Deep Learning-Powered Insight from Dark Resources

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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

Trainable Feature Extractor
(learns)

Trainable Classifier
(learns)
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

Input (7x7), (with pad of 1)

Kernel (3x3) (with stride of 2)

Output (3x3)
Convolutional Layer

3D Representation

(Number of feature maps = Number of filters)
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
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)

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


Problems

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

input → (conv1+pool1) → (conv2+pool2) → (conv3+pool3) → (conv4) → (conv5+pool5) → fc6 → fc7 → fc8
### Configurations

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

<table>
<thead>
<tr>
<th>Layer</th>
<th>Shape</th>
<th>Output Size</th>
<th>Parameter Shape</th>
<th>Learned Parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>Input</td>
<td>3@232x232</td>
<td>75x75</td>
<td>(64, 3, 10, 10)</td>
<td>19,264</td>
</tr>
<tr>
<td>conv1</td>
<td>64@10x10, s=3, p=0</td>
<td>37x37</td>
<td>(256, 64, 5, 5)</td>
<td>409,856</td>
</tr>
<tr>
<td>pool1</td>
<td>3x3, s=2, p=0</td>
<td>33x33</td>
<td>(288, 256, 3, 3)</td>
<td>663,840</td>
</tr>
<tr>
<td>conv2</td>
<td>256@5x5, s=1, p=0</td>
<td>16x16</td>
<td>(272, 288, 3, 3)</td>
<td>705,296</td>
</tr>
<tr>
<td>pool2</td>
<td>3x3, s=2, p=0</td>
<td>15x15</td>
<td>(256, 272, 3, 3)</td>
<td>528,984</td>
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<tr>
<td>conv3</td>
<td>272@3x3, s=1, p=1</td>
<td>13x13</td>
<td>(3584, 9216)</td>
<td>27,872,768</td>
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<tr>
<td>pool3</td>
<td>2x2, s=1, p=0</td>
<td>15x15</td>
<td>(2048, 3584)</td>
<td>7,342,080</td>
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<tr>
<td>conv4</td>
<td>256@3x3, s=1, p=0</td>
<td>6x6</td>
<td>(8, 2048)</td>
<td>16,392</td>
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<tr>
<td>pool5</td>
<td>3x3, s=2, p=0</td>
<td>6x6</td>
<td></td>
<td>37,558,480</td>
</tr>
</tbody>
</table>
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
<table>
<thead>
<tr>
<th>Region/Basin</th>
<th>Year</th>
<th>Cyclones</th>
</tr>
</thead>
<tbody>
<tr>
<td>Atlantic</td>
<td>1998</td>
<td>Mitch</td>
</tr>
<tr>
<td></td>
<td>2003</td>
<td>Isabel</td>
</tr>
<tr>
<td></td>
<td>2004</td>
<td>Ivan</td>
</tr>
<tr>
<td></td>
<td>2005</td>
<td>Emily, Katrina, Rita, Wilma</td>
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<tr>
<td></td>
<td>2007</td>
<td>Dean, Felix</td>
</tr>
<tr>
<td></td>
<td>2010</td>
<td>Alex, Bonnie, Colin, Danielle, Earl, Fiona, Five, Gaston, Igor, Julia, Karl, Lisa, Matthew, Nilcole, Otto, Paula, Richard, Shary, Tomas, Two</td>
</tr>
<tr>
<td></td>
<td>2011</td>
<td>Arlene, Bret, Cindy, Don, Emily, Franklin, Gert, Harvey, Irene, Jose, Katia, Lee, Maria, Nate, Ophelia, Philippe, Rina, Sean, Ten</td>
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<tr>
<td></td>
<td>2012</td>
<td>Alberto, Beryl, Chris, Debby, Ernesto, Florence, Gordon, Helene, Isaac, Joyce, Kirk, Leslie, Michael, Nadine, Oscar, Patty, Rafael, Sandy, Tony</td>
</tr>
<tr>
<td></td>
<td>2014</td>
<td>Edouard</td>
</tr>
<tr>
<td>Pacific</td>
<td>2002</td>
<td>Elida, Fausto, Hernan, Kenna</td>
</tr>
<tr>
<td></td>
<td>2005</td>
<td>Jova, Kenneth</td>
</tr>
<tr>
<td></td>
<td>2006</td>
<td>Bud, Daniel, Ioke, John, Lane</td>
</tr>
<tr>
<td></td>
<td>2007</td>
<td>Flossie</td>
</tr>
<tr>
<td></td>
<td>2008</td>
<td>Hernan, Norbert</td>
</tr>
<tr>
<td></td>
<td>2009</td>
<td>Felicia, Guillermo, Jimena, Rick</td>
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<tr>
<td></td>
<td>2010</td>
<td>Celia, Darby</td>
</tr>
<tr>
<td></td>
<td>2011</td>
<td>Adrian, Dora, Eugene, Hilary, Jova, Kenneth</td>
</tr>
<tr>
<td></td>
<td>2012</td>
<td>Bud, Emilia, Miriam, Paul</td>
</tr>
</tbody>
</table>
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)

