Classifying Methane Emission Sources From Publicly Available Satellite Imagery

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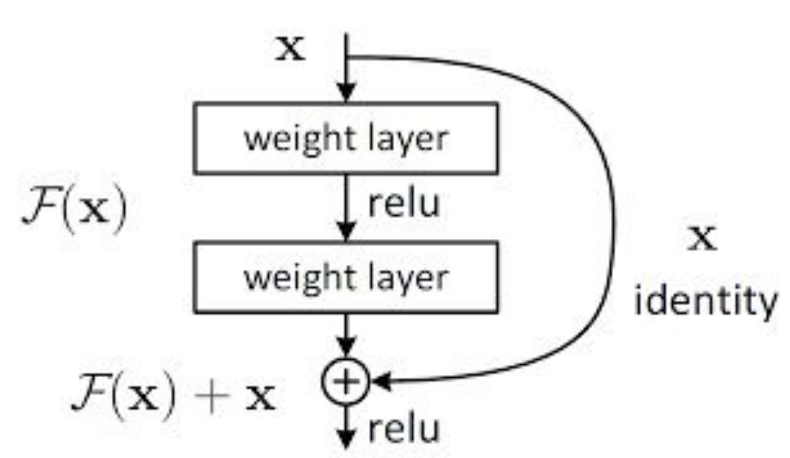
Problem Overview

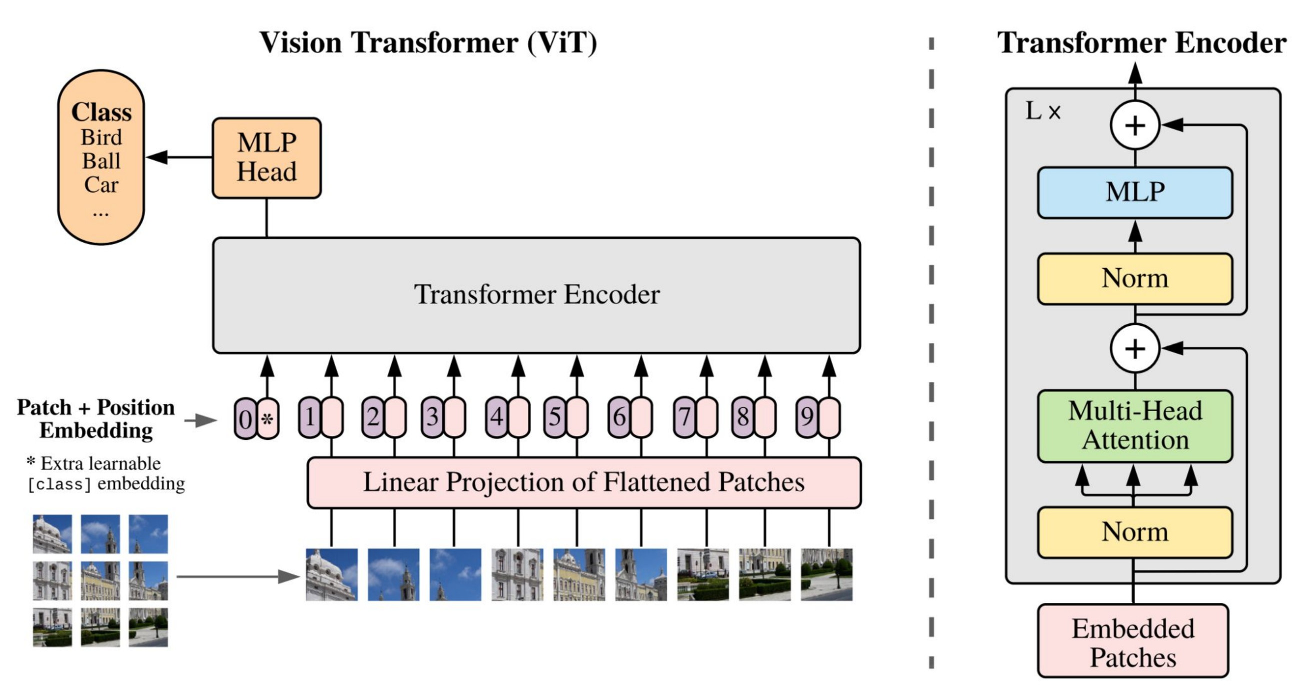
- Methane is the second-largest contributor to greenhouse gas effect
- Satellites provide methane concentrations in the atmosphere, but classifying the sources is a labor intensive and time consuming process
- Applications in carbon accounting, emissions surveys, and environmental regulation
- **Given the latitude and a longitude of a methane emitting facility, we collect a satellite image of the surrounding region and predict its class**

