Wildfire Mapping in Interior Alaska Using Deep Neural Networks on Imbalanced Datasets

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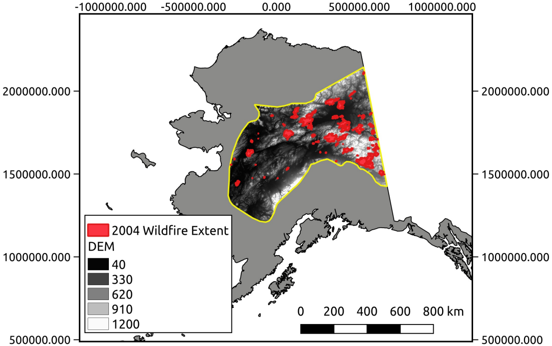
Research Questions

- Can we map wildfires in Interior Alaska based on imbalanced classes (wildfire vs. no-wildfire)?
- Use of MLP for supervised classification using MODIS as input and Monitoring Trends in Burn Severity (MTBS) as target variable.
- Does a weight-selection strategy on a deep MLP model based on the imbalanced class improve performance?

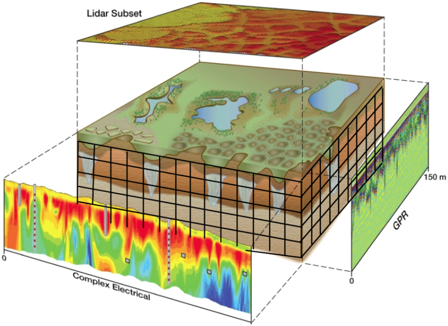


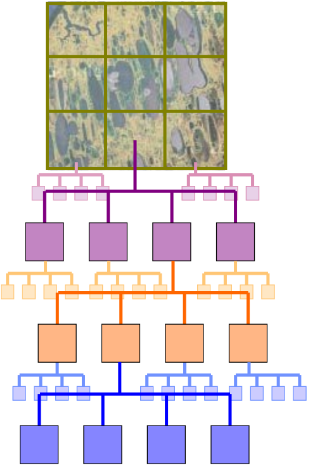
Overview

- Bounded by Interior Alaska, based on climate conditions.
- Background class (no-wildfire) significantly outweighs the wildfire class for 2004.
- 1,742,618 no-wildfire pixels and 105,072 wildfire pixels (500×500 m).
- Select MLP weights during training that reflect the imbalanced class.
- **Added segmentation algorithm and XGBoost for comparison.**

Motivation

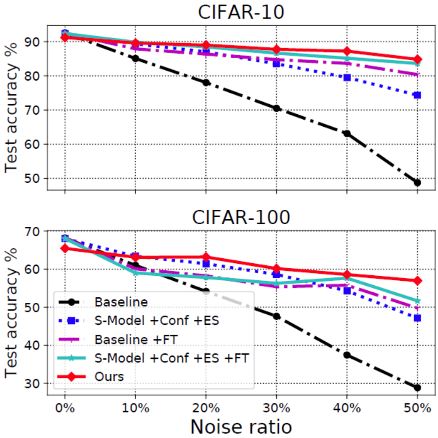
- Need to **provide unique datasets** for model parameterization on topics ranging from watershed hydrology to plant physiology that is being adopted by DOE's Earth System Modeling program and Next Generation Ecosystem Experiment (NGEE) Arctic (`https://ngee-arctic.ornl.gov/`).





NGEE Arctic Mission Statement `https://ngee-arctic.ornl.gov/mission`

Class Imbalance Problem

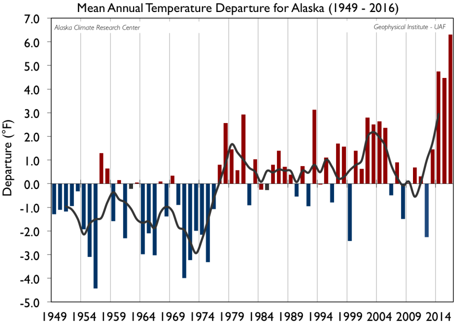


Learning to Reweight Examples for Robust Deep Learning (Ren et al., 2018)

