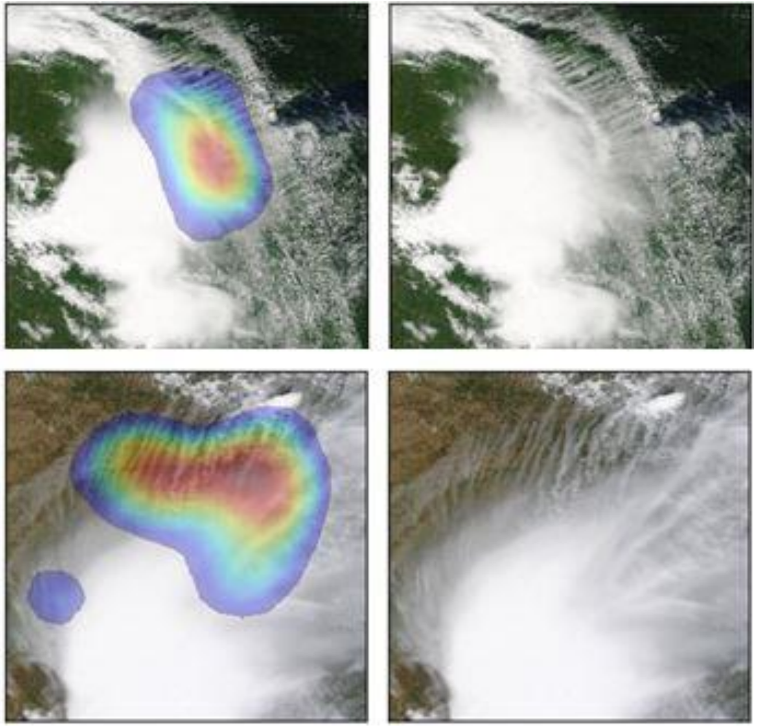
- Data
  - 5440 images (1 km MODIS RGB)
    - 1741 with transverse bands
    - 3699 without transverse bands
  - 20% for validation
  - 600 separate images for testing

- Architecture
  - VGG16 architecture
  - Replaced fully connected layers with global average pooling layer
  - First seven layers frozen (not trained)
  - Keras (Python)
  - NVIDIA GTX 960 GPU

- Classify 2013 GIBS tiles
- Geolocate transverse cirrus bands

Training Results

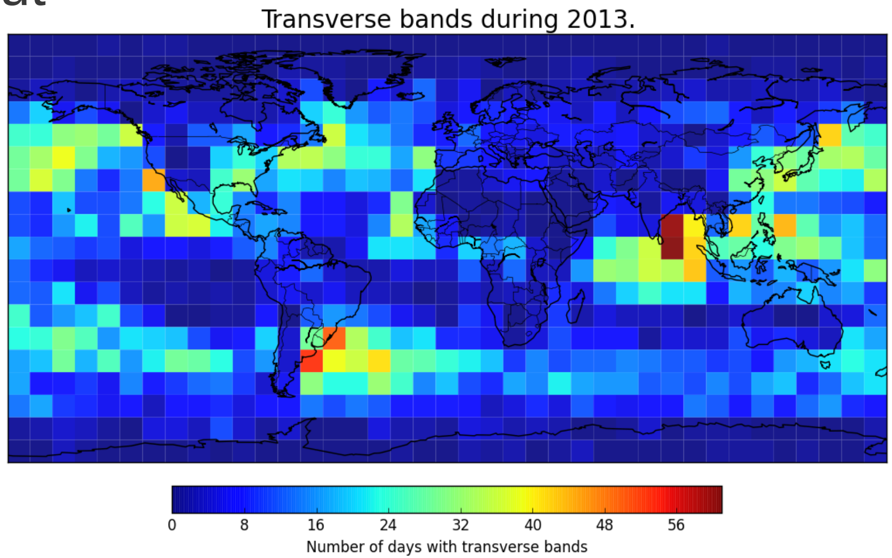
- Model trained for 52 epochs (6 hrs)
- Highest validation accuracy occurred at epoch 41 (0.937)
- Testing on the test set:
  - Accuracy: 94.67%
- Class activation maps show that the network is able to identify the regions of the image that contain transverse bands.



		Predictions	
		Bands	Not Bands
Truth	Bands	**107**	22
	Not Bands	10	**461**

Classifying 2013 GIBS tiles

- Some interesting areas stand out
  - Eastern coast of India
  - Western coast of Mexico/California
  - Southeastern coast of South America
- Jet stream appears to play a large role
- Eastern and Central US more than likely due to MCSs



Application:
Enabling New Science
Dust Climatology
Collaboration with Sundar Christopher, UAH

Enabling new science

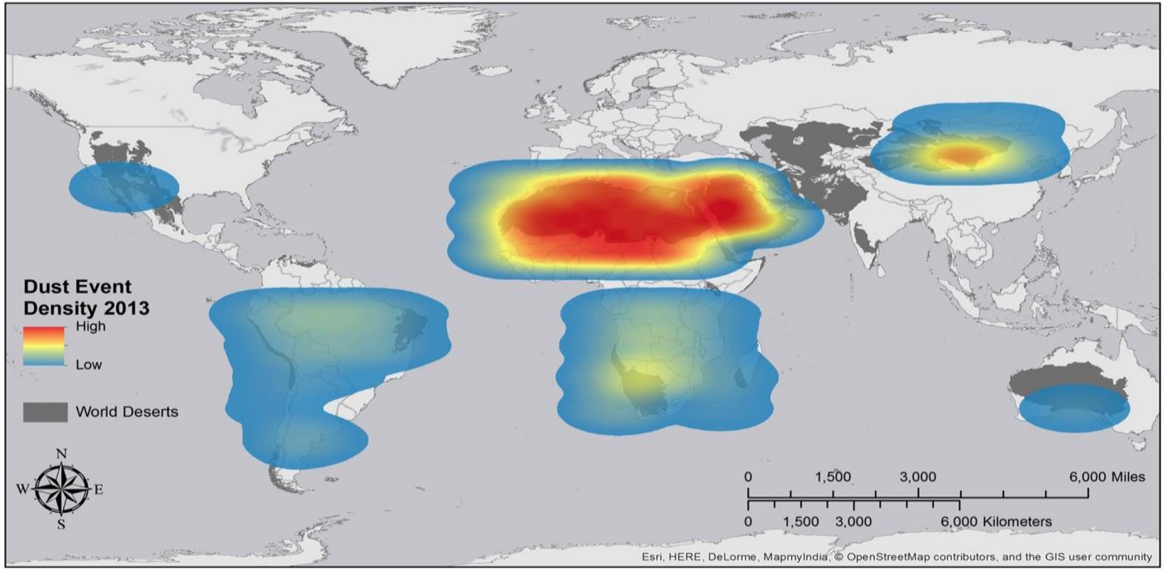
- Dust Climatology
- Dataset
  - Manually created truthset
- Dust/No Dust classification on GIBS tiles

Enabling new science

Confusion Matrix

True\Predicted	**Dust**	**Other**	Total
Dust	**1379**	379	1758
Other	260	**4932**	5192
	1639	5311	6950

Validation Accuracy = **91**%



Analysis

- Accuracy outperformed traditional approaches
- Training data
- Automatic validation of images
- Hyperparameters

Acknowledgement

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