Background

- Previous work has used manual labeling with satellite imagery and other sources of information such as location data in order to map sources of methane emissions
- The end goal is to have an end to end pipeline that automatically locates and identifies sources of methane emissions using only satellite data

Methods





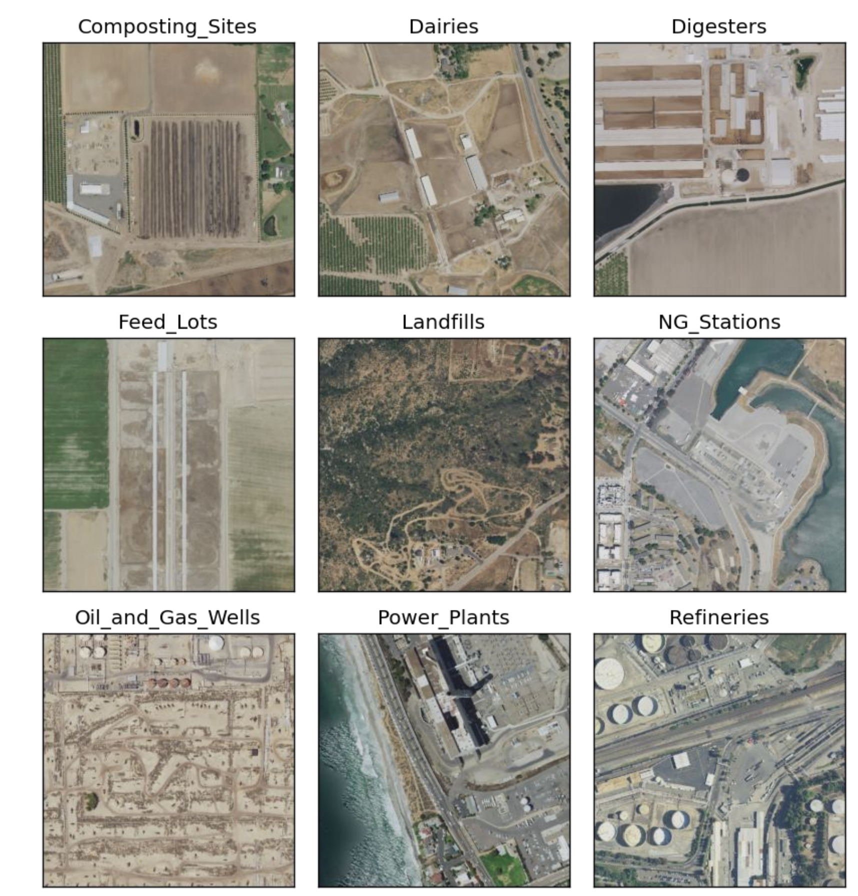
- We use two baseline methods (**Naive Bayes, SVM**) as well as two deep learning models, **ResNet** and **Vision Transformers**, to perform multi-class classification on our dataset
- Used models pre-trained on ImageNet, replaced the heads for a linear layer for our 15 classes and fine tuned on our dataset
- Tested various data augmentation and image transformation techniques