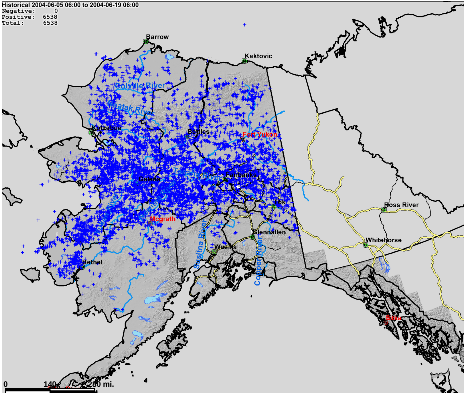
- Imbalanced data classification exists where one class (e.g., burned areas) contains a much smaller sample size than the others (e.g., unburned areas) in classification. It poses a great challenge for DNN architectures, due to the difficulty in recognizing the minority class (Sze-To and Wong, 2017).
- However, there has been a significant amount of research performed on the class imbalance problems using dataset resampling (Chawla et al., 2002), cost-sensitive weighting (Ting, 2000), and few-shot learning (Ravi and Larochelle, 2017).
- To determine the weights, Ren et al. (2018) method performs a meta gradient descent step on the current mini-batch example weights to minimize the loss on a clean unbiased validation set.

Alaska Wildfires – 2004

- One of the warmest and driest summers on record.
- Most lightning strikes recorded during summer.
- Wildland fires burned the largest area in recorded Alaska history.
- Total fires were 701 and area burned 6,600,000 acres.



Departure from average temperature across Alaska for every year since 1949. (Image Source: Alaska Climate Research Center)



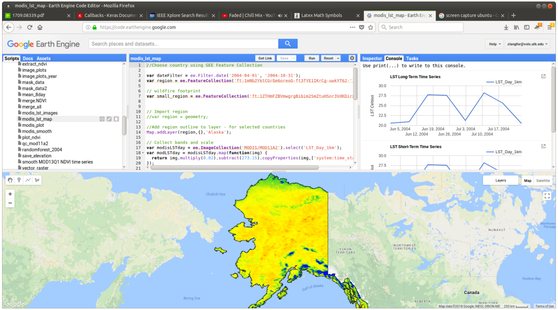
Number of lightnings strikes (6,538) in Alaska from June 5–19, 2004. The grand total was over 147,642 strikes.

Remote Sensing Datasets

We used Google Earth Engine (GEE) for processing images. Two types of datasets were used:

- MODIS: MOD09A1 (Surface Reflectance 8-Day L3 Global 500m)
- MODIS: MOD11A2 (Land Surface Temperature and Emissivity 8-Day L3 Global 1km)

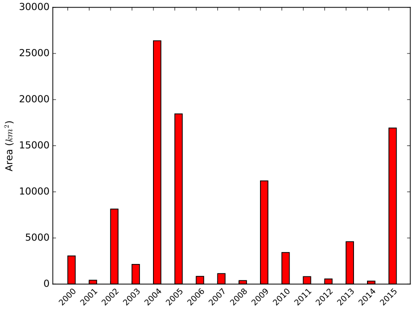
Description	Resolution	Variable
MOD09A1	500 m at 8 days	NDVI
	500 m at 8 days	EVI
	500 m at 8 days	SAVI
	500 m at 8 days	Bands 1–7 (459–2155 nm)
MOD11A2	1 km at 8 days	Daytime LST (Kelvin)



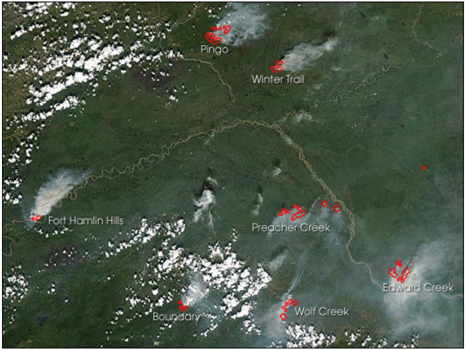
Google Earth Engine JavaScript API

Monitoring Trends in Burn Severity (MTBS)

- Includes all fires 1000 acres or greater in the western United States.
- Developed and managed by the USGS, USDA, and NASA using Landsat datasets.



