Methane detection using machine learning

1 Introduction

Methane is one of the most potent greenhouse gases, responsible for around 30 % of global temperature increases. Although it remains in the air for only 7 to 12 years, it traps more heat than a carbon dioxide molecule. It is the second biggest contributor to global warming after carbon dioxide[5].

Tracking Methane emissions is very important to monitor the state of the atmosphere correctly and to make better predictions regarding future extreme climate events.

60 % of methane emissions are anthropogenic, while the remaining 40 % are natural from places like wetlands. The biggest anthropogenic contributors to methane are agriculture, the energy sector, and the decomposing waste from landfills. Methane leaks from pipes during transport or from other sources during other steps of extracting and processing fossil fuels[9].

Despite all this tracking methane has been difficult. Methane can be locally monitored using research planes and balloons carrying equipment, but satellites are the only option for global monitoring. Satellites like the Copernicus Sentinel-2 mission, which monitors multiple things, or the newly launched MethaneSAT, which will focus on methane emissions provide us with much-needed monitoring of methane in the atmosphere[9]. All of these satellites generate image data which needs to be processed to inform our actions. For this, we need powerful methods to analyze and interpret these images quickly.

Most of the current methods are quite good at finding big methane emissions but struggle to find smaller leaks. Our project is trying to find a way to detect smaller leaks in the satellite data.

2 Literature Review

Methane has a short atmospheric lifespan but its impact on climate change is significant. Its removal from the atmosphere could rapidly reduce global warming in the next decades. Researchers have shown that large leaks, known as super-emitters, disproportionately increase atmospheric methane levels. Růžička et al. also highlighted this in their work on methane plume detection using hyperspectral machine learning models. Methane plume detection in remote sensing data is achievable; however, current methods often produce a high number of false positives and depend on manual input. The development in Machine Learning (ML) is constrained by the scarcity of extensive annotated real-world datasets[8]. Růžička et al. developed the HyperSTARCOP model that tops strong matched filter baseline by over 25% in F1 score. In addition to that, the false positive rate per grouped tile was reduced by over 41.83%[12][8].

Concentration of methane emissions from lakes is affected by various factors according to Johnson et al. "(a) lack of systematic approaches to explicitly account for temporal and spatial flux variability among lake environments and seasons; (b) limited reliable data on lake area and distribution; (c) minimal observations of timing and duration of ice-free/emission seasons; (d) not including ecoclimatic characteristics of lake systems; and (e) representativeness and utility of available flux observations". Their claim is that currently there are no large-scale, multi-lake emission estimates are available in spatially- and temporally-explicit formats [7].

In Oil and Gas Industry, methane emissions originates from production, transmission and storage of Oil and Gas. This industry contributes to one-fifth of the total methane emission[11]. Andrews et al developed methane sensors that incorporate Gaussian process regression, an ML method, that allows to achieve monitoring accuracies with handful of parameters and all this in real-time. Their sensors achieved an accuracy of 1 part per million methane (ppm) and can detect leaks at rates of less than 0.6 kg/h. The major limitation to their tool is the dynamic environmental conditions on the field. Lavaux et al. recently demonstrated 12% of all oil and gas methane emissions result from episodic ultra-emission events due to equipment failures on oil rigs, pipelines, or well pads[8].

Studies by Ashayari et al.,2021 suggests that advanced machine learning techniques, such as Convolutional Neural Networks (CNNs) are recognised for their excellent success in image recognition tasks from images in ways which is comparable to visual processing of humans[2]. Jahan et al developed a CNN model using a dataset generated from Large-Eddy Simulation (LES), which simulated Airborne Visible/Infrared Imaging Spectrometer (AVIRIS-NG) measurements at various source flux rates (5–100 kg/hr) and wind speeds (1–10 m/s). Their deep neural network architecture was optimized for model hyperparameters, enhancing accuracy and allowing for precise quantification of source flux rates. When tested on synthetic 2D image datasets, the model demonstrated mean absolute percentage errors of 2.15% on the training dataset, 5.02% on the validation dataset, and

4.84% on the test dataset for predicting source flux rates in kg/hr. In contrast, conventional flux inversion methods typically show prediction errors of around 25–50%, while the machine learning approach achieved an accuracy improvement of more than 17%[6]. However, the success of ML in emission quantification hinges on the availability of high-quality, comprehensive datasets and the development of algorithms that can navigate the intricacies of atmospheric science. Andrews et al. demonstrated that by utilizing extensive datasets from satellite imagery, aerial surveys, and ground-based sensors, machine learning algorithms can identify subtle patterns and changes in emission plumes that are often undetectable by conventional methods[1]. Study by Ravindiran et al. highlights that recent advances focuses on integrating consistent atmospheric process and employing use of ensemble techniques to quantify uncertainties[10].

