Computer Vision Approaches to Air Quality Prediction

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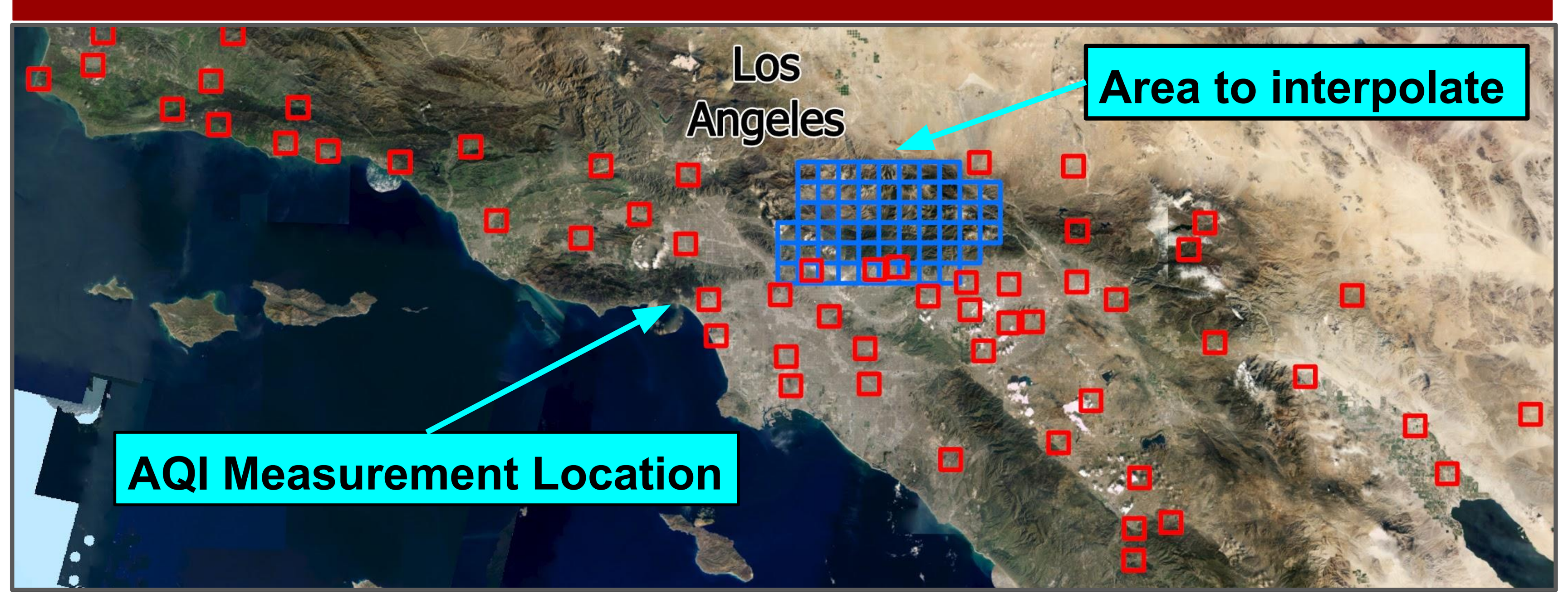
Motivation

- Air Quality Index (AQI) aggregates 5 major pollutants to report air health.
- AQI is affected by factors such as wildfires, industrialization, or weather which can be captured by satellite imagery.
- AQI between sensors is currently predicted through spatial interpolation of measurements at AQI locations. [1]
- **Can we make a more flexible model based upon satellite imagery data that improves these predictions?**

Datasets

- EPA Historic AQI and pollutant data: 55 sites collected from 2017 to 2020, final reported AQI which is the maximum of each of the 5 major pollutants (typically ozone or PM2.5).
- Planet Satellite Imagery: ~7600 images of PlanetScope 3-band visual asset. 3 meter resolution UTM projection RGB GeoTIFF raster items.
- Reduce six EPA AQI classes to three: Good - (0, 50), Moderate - (51, 100), and Unhealthy (100+)

Data Pipeline



$$x^{(i)} \in \mathbb{R}^{224\times224\times3} \rightarrow f(x^{(i)}) \rightarrow y^{(i)} \in \{0,1,2\}$$