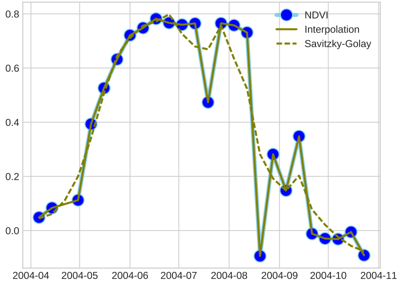
MTBS Area for Interior Alaska



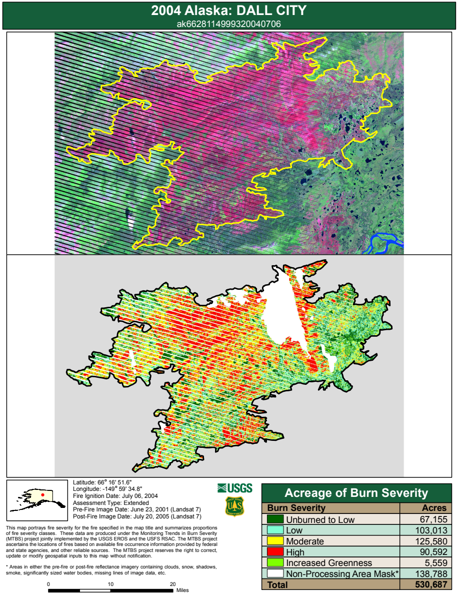
NASA Landsat 7 Image Over Interior Alaska

Image Processing

- Increased resolution to 500 m for all datasets, GEE performs nearest neighbor resampling.
- Linear interpolation for missing values.
- Savitzky-Golay filter was applied to smooth out noise.
- Converted MTBS vector boundary to raster pixels.

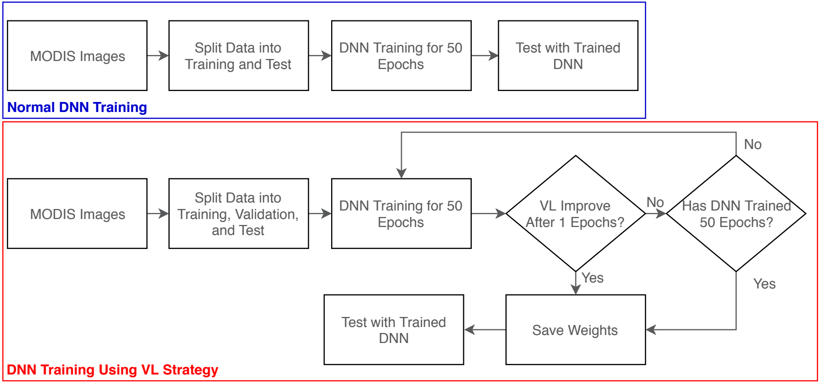


Example image processing workflow applied to a large wildfire, which occurred on July 6, 2004.



Fire severity for the Boundary fire based on Landsat 7. (Source: USGS and US Forest Service)

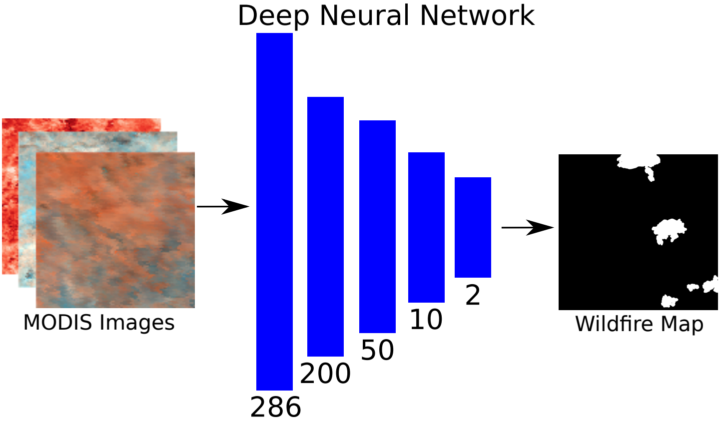
Validation-Loss Strategy



- Weight selection strategy from Sze-To and Wong (2017).
- Normal DNN training loss/accuracy measured on training data.
- VL strategy splits data into equal parts per class for for **selecting** weights.
- Split data equally between classes for measuring VL.
- Done by: keras.callbacks.ModelCheckpoint(filepath, monitor='val_loss', verbose=0, save_best_only=False, save_weights_only=False, mode='auto', period=1)

