Semantic Segmentation for Materials Classification of Nuclear Fuels

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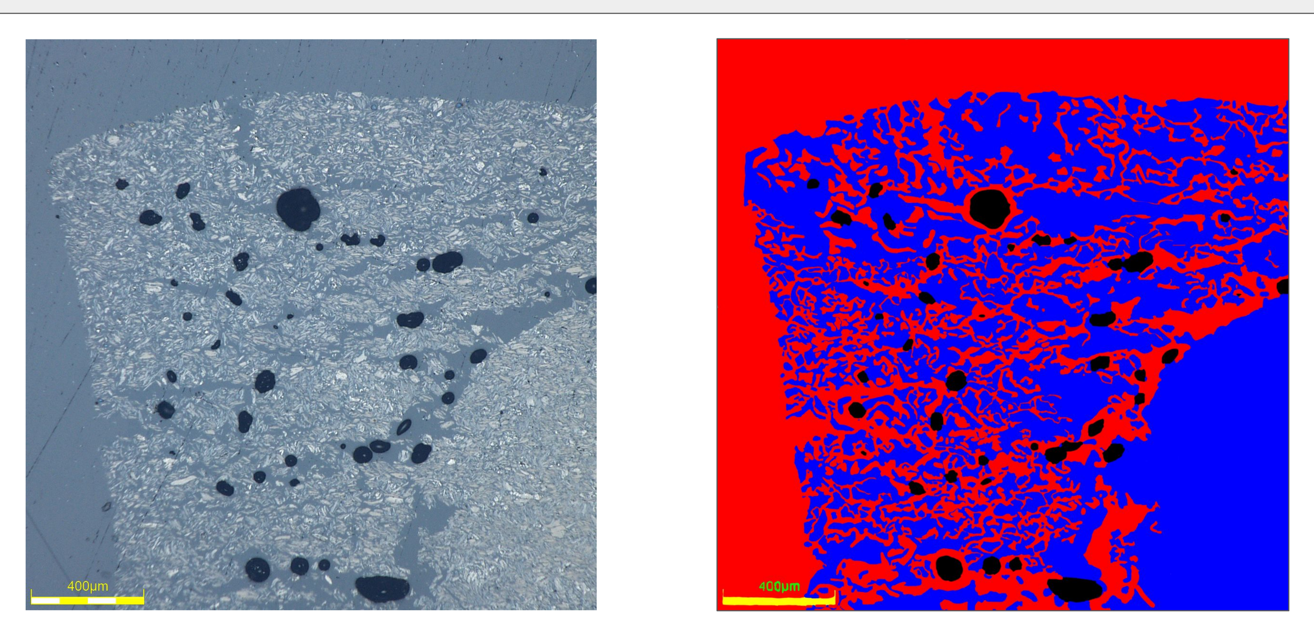
Abstract

Semantic segmentation, the task of classifying objects in an image at a pixel level, has been done since 2012. While our method is not new, our application is. Unlike most tasks which are on clearly-defined objects, the dataset we attempt to label is like Perlin Noise: seemingly random but with clear patterns throughout. Additionally, we had a very small dataset to work with, but preliminary results show that approaches used on more standard applications also work well in this novel application.

Introduction

- The UTSA EEML wanted to automate the process of detecting defects in nuclear fuels to save time and money. Material classification represents the first step toward achieving this goal, which we help automate with semantic segmentation.
- Due to the difficulty in creating labeled images by hand, the EEML was able to provide us with only 12 labeled high resolution images of varying sizes, this presented a challenge since traditional supervised neural networks require thousands of images.
- Neural networks train by trying to recognize patterns in increasing levels of complexity
  - The features here are simpler but more amorphous than most object detection datasets.
- The combination of both a small and Perlin Noise-like dataset make this a unique problem to tackle.

Figure 1: Example image and mask from the Cityscapes dataset [1]



Key: Red = epoxy/resin, black = pore, blue - graphite

Figure 2: An image (left) and mask (right) provided by the UTSA EEML.

Method

- Preprocessing
  - Cropped out the scale bar
  - Slicing tiles of 384x384 pixels to create 330 images from the 12 original

