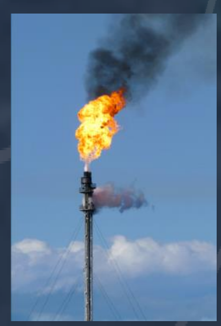
Automated Detection of Gas Flaring with Deep Learning

Charlie Leach | am19249@bristol.ac.uk | LinkedIn

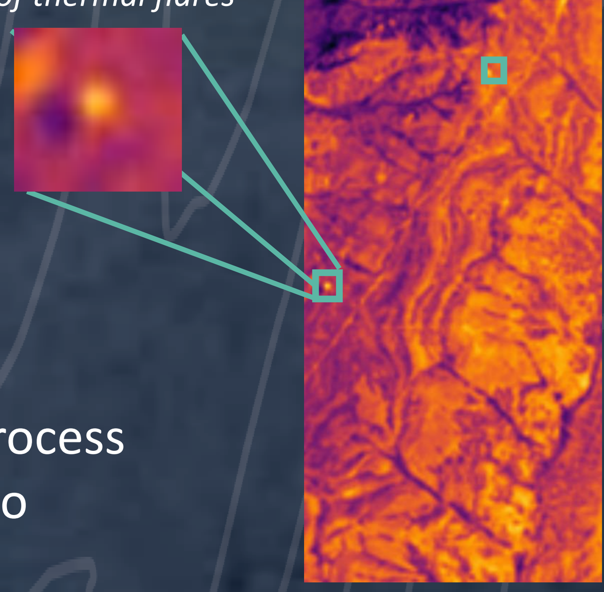
Background

- Terrabotics is a satellite data analytics start-up whose mission is to shine a light across supply chains in the energy sector.
- During the oil drilling process, natural gas is produced from the reservoir. Every year about 150 billion cubic meters of natural gas is flared that could be used for productive purposes. This emits an estimated 400 million tons of CO_2-equivalent emissions.[1]
- This project focuses on detecting natural gas flaring from Sentinel-2 (S2) imagery of the Permian basin, US.
- Sentinel-2 imagery is at a higher spatial resolution than other satellite products routinely used for flare detection (e.g. NASA VIIRS), meaning that it could be more sensitive to less powerful flares.
- Night time acquisitions of Sentinel-2 imagery are not available, meaning daytime specular reflections from roofs are a factor we have to consider when trying to classify flares.

Flare tower (right) Areal imagery of flaring (left)



Example of thermal flares



Pre-processing

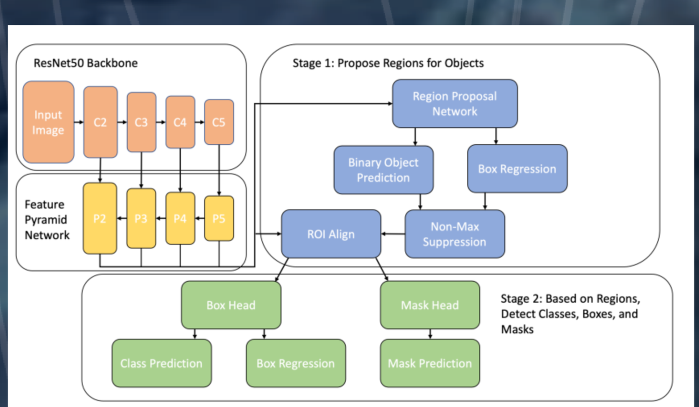
- One Band 12 Sentinel-2 raster was labelled using the below process
- This included 81 tiles containing flares which are augmented to generate a further 567 tiles.

Annotate S2 Images using QGIS → Generate Masks from GeoJSON → Split Images and Masks into Tiles with Overlap → Augment Tile Pairs → Save as tensorflow dataset and JSON file

Deep Learning Models

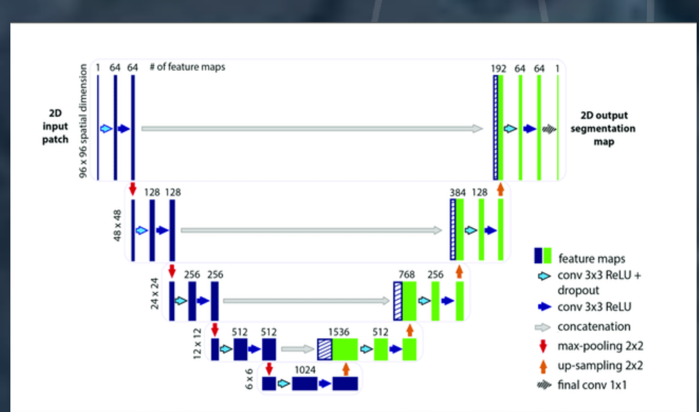
Mask R-CNN

- Convolutional Neural Networks (CNN) are used widely in image classification. A R-CNN is an extension of this, with R denoting Region, allowing us to assign a location to the detected object.
- Mask R-CNN is built on this concept using a Residual Network (ResNet) backbone.
- Originally trained on the Common Objects in Context (COCO) dataset containing 330,000 images.
- We transfer the weights to utilise it's feature extraction capabilities and retrain the head layers to classify flares



