Pixel Level Smoke Detection Model with Deep Neural Network

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Introduction

• Biomass burning smoke has numerous detrimental environmental and ecological impacts
  • Respiratory and cardiovascular illnesses
  • Radiation budget
  • Nutrient availability

• Impacts realized both near source and potentially thousands of kilometers downwind depending on
  • Fire duration
  • Amount and type of biomass burned
  • Meteorological and fuel conditions
  • Vertical distribution in the atmosphere

Spatial distribution of MODIS fire occurrence and NOAA HMS smoke for summer 2006-2015. From Kauflus et al. 2017 Figure 2.
Current detection methods present challenges for continuous smoke detection and monitoring

- In-situ monitoring
  - Temporal, spatial, and tracer monitoring limitations
- Remote sensing
  - Polar orbiting, once-daily overpass
  - Manual or computational intensive multispectral analysis
  - Large data volumes
  - Multiple class multispectral classification
• Deploy a smoke detection model using machine learning on satellite remote sensing observations
  • Leverage observations from the new generation of geostationary satellite
    • High spatial and temporal resolutions over large domains
  • Alternative to multispectral analysis
  • Eliminate time consuming, subjective manual analysis
Truth Dataset

• Geostationary Operational Environmental Satellite 16 shortwave reflectance data
  • Bands 1-6 (0.47, 0.64, 0.86, 1.37, 1.6 and 2.2 μm)
  • Access L1B radiance data from AWS
  • Convert to reflectance
  • Spatially resample to 1km
• National Oceanic and Atmospheric Administration (NOAA) Hazard Mapping System (HMS) smoke analysis
  • Satellite based operational daily analysis of smoke extent over the US and surrounding areas
  • Manual quality controlled by subject matter expert to correctly match smoke extent in GOES 16 image
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Truth Dataset

• Analyze 122 scenes containing smoke
  • 962691 smoke pixels
  • Smoke over low and high background reflectances (land and ocean)
  • Contain relevant classes to discriminate smoke from
    • Snow and ice
    • Clouds
    • Dust
  • 60% - 20% - 20% distribution of smoke pixels between training, validation and testing datasets
• Apply a pixel based Convolutional Neural Network (CNN)
  • Input \((N*2)*(N*2)\) neighborhood of reflectance values surrounding a center pixel (sample)
  • 3 convolutional layers
  • Each convolutional layer followed by max-pooling layer
  • Convolutional outputs are flattened into vectors
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Model Architecture

- Apply a pixel based Convolutional Neural Network (CNN)
  - 4 fully connected layers with activation function calculation $g(Wx + b)$
    - $x$ is the flattened input vector
    - $W$ is the weight matrix
    - $b$ is the bias vector
  - Dropout for each fully connected layer
Model Architecture

• Apply a pixel based Convolutional Neural Network (CNN)
  • 4 fully connected layers
  • Dropout randomly for each fully connected layer
Model Architecture
• The model outputs the probability, ranging from 0 to 1, that a pixel is smoke determined by a sigmoid function

\[ p(x) = \frac{1}{1 + e^{-x}} \]

• \( p > 0.5 \) threshold applied to define smoke
• Best neighborhood size (N) determined by iterating model development and testing for increasing N
  • All other parameters including data, learning rate and model hyper-parameters are held constant
• Best model selected when validation loss did not improve for 20 epochs
Development Testing

<table>
<thead>
<tr>
<th>N</th>
<th>Precision</th>
<th>Recall</th>
<th>F1-Score</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.654</td>
<td>0.328</td>
<td>0.437</td>
<td>0.897</td>
</tr>
<tr>
<td>3</td>
<td>0.650</td>
<td>0.384</td>
<td>0.483</td>
<td>0.900</td>
</tr>
<tr>
<td>5</td>
<td>0.724</td>
<td>0.449</td>
<td>0.554</td>
<td>0.912</td>
</tr>
<tr>
<td>7</td>
<td>0.835</td>
<td>0.419</td>
<td>0.558</td>
<td>0.919</td>
</tr>
<tr>
<td>9</td>
<td>0.639</td>
<td>0.498</td>
<td>0.560</td>
<td>0.905</td>
</tr>
</tbody>
</table>

Precision = \( \frac{TP}{TP + FP} \)

Recall = \( \frac{TP}{TP + FN} \)

Accuracy = \( \frac{TP + TN}{TP + TN + TP + FN} \)

F1 Score = \( 2 \cdot \frac{Precision \times Recall}{Precision + Recall} \)

• The F1 Scores, balance between Precision and Recall, for N=5,7,9 is comparable
  • Trade-off between quality and quantity of smoke predictions
• Best model has low false positive detection rate which drives high precision
  • Prefer conservative identification over incorrect classification
• Accuracy artifact of large number of True Negatives
• Model updated to account for variation in solar zenith angle
  • The training and testing datasets for the updated model differ from that used for the initial development
  • Results are comparable between the initial and updated models
• Better predictive capability of smoke over water
  • Compared to land, the relative decrease in true negatives over water drives a slight decrease in accuracy

<table>
<thead>
<tr>
<th></th>
<th>N=7</th>
<th>Precision</th>
<th>Recall</th>
<th>F1-Score</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
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<td>0.736</td>
<td>0.453</td>
<td>0.561</td>
<td>0.923</td>
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<tr>
<td>Land</td>
<td></td>
<td>0.631</td>
<td>0.383</td>
<td>0.476</td>
<td>0.928</td>
</tr>
<tr>
<td>Water</td>
<td></td>
<td>0.923</td>
<td>0.585</td>
<td>0.717</td>
<td>0.900</td>
</tr>
</tbody>
</table>
• Smoke identified over both land and ocean
  • Model identifies well defined plumes for scenes with absence of complex features
  • Probabilities resemble visually observed optical thickness
• Predictions closer resemblance to quality controlled shapefiles
24 March 2018 - Southern Florida

- Distinguishable from chlorophyll commonly found in coastal settings.
- Fair weather cumulus cloud discrimination.
- Spectral information for other classes not provided to the model.