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

The confusion matrix provides a summary of the performance of a classification model. It shows how many examples were correctly predicted and how many were misclassified.

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

(a) and (b) show the confusion matrix and normalized confusion matrix, respectively.
## Classification Report

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

<table>
<thead>
<tr>
<th>Category</th>
<th>RMSE</th>
<th>MAE</th>
</tr>
</thead>
<tbody>
<tr>
<td>NC</td>
<td>10.14</td>
<td>6.19</td>
</tr>
<tr>
<td>TD</td>
<td>6.59</td>
<td>2.18</td>
</tr>
<tr>
<td>TS</td>
<td>7.68</td>
<td>2.71</td>
</tr>
<tr>
<td>H1</td>
<td>12.17</td>
<td>6.59</td>
</tr>
<tr>
<td>H2</td>
<td>12.43</td>
<td>6.82</td>
</tr>
<tr>
<td>H3</td>
<td>12.44</td>
<td>6.31</td>
</tr>
<tr>
<td>H4</td>
<td>10.50</td>
<td>4.09</td>
</tr>
<tr>
<td>H5</td>
<td>10.08</td>
<td>5.32</td>
</tr>
<tr>
<td>Total Average</td>
<td>9.19</td>
<td>3.77</td>
</tr>
</tbody>
</table>
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

(a) NC:  [TD --> 99.98]  [TS --> 0.01]
(b) TD:  [TS --> 96.7]  [H1 --> 3.03]
(c) TS:  [H1 --> 97.93]  [H2 --> 1.33]
(d) H1:  [H3 --> 61.31]  [H2 --> 23.06]
(e) H2:  [TS --> 100.0]  [H1 --> 0.0]
(f) H3:  [H4 --> 97.32]  [H5 --> 2.22]
(g) H4:  [H2 --> 54.0]  [H3 --> 36.79]
(h) H5:  [H4 --> 99.71]  [H3 --> 0.13]
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

<table>
<thead>
<tr>
<th>True/Pred</th>
<th>Dust</th>
<th>Hurricane</th>
<th>Smoke</th>
<th>Other</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dust</td>
<td>287</td>
<td>8</td>
<td>32</td>
<td>33</td>
</tr>
<tr>
<td>Hurricane</td>
<td>0</td>
<td>379</td>
<td>1</td>
<td>10</td>
</tr>
<tr>
<td>Smoke</td>
<td>12</td>
<td>443</td>
<td>9</td>
<td></td>
</tr>
<tr>
<td>Other</td>
<td>33</td>
<td>9</td>
<td>23</td>
<td>211</td>
</tr>
</tbody>
</table>

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).
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.

<table>
<thead>
<tr>
<th>Truth</th>
<th>Predictions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bands</td>
<td>107</td>
</tr>
<tr>
<td>Not Bands</td>
<td>10</td>
</tr>
<tr>
<td>Bands</td>
<td>22</td>
</tr>
<tr>
<td>Not Bands</td>
<td>461</td>
</tr>
</tbody>
</table>
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

<table>
<thead>
<tr>
<th>True\Predicted</th>
<th>Dust</th>
<th>Other</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dust</td>
<td>1379</td>
<td>379</td>
<td>1758</td>
</tr>
<tr>
<td>Other</td>
<td>260</td>
<td>4932</td>
<td>5192</td>
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<tr>
<td></td>
<td>1639</td>
<td>5311</td>
<td>6950</td>
</tr>
</tbody>
</table>

Validation Accuracy = 91%
Analysis

• Accuracy outperformed traditional approaches

• Training data

• Automatic validation of images

• Hyperparameters
Acknowledgement

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