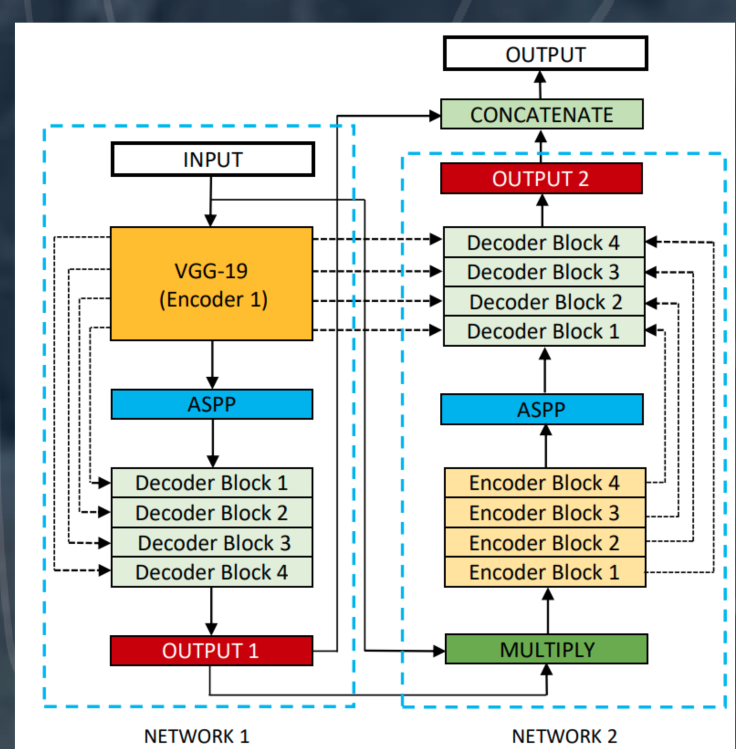
U-Net

- U-Net is an architecture originally developed to analyse biomedical images where it is important to not only classify an object but determine it's location too.
- U-Net follows an autoencoder based structure, reducing the input dimensionality to extract features before increasing back to the original image size
- Concatenating these features with each layer of the decoder provides the context required to generate the mask.
- We use pretrained VGG-16 layers for the encoder to speed up the training process and improve feature extraction.



Double U-Net

- Double U-Net is a combination of two U-Nets stacked on top of each other.
- The first uses VGG-19 layers that have been pretrained on the ImageNet dataset
- Context of features are translated using Atrous Spatial Pyramid Pooling (ASPP) and full architecture is illustrated below:



Thresholding Method

- Thresholding methods are currently widely used across sectors to detect gas flaring in satellite imagery.
- This method begins to under-perform in the scoring process as the optimal threshold differs from image to image depending on the time of day and weather conditions.
- Thresholding works well for night time imagery where flares are by some margin, the brightest pixels in the image. However fails to distinguish

Split tiled data into train and test → Use the bisection method to find the optimal threshold → Calculate IoU and Dice Coefficient on test set

Evaluation Metrics

$$\text{Intersection over Union (IoU)} = \frac{\text{Area of Intersection}}{\text{Area of Union}}$$

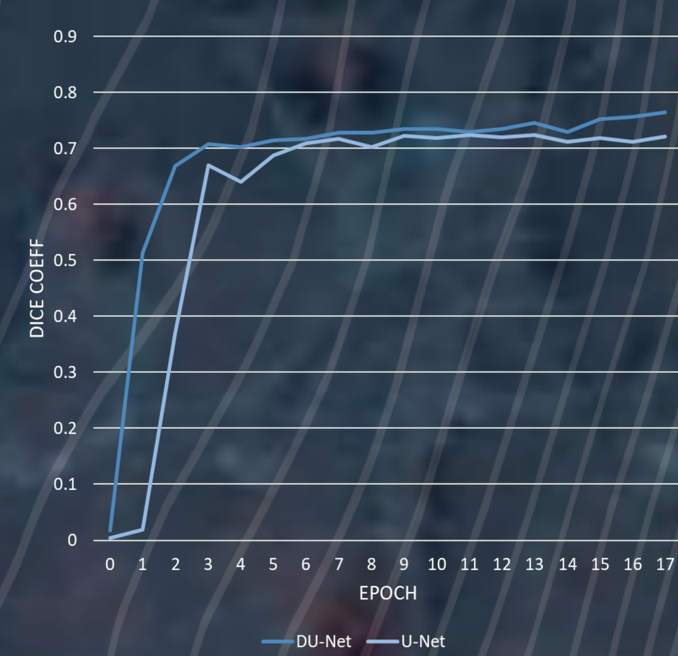
$$\text{Dice Coefficient} = \frac{\text{2x Area of Intersection}}{\text{Total Area}}$$

