Methane Plume Detection with Future Orbital Imaging Spectrometers

Jake Lee[1], Steffen Mauceri[1], Sharmita Dey[1], Arjun Rao[1], Ryan Alimo[1], Andrew Thorpe[1], Siraput Jongaramrungruang[2], Riley Duren[1,3,4]

[1]Jet Propulsion Laboratory, California Institute of Technology, Pasadena, CA
[2]California Institute of Technology, Pasadena, CA
[3]University of Arizona, Tucson, AZ
[4]CarbonMapper.org, Pasadena, CA

Introduction

Despite methane's important role as a greenhouse gas, the contribution of individual sources to rising concentrations in Earth's atmosphere is poorly understood. This is in part due to the lack of frequent measurements on a global scale. Future missions such as Earth Surface Mineral Dust Source Investigation (EMIT), Surface Biology and Geology (SBG), and Carbon Mapper promise to provide global, spatially resolved spectroscopic observations that will allow for the mapping of methane sources. However, the detection of individual sources is challenged by expected retrieval artifacts and noise in matched filter retrieved methane concentrations from these sensors. These artifacts make simple thresholding for high concentrations infeasible, requiring more complex plume detection models capable of considering plume morphologies and other characteristics.

To advance reliable methane plume detection machine learning methods,

- **We developed several plume detection methods for 30m hyperspectral imagery downsampled from airborne campaigns.**
- **We evaluated their performance and sensitivity.**

Data Processing

Tile Sampling

Domain experts labeled methane source coordinates in methane matched filter products of the 2018 AVIRIS-NG CA CH4 campaigns. Based on these coordinates, 256 by 256 square tiles were sampled with a plume-to-background ratio of 1:20 to create a classification dataset.

Downsampling

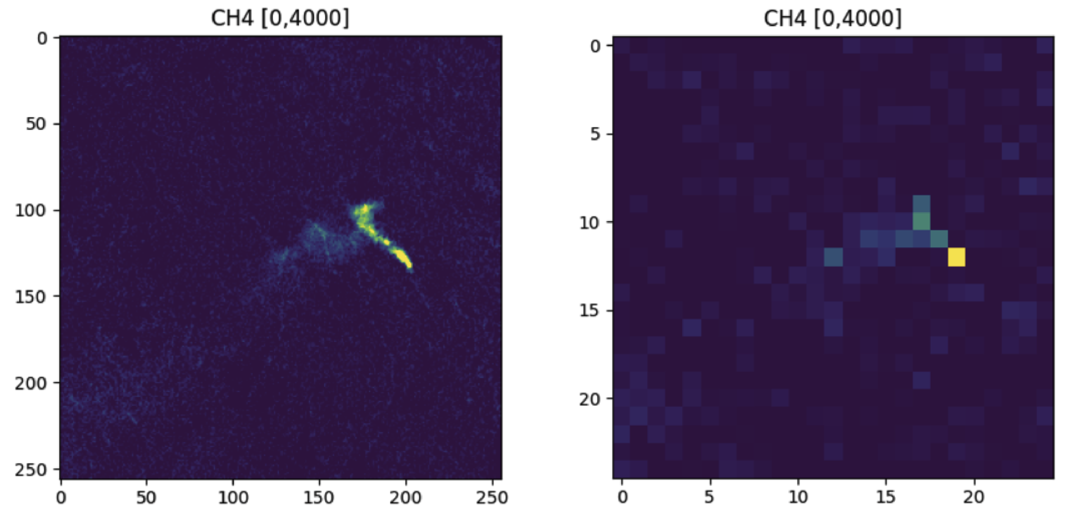
To simulate space-borne observations, we downsample these tiles from 3m to 30m ground sampling distance while increasing the signal-to-noise ratio by a factor of two.

Plume Filtering

To investigate the sensitivity of plume detection methods to different plume sizes and intensities, we subsample the tiles by applying a combination of filters to only keep plumes with a minimum concentration (250, 500, 1000, and 2000 ppmm) and pixel footprint (greater than 0, 1, and 4 pixels). This results in a total of 12 datasets. More aggressive filtering creates an easier task, but also results in less training data for the models.

Methodology

We evaluate the performance of three machine learning models on each dataset. As a baseline, we evaluate a **linear support vector classifier** on the maximum enhancement of each tile. Additionally, we evaluate **texturecam** [1], a decision tree classifier that can also consider spatial context. As our state of the art model, we evaluate the **GoogLeNet** [2] convolutional neural network (CNN). We repeat these experiments with the original 3m resolution tiles to quantify the performance loss caused by the lower resolution satellite data. We also repeat the CNN experiments by adding 729 tiles of unfiltered Large Eddy Simulation (LES) plumes [3] to all datasets to determine if simulated data can improve performance.