Conclusion and Future Work

- ResNet is more suited than ViT for this task, but deep learning methods provide the best performance in automatically classifying methane emissions
- Model could be built in end to end framework to find and classify methane emissions, which paves the way for future systems that can perform this task on a global scale

Dataset

- Sources of Methane Emissions (Vista-CA) dataset, created by NASA under the North American Carbon Program
  - 15 classes of methane emitting facilities + locations
  - ex. Dairies, Oil and Gas, Power Plants, Landfills
- Collected 1 m/pixel resolution RGB satellite images corresponding to 0.25 km^2 area around each location
- Randomly selected up to 1000 examples from each class, with 5938 total data points
- Used 80/20 split for training and validation



Results

Figure (right): Confusion matrix of the ResNet-50 model for the validation data. The true class appears on the y-axis, and the predicted class is on the x-axis

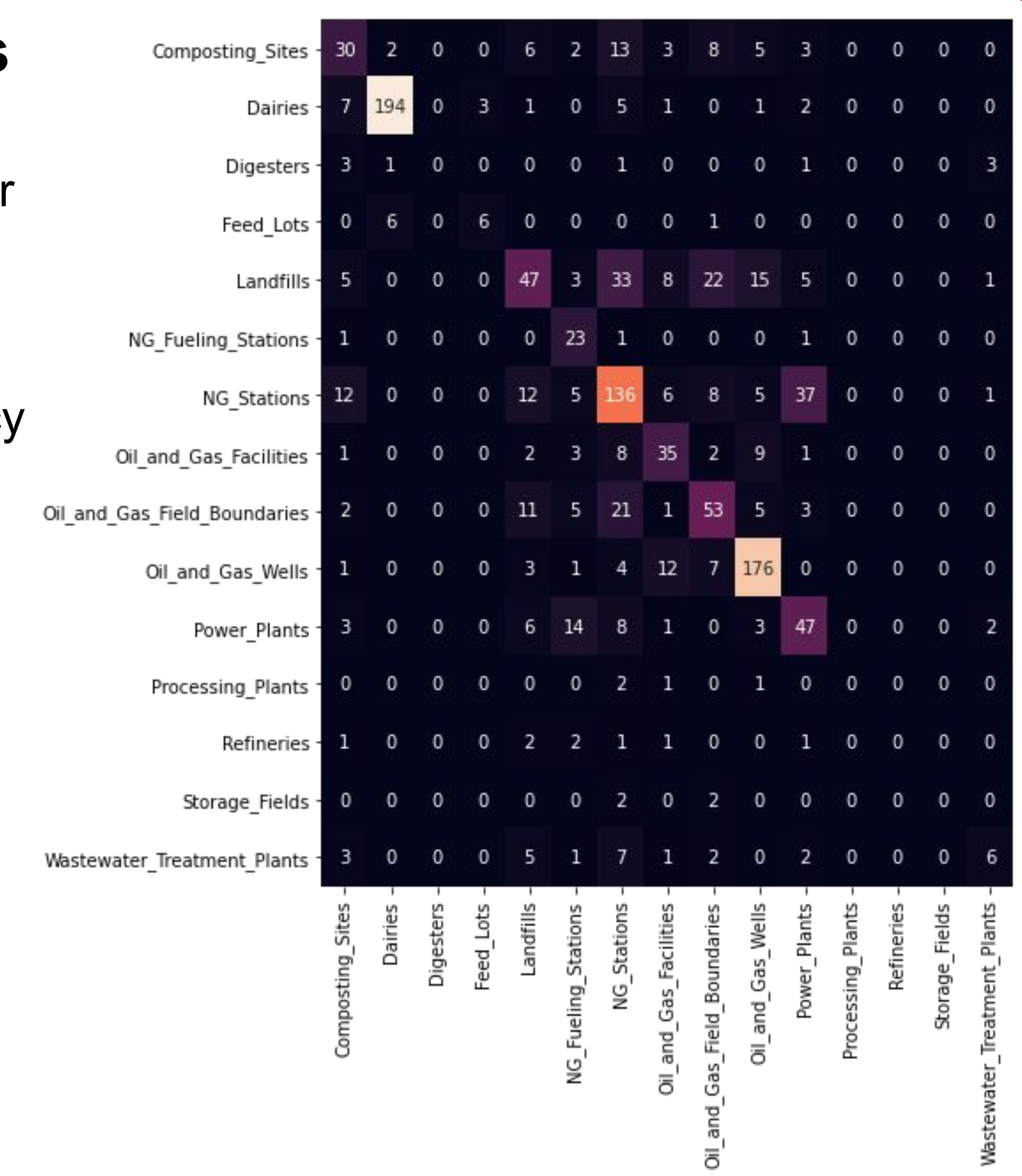


Figure (below): example image with corresponding saliency map for ResNet and ViT. As seen, ViT struggles due to the patch size for these satellite images

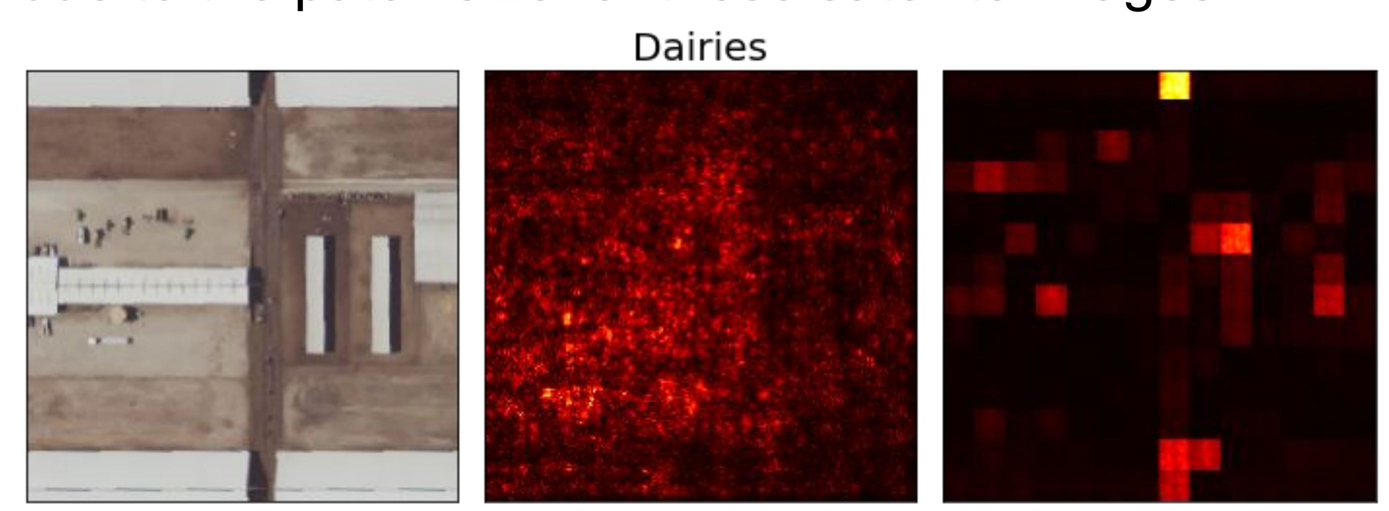


Table 1. Results for Classification Models

Model	Training Acc	Validation Acc
Naive Bayes	0.2378	0.2205
SVM	0.9915	0.3047
ResNet50 - Cropped	0.9385	0.6305
ResNet50 - Resized	0.9242	0.6069
ResNet50 - Rand Crop	0.8432	0.6571
ResNet50 - Rand Crop + Flip	0.8276	0.6838
ViT-B/16	0.4817	0.4857

Table: Depicts various models and their training and validation accuracy. The best performing model was ResNet at 68% accuracy. Vision Transformers performed considerably worse, most likely due to the identifying features of the image being too large for the 16x16 patches