Results

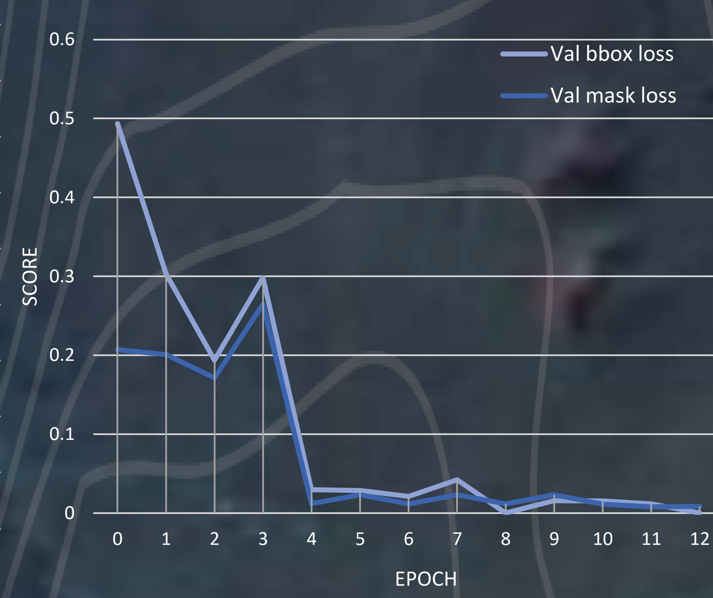
- All training was performed using Microsoft Azure Virtual Machines over a limited time period.
- Although results could be improved through further training or implementing a training strategy, some preliminary findings are presented below.

	Thresholding	Mask R-CNN	U-Net	Double U-Net
IoU	0.53	0.62	0.59	0.63
Dice Coeff	0.62	0.77	0.72	0.75
Run Time (per epoch)	70s	1720s	356s	378s

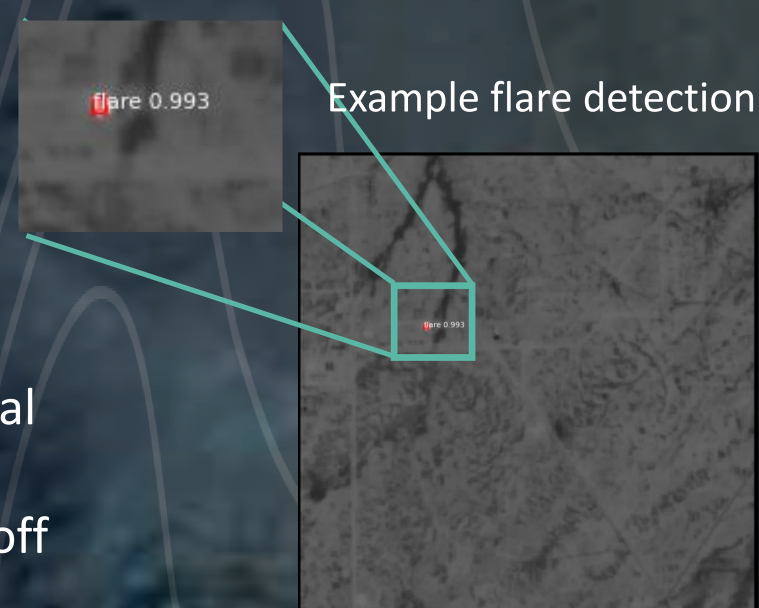
U-Net and Double U-Net Dice Coeff



Mask R-CNN Validation Loss



- All of the deep learning approaches out-perform the thresholding method however are much more computationally expensive.
- With each flare 6-12 pixels in size the spatial metrics fluctuate greatly if the mask is off by only a few pixels



Example flare detection

Future Work

- Using a stack of multiple S2 band to help distinguish between flares and reflective objects
- Annotate and include S2 imagery from different locations and time of year to diversify the dataset
- Investigate more aggressive methods of augmentation with noise to replicate cloud cover or different ground temperatures
- Consider Hyperparameter tunning including tile size, learning rate and momentum
- With access to greater computational power it would be possible to cascade multiple U-Net architectures

References

[1] https://blogs.worldbank.org/energy/we-can-end-routine-gas-flaring-2030-heres-how

[2] He, K., Gkioxari, G., Dollár, P. and Girshick, R., 2017. Mask r-cnn. In Proceedings of the IEEE international conference on computer vision (pp. 2961-2969).

[3] D. Jha, M. A. Riegler, D. Johansen, P. Halvorsen and H. D. Johansen, "DoubleU-Net: A Deep Convolutional Neural Network for Medical Image Segmentation," *2020 IEEE 33rd International Symposium on Computer-Based Medical Systems (CBMS)*, 2020, pp. 558-564

Acknowledgement

I would like to thank my supervisor Dr Sian Williams Page and the rest of the Terrabotics team for their support and throughout the project.