Satellite Imagery Based Wildfire Detection

Glynnis Millhouse
glynnis@stanford.edu

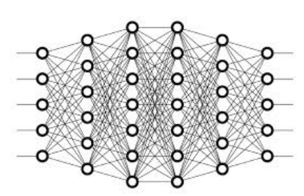
Emily Wu
emilyw12@stanford.edu

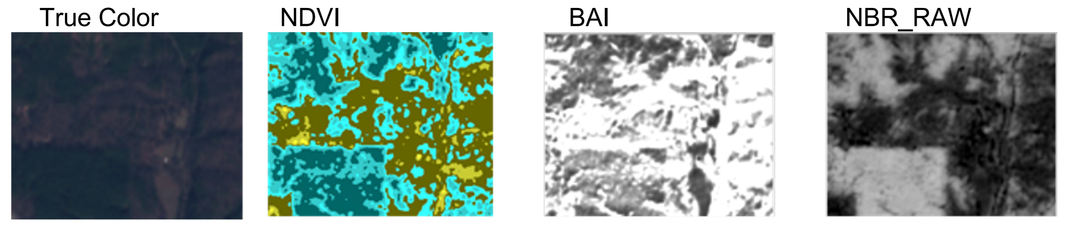
Olamide Oladeji
oladeji@stanford.edu

https://www.youtube.com/watch?v=lrAwixEmogU

Project Overview

- Minimizing response delay has become even more crucial for improved wildfire mitigation.
- Deep learning and computer vision + Granular satellite imagery with multiple channels can help in rapid detection
- and response.
- We use the **Sentinel-2** satellite with better temporal (every 5 days) and spatial resolution (10m to 30m) than the frequently used Landsat from literature.
- US Geological Survey (USGS) tracks location, perimeter polygon and date of all historical wildfires.
- Using historical wildfire + non-wildfire data, we train deep learning models on satellite imagery on the following relevant channels:
  - the true color,
  - the Normalized Difference Vegetation Index (NDVI),
  - Burned Area Index (BAI),
  - and the Normalized Burn Ratio (NBR-RAW) layers as channels for data points



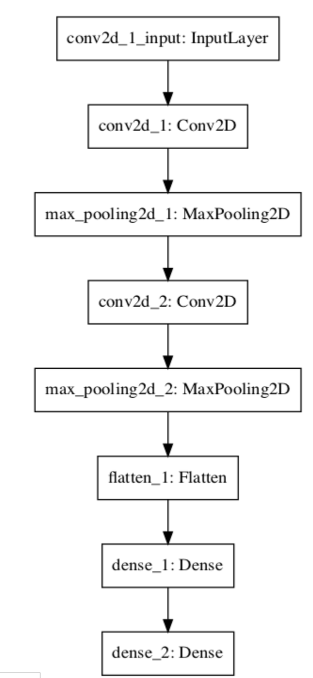


Models

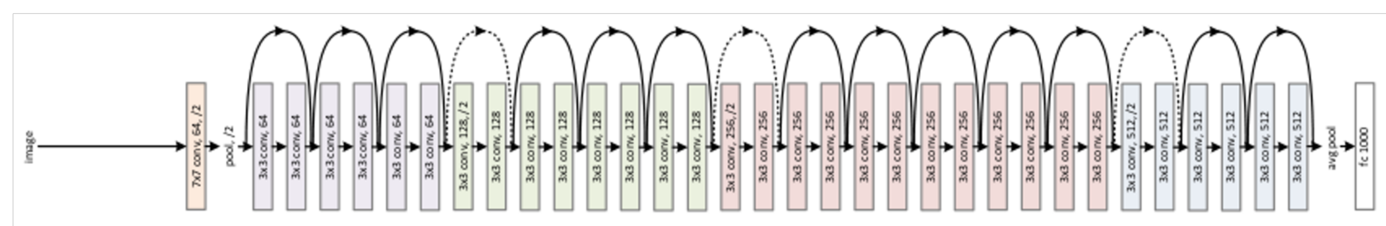
- We use a simple CNN models in three ways:
- Model 1: CNN + 3 channel data: RGB
- Model 2: CNN + 8 channel data: RGB + NDVI + BAI + NBR_RAW
- Model 3: CNN + Regularization (dropout) + 8 channel data (RGB + NDVI + BAI + NBR_RAW)
- Our loss function was a binary cross-entropy loss:

$$\frac{1}{m}\sum_{i=1}^{m}(-y(log(\hat{y})) + (1-y)(log(1-\hat{y})))$$

- We also use a transfer learning model: ResNet-50 with pretrained weights + retraining last 2 layers