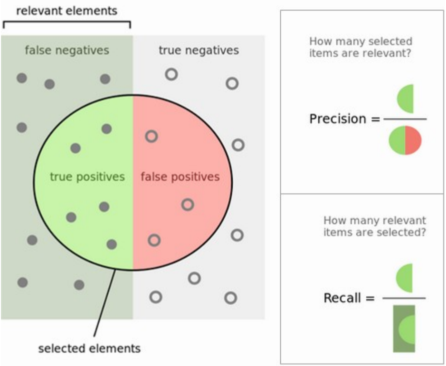
Deep MLP Models

```
self.model = Sequential()
self.model.add(Dense(60, activation=relu, kernel_initializer=normal, input_dim=nb_bands))
self.model.add(Dense(30, kernel_initializer=normal, activation=relu))
self.model.add(Dense(10, kernel_initializer=normal, activation=relu))
self.model.add(Dense(nb_classes, kernel_initializer=normal, activation=softmax))
self.model.summary()
self.model.compile(optimizer=Adam(), loss=sparse_categorical_crossentropy, metrics=[accuracy])
```



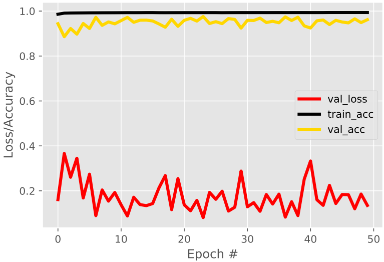
Training/Testing/Validation Datasets

Dataset	No-Fire	Fire	Percentage
Dataset-0 Train	1154333	70493	75%
Dataset-0 Test	427115	26356	25%
Dataset-0 Validation	7947	7947	10%
Dataset-1 Train	384375	23477	25%
Dataset-1 Test	1282862	78702	75%
Dataset-1 Validation	2617	2617	10%
Single Wildfire	9724	276	<1%

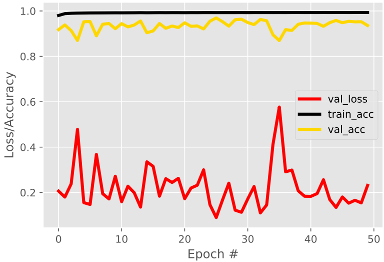


- Number of pixels (500×500) used for training, testing, and validation.
- The validation column was only applied when using the VL strategy.
- Precision – high value means that an algorithm returned substantially more relevant results than irrelevant ones.
- Recall – high value means that an algorithm returned most of the relevant results

Results – MLP Training



Dataset-0 training



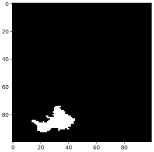
Dataset-1 training

- Showing scores during VL mode when classes are split equally for validation.
- Weights selected using lowest VL.
- Dataset-0 Validation Samples (7947) for each class.
- Dataset-1 Validation Samples (2617) for each class.

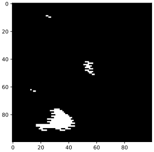
Results – Conventional DNN Training

Conventional DNN training method precision, recall, and number of test samples

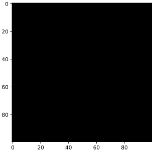
Dataset	Class	Precision	Recall	Samples
0	Fire	0.90	0.90	26356
	No-Fire	0.99	0.99	427115
1	Fire	0.00	0.00	78702
	No-Fire	1.00	1.00	1282862



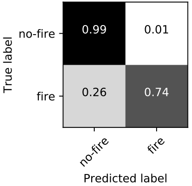
Test Image



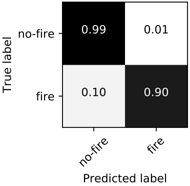
Dataset - 0



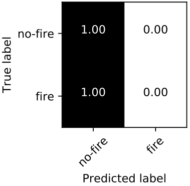
Dataset-1



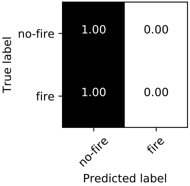
Dataset-0 single fire



Dataset-0 all



Dataset-1 single fire

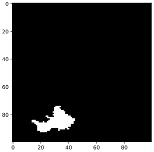


Dataset-1 all

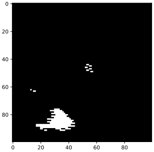
Results – VL DNN Training

VL DNN training method precision, recall, and number of test samples

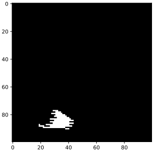
Dataset	Class	Precision	Recall	Samples
0	Fire	0.68	0.95	26356
	No-Fire	1.00	0.97	427115
1	Fire	0.61	0.96	78702
	No-Fire	1.00	0.96	1282862