(a) AVIRIS-NG tile *(b) Spaceborne tile*

Figure 1. Example of a downsampled tile

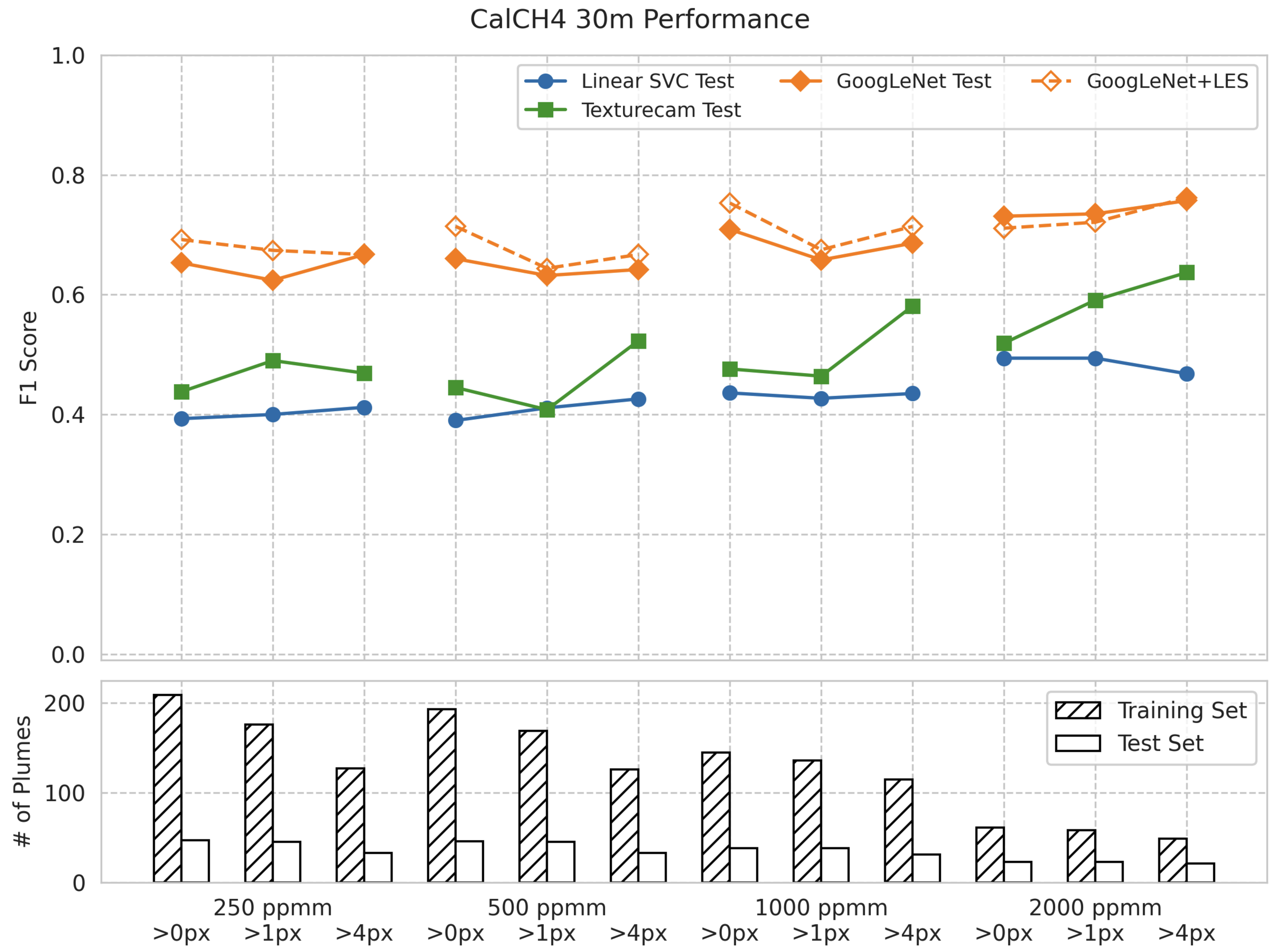


Figure 2. Classifier performance on data downsampled to 30m resolution.

Results

Fig. 2 shows the F_1-scores of models tested on held-out 30m data.

- As expected, the CNN outperforms other baseline methods.
- Performance trends upwards as only stronger/larger plumes are kept.
- Including LES plumes for CNN training results in small perf. gains.

Fig. 3 shows the F_1-scores of models tested on the same data at 3m.

- The information gain from using the original resolution accounts for an increase of up to 0.15 F_1-score in detection performance.