<table>
<thead>
<tr>
<th>Class</th>
<th>Precision</th>
<th>Recall</th>
<th>F1-Score</th>
<th>Accuracy</th>
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</thead>
<tbody>
<tr>
<td>All</td>
<td>0.744</td>
<td>0.604</td>
<td>0.666</td>
<td>0.948</td>
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<tr>
<td>Land</td>
<td>0.847</td>
<td>0.244</td>
<td>0.379</td>
<td>0.976</td>
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<tr>
<td>Water</td>
<td>0.742</td>
<td>0.623</td>
<td>0.677</td>
<td>0.943</td>
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</table>
9 October 2017 - Central California

- Large and small plumes
- Identification over both land and ocean
- Coastal stratus clouds

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<td>0.970</td>
<td>0.919</td>
<td>0.944</td>
<td>0.961</td>
</tr>
<tr>
<td>Land</td>
<td>0.904</td>
<td>0.754</td>
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<td>0.920</td>
</tr>
<tr>
<td>Water</td>
<td>0.986</td>
<td>0.965</td>
<td>0.975</td>
<td>0.980</td>
</tr>
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• Successfully discriminates land surface snow/ice from smoke
  • Over snow capped mountains for this case
• Detection challenges for optically thin smoke over arid regions

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</thead>
<tbody>
<tr>
<td>All</td>
<td>0.848</td>
<td>0.318</td>
<td>0.462</td>
<td>0.977</td>
</tr>
<tr>
<td>Land</td>
<td>0.848</td>
<td>0.319</td>
<td>0.463</td>
<td>0.977</td>
</tr>
<tr>
<td>Water</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>0.984</td>
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</table>
• Other atmospheric aerosols not classified as smoke
• Large dust storm case
  • Represents a major source of aerosols in the atmosphere
  • Expected over regions where smoke is also common

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<tbody>
<tr>
<td>All</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>0.996</td>
</tr>
<tr>
<td>Land</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>0.996</td>
</tr>
<tr>
<td>Water</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
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Smoke not detected at very low sun angles
- Compounded by low optical thickness over relatively high reflective surface
- Probability of being smoke is low for few pixels that are identified

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<tbody>
<tr>
<td>All</td>
<td>0.995</td>
<td>0.093</td>
<td>0.171</td>
<td>0.823</td>
</tr>
<tr>
<td>Land</td>
<td>0.995</td>
<td>0.093</td>
<td>0.171</td>
<td>0.822</td>
</tr>
<tr>
<td>Water</td>
<td>0.923</td>
<td>0.585</td>
<td>0.717</td>
<td>1.000</td>
</tr>
</tbody>
</table>
• Overprediction of plume extent
  • Artifact of large (N=7) neighborhood size
  • Non-zero floor to number of false positives

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<tr>
<td>All</td>
<td>0.830</td>
<td>0.738</td>
<td>0.781</td>
<td>0.981</td>
</tr>
<tr>
<td>Land</td>
<td>0.830</td>
<td>0.738</td>
<td>0.781</td>
<td>0.981</td>
</tr>
<tr>
<td>Water</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>0.993</td>
</tr>
</tbody>
</table>
• Currently testing new deployment in operational environment
  • Anticipate operational October 2019
• Fully deployed in cloud using Amazon S3 and Cloud Computing Services
• End-to-end analysis and visualization pipeline
  • Full disk GOES observation available ~10 min intervals
  • Model prediction available ~15 min after data availability
    • Preprocessing ~10 min
    • Prediction and Postprocessing ~5min
Operational Capabilities - Postprocessing

- Spatial grouping of predicted pixels to define plumes
  - Convert predicted pixels to bitmap image
  - Blurring to smoothen edges
  - Contour blurred image to group smoke pixels into plumes
  - Plumes visualized and geojson representation of plume extents available for download in the Phenomena Portal ([http://phenomena.surge.sh](http://phenomena.surge.sh))
Summary

• Developed end-to-end machine learning smoke detection pipeline for next-generation of geostationary satellites
  • Well curated smoke extent dataset
  • Scalable smoke detection deep learning model, requiring only smoke spectral information, and capable of detecting smoke with:
    • Varying optical thicknesses
    • Over low and high reflectance background surfaces
    • Discriminates from common, spectrally similar, features
  • Fully automated operational deployment of model in development
    • Plume visualization and extent data accessible in online platform
Future work

• Expand training data to account for identified weaknesses
  • Low sun angles
  • Thin smoke over arid regions
  • Thin clouds

• Refinement of the machine learning model
  • Confirmation of N=7 as best performing model
    • Explore trade-off between neighborhood size and prediction capabilities
  • Stepwise band selection considering all 16 GOES bands
  • Robust model validation
    • Band exclusion to identify contribution to feature learning

• Performance assessment for operational improvements
Thank you!

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