Improving on Deep Learning-Based Smoke Detection with a Multi-Model Ensemble Approach

Author Name
Institution
email@example.com

Abstract

With the increasing frequency and severity of wildfires associated with climate change, there is an urgent need for effective and rapid wildfire and smoke detection tools. Recent advancements in computer vision have demonstrated the potential of deep learning models to automate the semantic segmentation of high-resolution images by training encoder-decoder networks on large labeled datasets. However, single-model approaches can struggle with generalization and accuracy in diverse conditions. To address these challenges, we propose creating an ensemble of deep learning models to produce accurate and representative predictions of wildfire smoke plumes and their relative density (low, medium, high) in Geostationary Operational Environmental Satellite (GOES) imagery. Our preliminary results indicate that this ensemble technique can significantly improve performance compared to using a single model. This multi-model data-driven ensemble is expected to support fire and hazard management by being able to automate the monitoring of smoke in real-time from satellite imagery, providing a valuable tool for fire and hazard management in the face of worsening widfires.

1 Introduction

Climate change is driving an increase in the frequency and severity of wildfires [CITATION]. Wildfires increase smoke and particulate matter in the atmosphere [CITATION], posing more risks of respiratory issues and other air quality-induced health problems in recent years (Burke et al., 2021). Effective and timely wildfire and smoke detection tools are thus essential for supporting hazard management and mitigating risks to human health.

The NOAA Geostationary Operational Environmental Satellites (GOES) provide high spatial and temporal resolution imagery of North America (Goodman et al., 2019), which can be leveraged to detect the presence and density of smoke plumes. The Hazard Mapping System (HMS) Fire and Smoke Product currently relies on human analysts to annotate the presence of smoke over North America using imagery from the GOES imagery (McNamara et al., 2004). However, this product is limited by the availability of human analysts, outputting annotations once to several times a day.

To address this limitation in the frequency of smoke data, we are leveraging advancements in deep learning to automate the detection of smoke from GOES imagery. Deep learning models, particularly encoder-decoder neural networks, have shown promise in automating the semantic segmentation of high-resolution images [CITATIONS]. By automating this task, we can enable more frequent and consistent detection of smoke plumes.

This proposal focuses on enhancing the capability of smoke detection with deep learning through the use of multi-model ensemble techniques. It has been shown for classification that ensemble methods that combine the predictions of multiple classifers can often perform better than a single classifer (Dietterich, 2000). Particularly, utilizing a diverse set of classifiers in an ensemble is important to achieve the improvement in performance (Kuncheva and Whitaker, 2003). In the neural network setting, combining the predictions of multiple independently-trained models can improve generalization and prediction accuracy of neural networks (Hansen and Salamon, 1990), (Cheng Ju and van der Laan, 2018).

This approach aims to provide a more reliable and accurate tool for real-time monitoring of smoke, ultimately supporting fire and hazard management efforts and contributing to climate resilience and adaptation strategies.

2 Data and Methods

The dataset we use consists of 183,672 samples, each with three spectral channels (C1-C3) of GOES imagery paired with HMS smoke annotations (pixel-wise labels of smoke density low, medium, or high) for a specific datetime and location. The data spans 2018-2024, and we set aside 2023 for validation and 2022 for testing, with the remaining years used for training.

We are utilizing a variety of pre-developed encoder-decoder architectures that were created and optimized for semantic segmentation (labelling images on a pixel-wise basis with multiple classes) contained within the Segmentation Models package (Iakubovskii, 2019). The differences between these architectures consists of features such as atrous spatial pyramid pooling, model scaling, and residual connections (Chen et al., 2018), (Li et al., 2018), (Zhou et al., 2018). A collection of these models are trained independently on 8 Nvidia P100 GPUs using the Adam optimizer with a learning rate of 0.001 and batch size of 128.