CNNs are the best spaceborne plume detection method despite our limited training set. Future work with a larger, more diverse dataset with more machine learning methods is needed to prepare for future orbital imaging missions.

References

[1] Wagstaff, K. L., et al. "Smart, texture-sensitive instrument classification for in situ rock and layer analysis." Geophysical Research Letters 40.16 (2013): 4188-4193.
[2] Szegedy, Christian, et al. "Going deeper with convolutions." Proceedings of the IEEE conference on computer vision and pattern recognition. 2015.
[3] Rao, Arjun, et al. "Improving Imaging Spectrometer Methane Plume Detection with Large Eddy Simulations." AGU Fall Meeting. 2021. Poster GC45B-0838.

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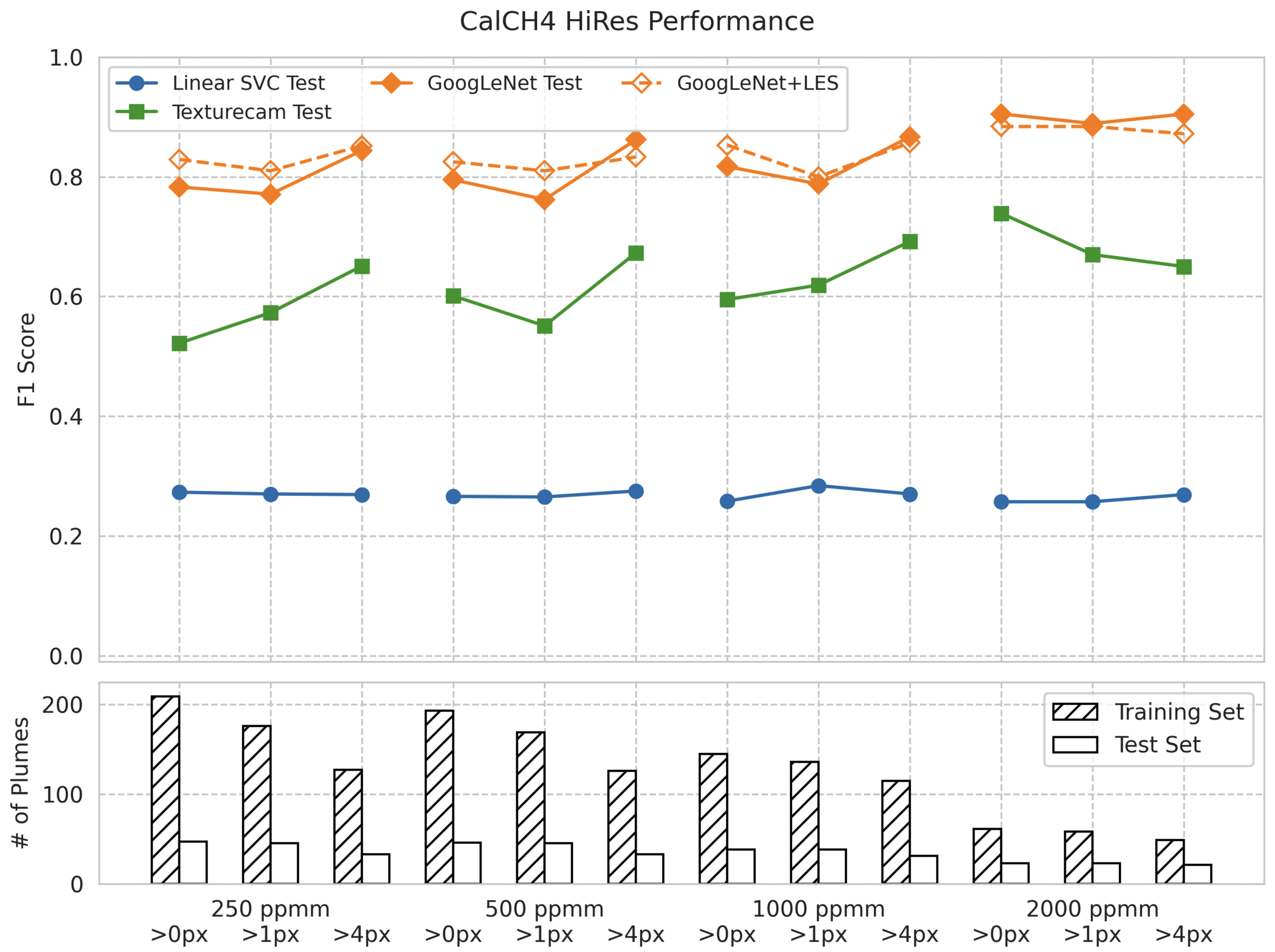

Figure 3. Classifier performance on original resolution data.