Methane mitigation efforts stand to benefit greatly from such scalable, advanced analytical approaches tailored to handle real-world complexity not feasibly managed by traditional methods alone, offering unprecedented accuracy and efficiency in identifying and measuring greenhouse gas emissions[6].

3 Proposed Method

We are proposing using Vision Language Models (VLM) inside a U-Net architecture, with VLM replacing the encoder section as was done by Rouet-Leduc et. al. [11] but we propose modifying their architecture by introducing an edge detection algorithm that takes the input from every decoder layer, which is then combined to produce an image that further combined with the decoder output yields a final image; this is the E-UNet architecture by Han et al [4]. But for edge detection, we are choosing to use a quantum algorithm for image extraction based on the Kirsch operator by Xu et al. [13], instead of a machine learning model.

Traditional image segmentation requires explicit target objects or pre-defined categories for pixel-level classification. But this method severely limits the application of image segmentation in the real world, where the objects could be out of the training set or just to be able to understand complicated human instructions such as in self-driving cars and augmented reality. With the advent of VLM, image segmentation has undergone a paradigm shift. From closed-set segmentation where the targets are predefined categories to open-vocabulary segmentation where the model can segment unseen object categories as well. One of the most notable strengths of these foundation models is their robust zero-shot learning abilities. This feature enables them to be seamlessly adapted to the image segmentation task, demonstrating remarkable efficacy without the need for expensive and time-consuming fine-tuning. Some examples of such models include Segment Anything Model (SAM), DINOv2, and CLIP. Leduc et al. in their paper " Automatic detection of methane emissions in multispectral satellite imagery using a vision transformer. Using synthetic methane plumes embedded into real satellite images they were able to train an encoder-decoder model. They averaged 26% detection rate of methane leaks [11].

We can finetune a VLM for image segmentation using a similar workflow. With the performance of VLMs getting better and better we surely can target a better detection rate or even make a general model that can detect plumes in other hyperspectral data.

The E-UNet Architecture performs better than the traditional U-Net architecture on datasets like the Massachusetts Buildings Dataset [4]. By incorporating the VLM for the encoder, we can overcome the disadvantages of the traditional CNN encoder.

To use the E-Unet architecture with the quantum algorithm we would need to encode images from every decoder step into the NEQR model that the algorithm can understand, after we get that image we can proceed normally for the E-UNet architecture [13].

The advantage of using the quantum algorithm is that it avoids all the usual pitfalls that come with using models for edge detection. The edges of methane plumes can be vast and have shapes that the model might not have encountered during its training. As the state-of-the-art classical edge detection algorithms don't perform as nearly as well as machine learning or the quantum algorithm, using the quantum algorithm here is beneficial.

One of the disadvantages of using the quantum algorithm instead of machine learning or classical operators is that it requires an extra encoding step for the image, which we don't need in the other cases. However, this method is faster than even the classical operator methods, which is an advantage [13].

Using VLM during the encoder stage increases the computational resources required to train a model, but it provides better results than the traditional Convolutional Neural Network (CNN) [3].

Using VLM in the U-Net architecture provided better performance than previous methods as demonstrated by Rouet-Leduc et. al [11]. Their detection capabilities were near the detection capabilities. They could reliably detect leaks around 200 kg/hr to 300 kg/hr after which the model was more prone to errors.

We believe that by using a VLM in E-UNet architecture we can further improve this performance.

4 Future Work

We would like to code and test the model we proposed.
Our main concern is the Kirsch operator algorithm, while it showed great results,

the images used in its testing were all free of noise. We would like to further test and refine the algorithm so that it can be useful for this task and perform it on par with the standard edge detection algorithms.We would like to code and test the model we proposed. Our main concern is the Kirsch operator algorithm, while it showed great results, the images used in its testing were all free of noise[13]. We would like to further test and refine the algorithm so that it can be useful for this task and perform it on par with the standard edge detection algorithms.

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