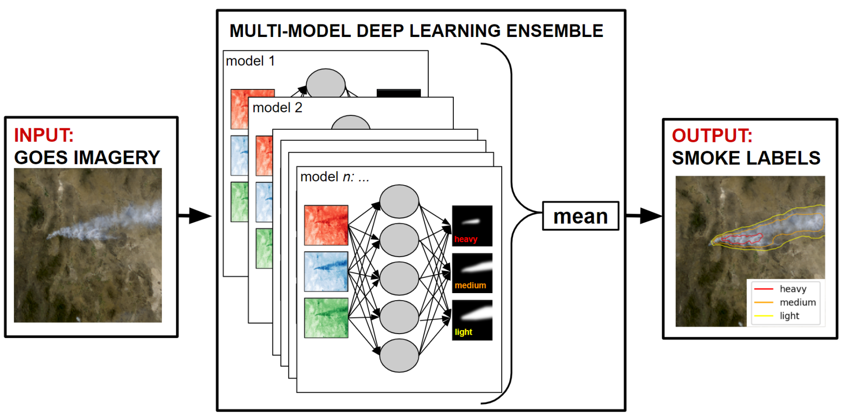

Figure 1: Multi-Model Ensemble Framework.

3 Results

results

4 Conclusions and Future Work

conclusions

References

Marshall Burke, Anne Driscoll, Sam Heft-Neal, Jiani Xue, Jennifer Burney, and Michael Wara. The changing risk and burden of wildfire in the united states. *Proceedings of the National Academy of Sciences*, 118(2):e2011048118, 2021. doi: 10.1073/pnas.2011048118. URL https://www.pnas.org/doi/abs/10.1073/pnas.2011048118.

Liang-Chieh Chen, Yukun Zhu, George Papandreou, Florian Schroff, and Hartwig Adam. Encoder-decoder with atrous separable convolution for semantic image segmentation, 2018. URL https://arxiv.org/abs/1802.02611.

Aurélien Bibaut Cheng Ju and Mark van der Laan. The relative performance of ensemble methods with deep convolutional neural networks for image classification. *Journal of Applied Statistics*, 45(15):2800–2818, 2018. doi: 10.1080/02664763.2018.1441383. URL https://doi.org/10.1080/02664763.2018.1441383. PMID: 31631918.

Thomas G. Dietterich. Ensemble methods in machine learning. *Multiple Classifier Systems*, pages 1–15, 2000.

S. J. Goodman, T. J. Schmit, J. Daniels, and R. J. Redmon. *The GOES-R Series: A New Generation of Geostationary Environmental Satellites*. Elsevier, 2019.

L.K. Hansen and P. Salamon. Neural network ensembles. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 12(10):993–1001, 1990. doi: 10.1109/34.58871.

Pavel Iakubovskii. Segmentation models pytorch. https://github.com/qubvel/segmentation_models.pytorch, 2019.

Ludmila I. Kuncheva and Christopher J. Whitaker. Measures of diversity in classifier ensembles and their relationship with the ensemble accuracy. *Machine Learning*, 51 (2):181–207, 2003. ISSN 1573-0565. doi: 10.1023/A:1022859003006. URL https://doi.org/10.1023/A:1022859003006.

Hanchao Li, Pengfei Xiong, Jie An, and Lingxue Wang. Pyramid attention network for semantic segmentation. *CoRR*, abs/1805.10180, 2018. URL http://arxiv.org/abs/1805.10180.

Donna McNamara, George Stephens, Mark Ruminski, and Tim Kasheta. The hazard mapping system (hms) - noaa's multi-sensor fire and smoke detection program using environmental satellites. *Conference on Satellite Meteorology and Oceanography*, 01 2004.

Zongwei Zhou, Md Mahfuzur Rahman Siddiquee, Nima Tajbakhsh, and Jianming Liang. Unet++: A nested u-net architecture for medical image segmentation. *CoRR*, abs/1807.10165, 2018. URL http://arxiv.org/abs/1807.10165.