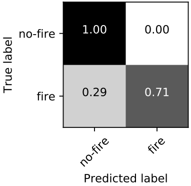
Test Image



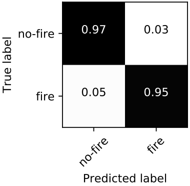
Dataset - 0



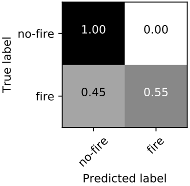
Dataset-1



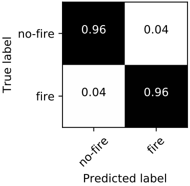
Dataset-0 single fire



Dataset-0 all



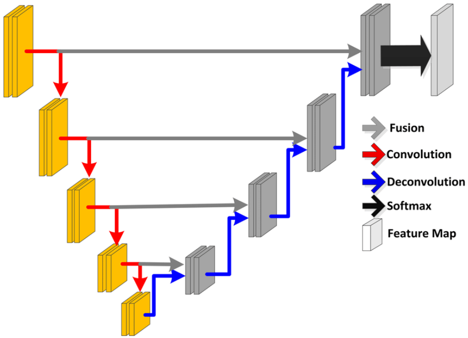
Dataset-1 single fire



Dataset-1 all

Results – U-Net Segmentation

- U-Net is 2D CNN architecture for fast and precise segmentation of images Ronneberger et al. (2015).
- Consists of a contracting path (left side) and an expansive path (right side).



U-Net training method precision, recall, and number of test samples

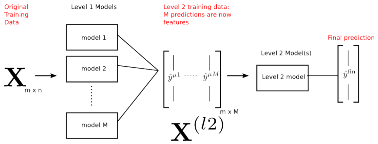
Dataset	Class	Precision	Recall	Samples
0	Fire	0.00	0.00	518879
	No-Fire	0.95	1.00	27293

Results – XGBoost Algorithm

- XGBoost is a scalable and accurate implementation of gradient boosting machines (Chen and Guestrin, 2016).
- XGBoost used a more regularized model formalization to control overfitting.

Table: XGBoost method scores for precision, recall, and number of test samples

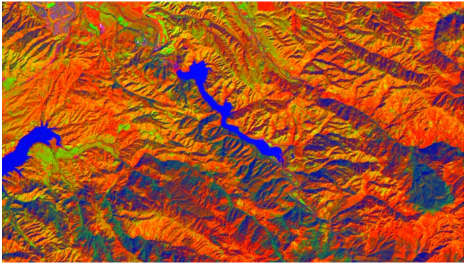
Dataset	Class	Precision	Recall	Samples	Region
0	Fire	0.94	0.85	26,356	Study Region
	No-Fire	0.99	1.00	427,115	Study Region
	Fire	0.88	0.77	276	Single Wildfire
	No-Fire	0.99	1.00	9,724	Single Wildfire
1	Fire	0.94	0.85	78,702	Study Region
	No-Fire	0.99	1.00	1,282,862	Study Region
	Fire	0.88	0.76	276	Single Wildfire
	No-Fire	0.99	1.00	9,724	Single Wildfire

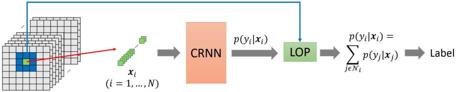


Source:https://www.kdnuggets.com

Conclusions and Next Steps

- MODIS bands can be used to predict spatial extents of wildfire with good accuracy.
- Google Earth Engine provides a powerful platform for processing and analyzing datasets without moving data.
- VL DNN training strategy significantly improves performance and possibly captures unknown wildfires outside MTBS dataset.
- Next steps: more sophisticated algorithms utilizing sequential data and meta-learning approaches.





Source: Convolutional Recurrent Neural Networks for Hyperspectral Data Classification Wu and Prasad (2017)

Acknowledgments

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Code and slides will be available at
`https://github.com/langfordzl/zlangford_icdm2018`

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