Environment-Agnostic Wildfire Detection with Satellite Imagery

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Summary

We aim to combine high resolution satellite data from Landsat 8 with deep learning models to **detect fires** and improve upon currently used equation based models [1]. The current active fire detection model for Landsat uses a two-channel fixed-threshold plus contextual approach. Previous NN applications focuses on structured indicator data or geo-specific datasets. [2-4]

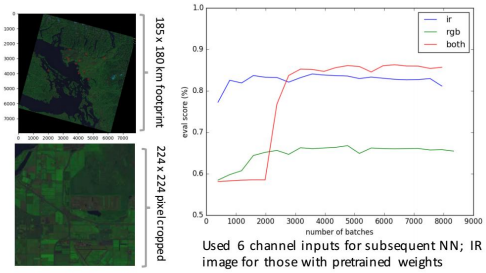
Data

- **Landsat 8** Operational Land Imager (OLI) images from 2016 and 2017
- Each footprint is 185 km × 180 km with a 30 m spatial resolution per pixel. Cropped down to 224x224 pixel images either containing an active fire or no fire.
- Six "bands" (wavelength regimes)

Band number	Wavelength (microns)
1	0.43–0.45
2	0.45–0.51
3	0.53–0.59
4	0.64–0.67
6	1.57–1.65
7	2.11–2.29

Filtered for a cloud coverage of 10% or less and in the continental US. Train/dev/test split **39642/4955/4957**.

Features

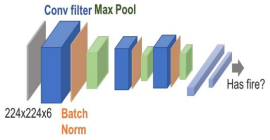


Used 6 channel inputs for subsequent NN; IR image for those with pretrained weights

Models

Basic CNN: 3 conv layers. Used to determine RGB, "IR", or 6 channel selections

Customized CNN: Various architectures. Arch5 shown on right yielded best result



Custom CNN structure
Conv2D 64 * 3x3 Conv2D 64 * 3x3
Conv2D 32 * 3x3
Conv2D 24 * 3x3
Conv2D 12 * 3x3
Conv2D 12 * 3x3
Fc 256 Dropout keepprob = 0.5 Fc 128 Dropout keepprob = 0.5 Fc 128

VGG: Used first 3 block of pretrained model from Caffe as a feature extractor. Added two more convolutional blocks and two fully connected layers

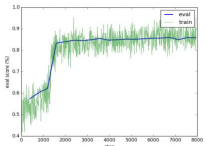
InceptionV3 (GoogLeNet): Pretrained model from Keras. Added a single fully connected 1024 neuron layer (ReLu) and a single neuron (sigmoid) output layer. Adam optimization.

ResNet50: Added same 2 fully connected layers as Inception. Trained top conv block. Adam optimization.

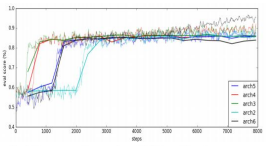
Results/Discussion

Found deeper networks including VGG16, ResNet and Inception all largely overfit and did not generalize well. Focused on various custom CNN architectures for hyperparameter search.

Model	Training Accuracy	Test Accuracy
Basic model	0.85	0.85
VGG16	0.88	0.64
Inception	0.98	0.67
ResNet 50	0.99	0.69
Custom CNN	0.87	0.86



Training and evaluation curve for Arch5 model

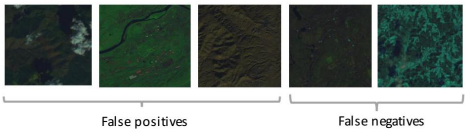


Training curve for custom CNN architectures

Best Model

Random grid search on ConvNet yields the highest test accuracy of 86%: learning rate: 0.005, batch size 100. Used binary cross entropy loss.

Activation for first conv layer (right) and activation for third conv layer (left)



False positives | False negatives

Sample of 900 test images yield [420 34 98 348] confusion matrix. High cloud cover, buildings, mountain regions problematic. False negatives had more night-time images.

Future Work

Benefit of satellite images is that it's **easily extendable** - can be applied to burn area prediction, combined with meteorological information (wind speed, rainfall, drought codes) or geographical information to assist with problematic terrains etc.. YOLO/object detection is possible, particularly if integrated with higher temporal resolution satellite datasets such as MODIS.

References: [1] Schroeder, Wilfrid, et al. "Active fire detection using Landsat-8/OLI data." Remote sensing of environment (2016) [2] Sakr, George E, et al. "Artificial intelligence for forest fire prediction (2010) [3] Romero, Adriana, Carlo Gatta, and Gustau Camps Valls. "Unsupervised Deep Feature Extraction for Remote Sensing Image Classification." 2016) [4] Jaiswal, Rajeev K, et al. "Forest fire risk zone mapping from satellite imagery and GIS." (2002)