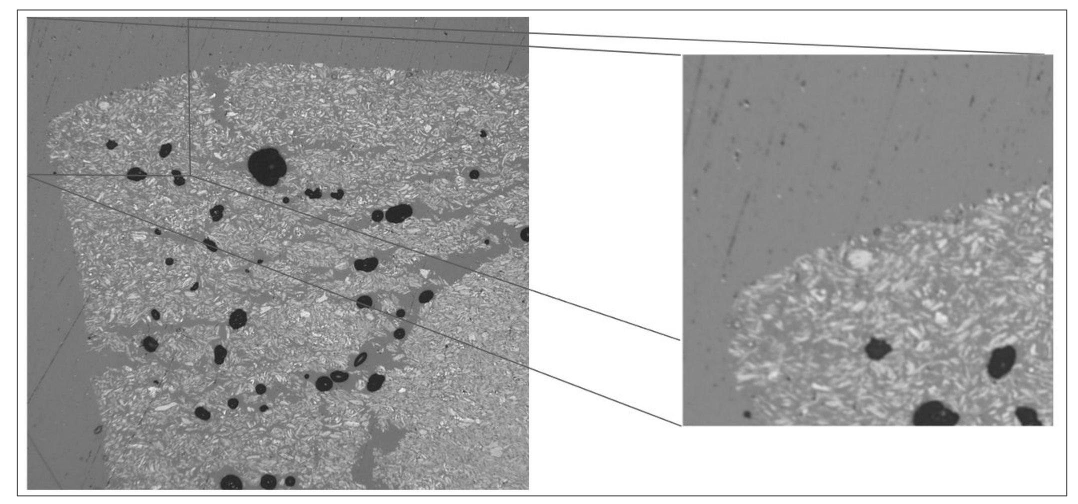


Figure 3: Example of slicing a 384x384 tile (right) from a high-res image (left)

- Cut out coarsely-labeled images from dataset
  - Model struggled with the inconsistent labeling
  - Down to 75 images but model performed better with only fine labels

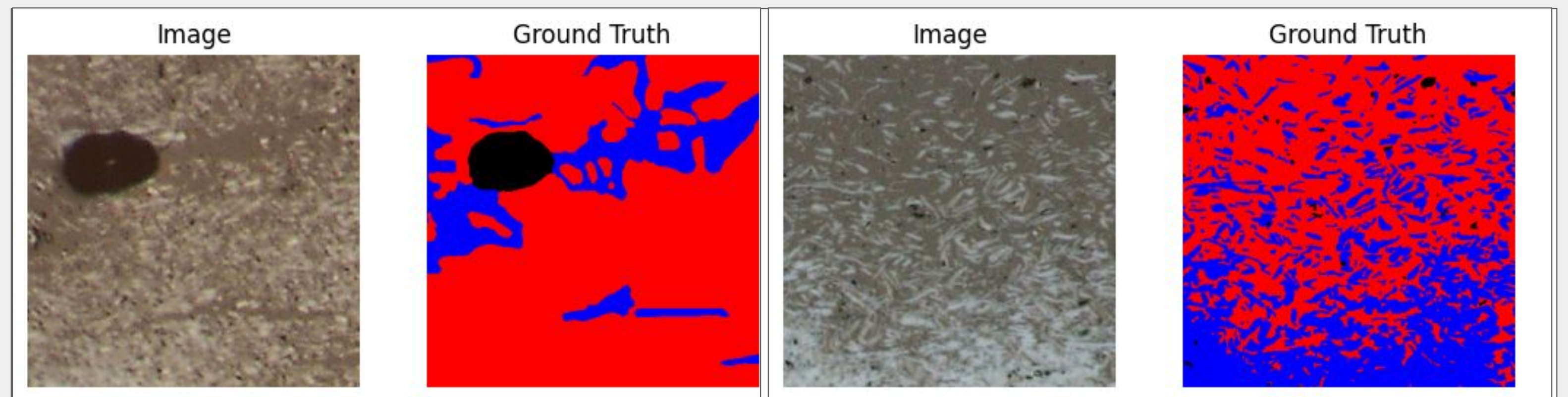


Figure 4: Example of a coarse (left) and fine (right) label

- Data Augmentation
  - 75 to 375 tiles by 90-degree rotations and mirroring along 2 axis

- Using binary classifiers to improve results of important classes
  - Hard to reproduce
  - Prevalence of false positives