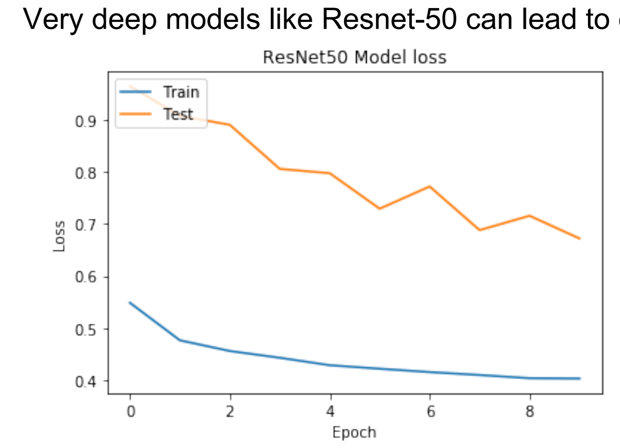
Our Basic CNN model



ResNet-50

Discussion

- Simple CNN + More (8) channels works best (low bias)
- Very deep models like Resnet-50 can lead to overfitting on the data:



	Training	Validation	Test
Accuracy	82.61%	63.49%	64.09%

	Precision	Recall	F1	Support
0.0	0.79	0.47	0.59	601
1.0	0.57	0.85	0.68	499
weighted avg	0.69	0.64	0.63	1100

Performance with ResNet-50

- 10 epochs too small for convergence without regularization ➔ Adding dropout regularization for variance also led to significant test accuracy improvements under 10 epochs.
- Our best model (95.09% accuracy) beat:
  i. state of the art with Landsat (~87%)
  ii. Human level accuracy on labelled true color satellite imagery (~85%).

Data

- Historical wildfire perimeter data is from US Geological Survey database known Wildland Fire Support Geospatial Multi-Agency Coordination (GeoMAC). The database contains location, perimeter polygons and date of all wildfires in the United States and is stored as 30m x 30m raster level (.shp) shapefiles.
- We focused on wildfire perimeter data from 2016 to 2019, resulting in 20946 historical wildfire incidents. We used 5000 of these incidents to generate our 11000- image data set.
- We used the Sentinel-2 satellite as the source of these satellite images, leveraging on a Web Map Service (WMS) provided by Sentinel-Hub [15]. The WMS also allows us to query and obtain other satellite extracted images/features for those wildfire location-date pairs that correspond to information on Vegetation, Normalized Burn Index and Burned Area Index, and Moisture content.
- For each of the historical wildfire data points, we used the perimeter polygon and date properties to define bounding boxes that are then used to generate corresponding satellite imagery for that wildfire at that location.
- We make sure to standardize the zoom/resolution level for each historical wildfire perimeter polygon and date pair to a 0.5 km radius from the perimeter polygon's inner centroid, retrieving an array of layers (channels) corresponding to a 256 x 256 image for that data point.
- As our problem is a classification problem, we also obtain data for the non-wildfire class in two ways. First, we extract images for the same wildfire location but 150 days prior (to a date for which we assume there was no wildfire). Secondly, to avoid over-fitting to the same locations, we also add additional satellite image tiles of random, non-fire locations in the United States at random dates, to complete our non-fire dataset and serve as 10% of the whole data.
- For the 3 channel RGB-only model, we also augment 10% of the images with horizontal flipping and right rotations.

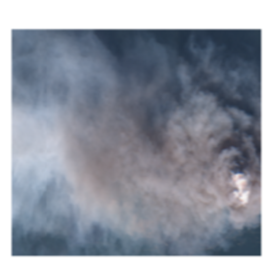


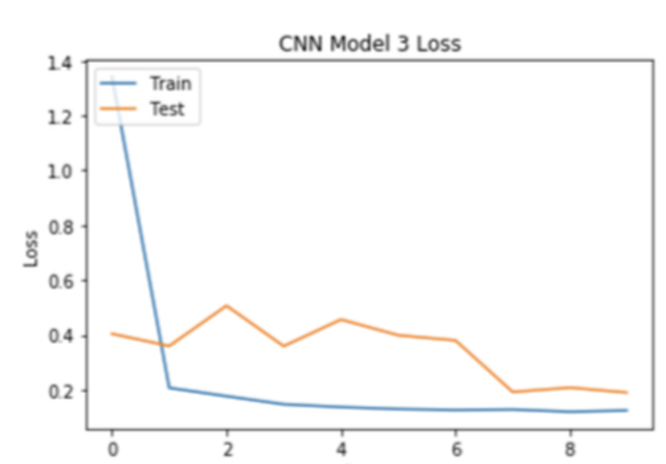
Figure 1: Sample 256 x 256 RGB Satellite Image showing Wildfire