Train	Dev	Test	Unlabeled Evaluation
3333	1111	1111	58

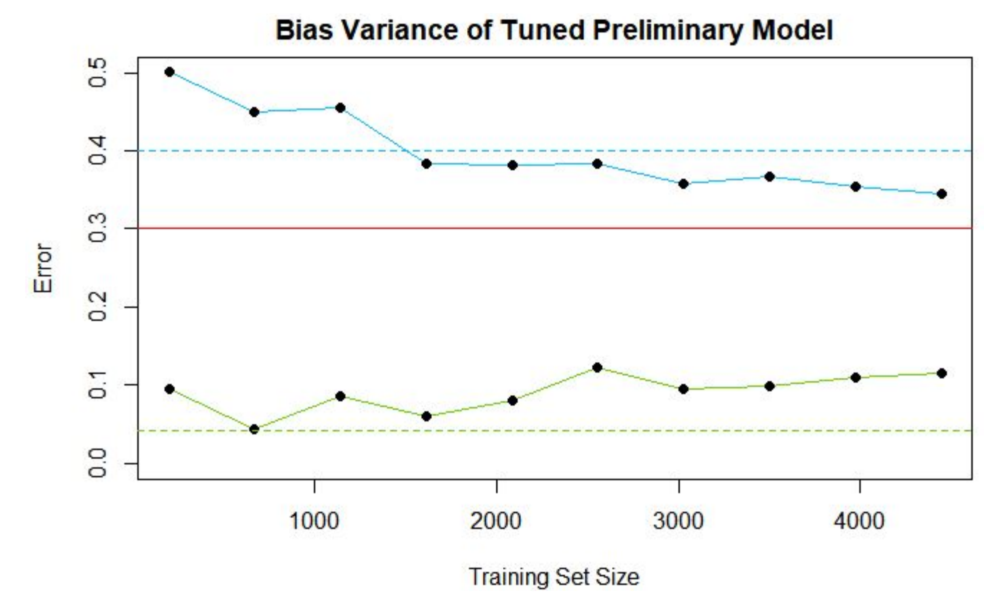
Machine Learning Approaches

Model	Regularization	Penalty	Implementation	Test Accuracy
Softmax regression	L2	1.0000	LogisticRegression	0.6148
RBF SVM	L2	1.0000	SVC	0.6450
Linear SVM	Elastic Net	0.0001	SGDClassifier	0.6481
Tuned Linear SVM	L2	1.0000	SGDClassifier	0.6602

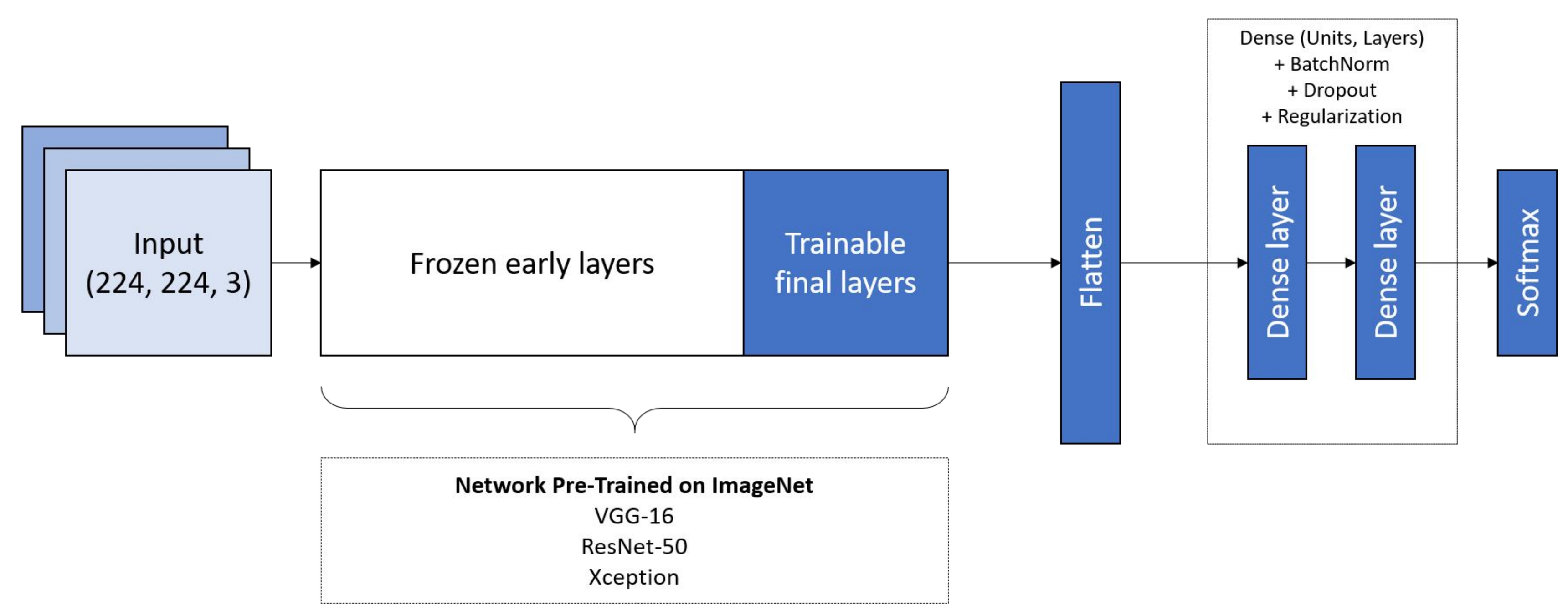
Observation
- Pixel-level models give promising results in spite of simplicity; also have advantage of fast training times