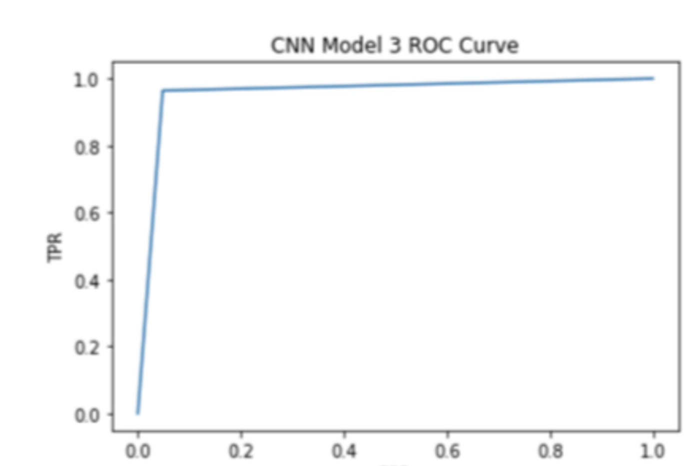
Results

- Our best model was the CNN with dropout layers and 8 channel data (Model 3)
- We exhibit very low variance, and some bias
- We estimated Bayes Optimal Error with non-expert human labeling to be ~15%. We believe that we were able to beat this accuracy by synthesizing multiple channels of data, which is not comprehensible to the human eye. Expert human labels may have also yielded a smaller Bayes Optimal Error.

	Training	Validation	Test
Accuracy	95.84%	94.73%	95.09%

	Precision	Recall	F1	Support
0.0	0.98	0.93	0.95	596
1.0	0.92	0.98	0.95	504
weighted avg	0.95	0.95	0.95	1100





Future Work

- As expected, adding additional channels of data significantly improved our results, increasing test accuracy by 8 percentage points. We believe that this is because significant information is contained in these supplemental satellite images.
- Dropout Layers also significantly improved out results, increasing test accuracy by 17 percentage points. Although dropout is a regularization technique and thus is primarily intended to reduce variance, this drastic reduction in our model bias as well was an interesting and welcome result. Our interpretation of this is that since we were only able to train for limited - 10 - epochs in either case, i.e. with and without dropout, our training without dropout was not near convergence. This non-dropout training accuracy may have been higher than the 95.84% obtained with dropout if we had sufficient computational resources to train for longer epochs. However, the dropout may have made sped up training such that the accuracy obtained after only 10 epochs may be the near-converged training accuracy with dropout
- The ineffective use of transfer learning with the application of ResNet-50 we attribute to overfitting, since we see a large widening of the variance as well as a drop in performance overall with this method.

Reference

[1] U.S. Department of Agriculture, Wildland Fire Support Geospatial Multi-Agency Coordination (GeoMAC) https://www.geomac.gov/services.shtml
[2] United States Geological Service, GloViS https://glovis.usgs.gov/app?fullscreen=0
[3] DevelopmentSeed. Landsat-util https://pythonhosted.org/landsat-util/
[4] NOAA, Climate Data Online (CDO). https://www.ncdc.noaa.gov/cdo-web/
[5] National Renewable Energy Laboratory (NREL). Wind Integration Data (WIND) Toolkit https://www.nrel.gov/grid/wind-toolkit.html
[6] United States Geological Service. 3D Elevation Program. https://www.usgs.gov/core-science- systems/ngp/3dep
[7] D. Radke, A. Hessler and D. Ellsworth. FireCast: Leveraging Deep Learning to Predict Wildfire Spread. Proceedings of the Twenty-Eight International. Joint Conference on Artificial Intelligence, 2019. [Available Online] https://www.ijcai.org/Proceedings/2019/0636.pdf
[8] A. Khan et al. A Survey of the Recent Architectures of Deep Convolutional Neural Networks. ArXiv. 2019. https://arxiv.org/pdf/1901.06032
[9] P. Cortez et. al. A Data Mining Approach to Predict Forest Fires using Meteorological Data Proceedings of the 13th Portuguese Conference on Artificial Intelligence
[10] E. J. S. Nhongo, et. al. Probabilistic modelling of wildfire occurrence based on logistic regres- sion, Niassa Reserve, Mozambique, Geomatics, Natural Hazards and Risk, 2019. 10:1, 1772-1792, DOI: 10.1080/19475705.2019.1615559.
[11] Y. Chang. et al. Predicting fire occurrence patterns with logistic regression in Heilongjiang Province, China. Landscape Ecology, 2013.
[12] N. T. Toan, P. T. Cong. N Quoc, V. Hong, J. Jo. A deep learning approach for early wildfire detection from hyperspectral satellite images 2019 7th International Conference on Robot Intelligence Technology and Applications (RiTA) November 1 - 3, 2019, Daejeon, Korea.
[13] M. Souza, A. Moutinho. and M. Almeida. Wildfire detection using transfer learning on augmented datasets. Expert Systems with Applications, vol. 142, Elsevier. March 2020.
[14] J. Lin, and Y Zhu. Environment-Agnostic Wildfire Detection with Satellite Imagery, Stanford CS230 Class Project, Winter 2018. [Available Online] https://cs230.stanford.edu/files_winter_2018/projects/6935030.pdf
[15] Modified Copernicus Sentinel data [2020] / Sentinel Hub Sentinel Hub, https://sentinel-hub.com/, Sinergise Ltd.