Bias-Variance
- Baseline linear SVM (averages shown by dashed lines) highly variable
- Tuned model (solid lines) reduces variance by regularization
- Weights improved class imbalance

$$w_{y^{(i)}} = \frac{\#\ \text{samples in largest class}}{\#\ \text{samples for } y^{(i)}}$$



Convolutional Neural Network



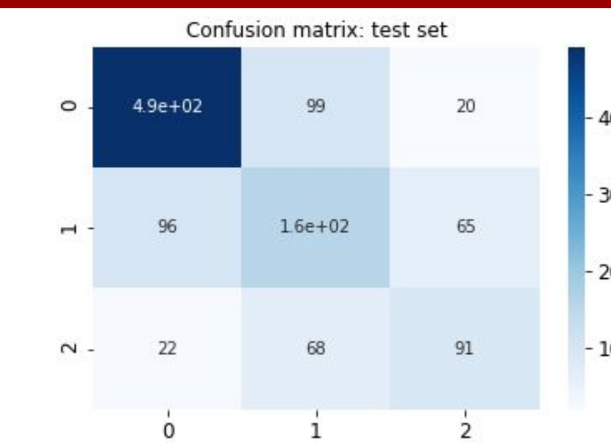
Base Model	Layers	Dropout	L2 Factor	Strategy	Optimizer	Unfrozen Layers	Test Accuracy
Xception	128, 64	0.5	0.0	Staged	Adam	15	0.6526
Xception	Global avg. pool			Staged	Adam	25	0.6373
Xception	1024 x 2	0.5	0.05	Direct	Slow SGD	15	0.6454
Xception	1024 x 2	0.3	0.0	Staged	Adam	15	0.6580
Xception	1024 x 2	0.3	0.0	Staged	1-Cycle	32	**0.6670****

Training Strategy:
- Direct: begin training immediately with layers unfrozen; use low learning rate
- Staged: first train classification output with high learning rate; then, lower rate and unfreeze layers

Classification Module:
- Fully connected or global average pooling

Optimizer:
- SGD or Adam; employ one of exponential, power, or 1-Cycle learning rate scheduling

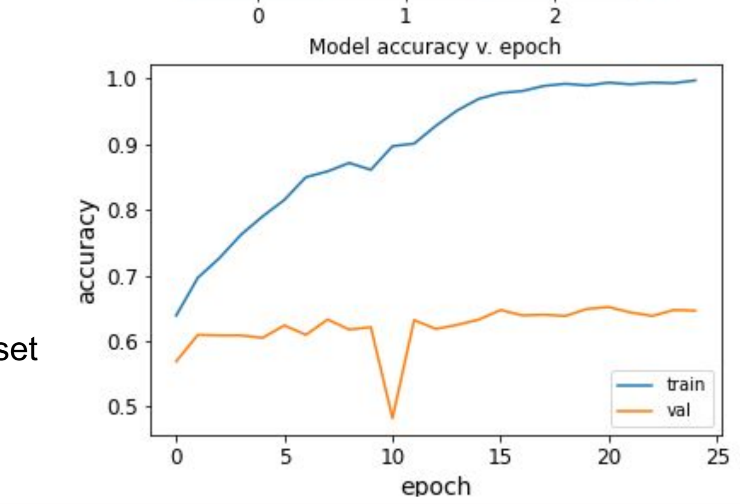
Results



Challenges training with small dataset
- Unstable learning curves
- Satellite images unlike ImageNet base task
- Small dataset - difficult to see signal

Promising results from experimentation
- Class weights ensure balance
- Best CNN**: 66.70% test accuracy
- Best tuned SVM: 66.02% test accuracy

Expansive hyperparameter search
- Potential for further iteration over options
- Second round of pre-training on other satellite dataset



Unsupervised Analysis

Imagery from 9/26/2020

9/20 Fires:
1. Unnamed
2. Bobcat Fire
3. Dam Fire
4. Ranch Fire

Good
Moderate
Unhealthy
MODIS Fire

Conclusion

Key Findings
- Able to correctly classify nearly 70% of real-time AQI images with small training dataset
- More work needed to discriminate between clouds and severely unhealthy AQI conditions as well as hue differences in seasonal patterns (i.e. Fall vs Spring).

Future Study
- More training images to improve real-time prediction
- Image bands beyond RGB: infrared, topographical
- Time series dependency of AQI

References:
[1] A. Reff, D. Mintz, and L. Naess, “The 03 NowCast: U.S. EPA’s method for characterizing and communicating current air quality.” [Online].
[2] G. Technology and A. Center, “Modis fire detection.”https://fsapps.nwcg.gov/googleearth.php, 2020.