Model

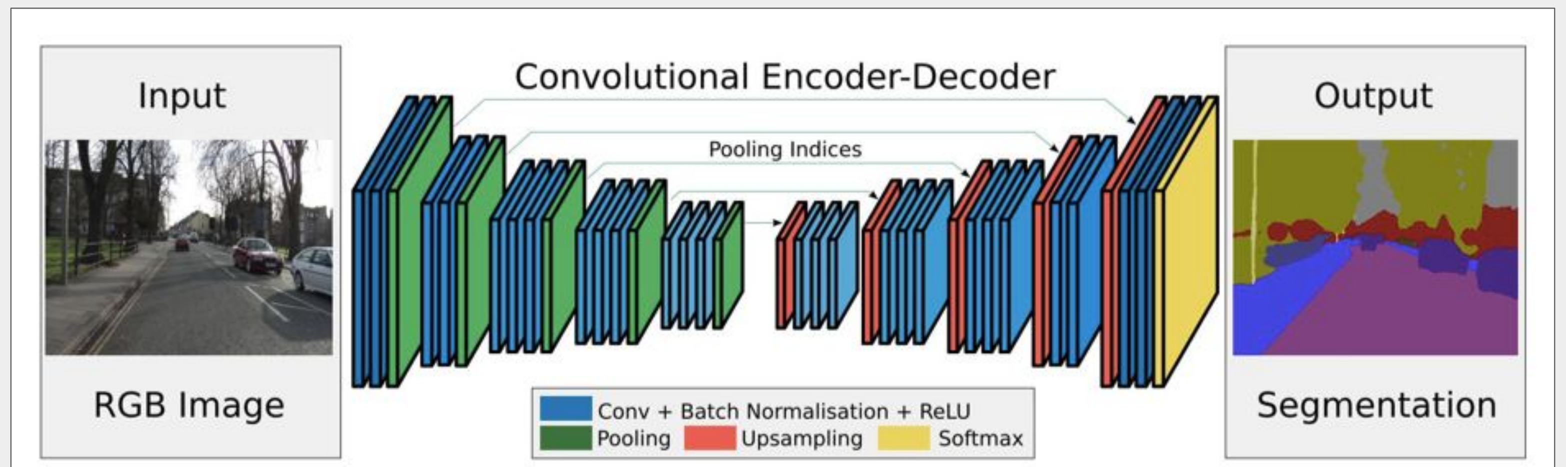


Figure 5: Example of a model used in semantic segmentation [2]

Preliminary Results

Model:	vgg19	vgg11	dpn68	resnet18	resnet152
mIoU:	0.8197	0.8179	0.81	0.7886	0.7831

Table 1: Baseline performance of various models using the Mean Intersection Over Union metric.

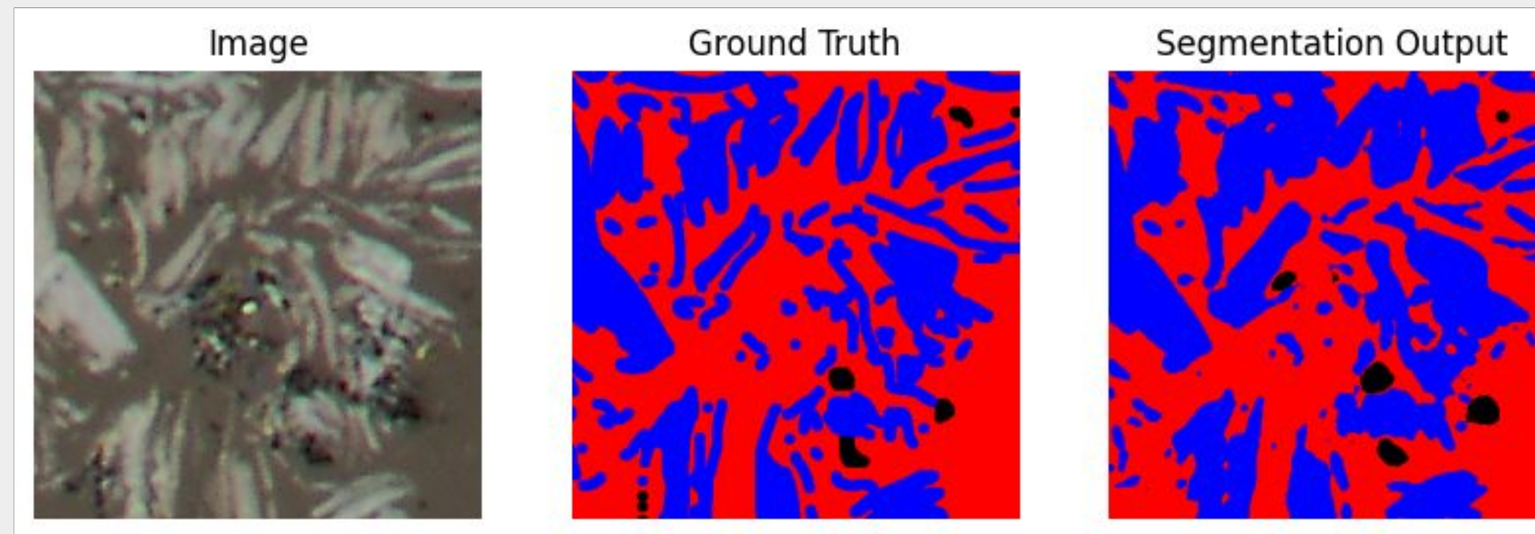


Figure 6: Image, expected mask and mask produced by our model

Conclusion/Open Questions

- Preliminary results on a stock, vgg19 model pre-trained on ImageNet show promising results, and produce labelings similar to those of a human in seconds rather than hours
- **Open Research Questions**
  - Are there other models which are better-suited for this task?
  - Why do the binary classifiers struggle with the red and blue classes?
  - Why does the model fail on specific cases?

Acknowledgements

This work was supported by the National Nuclear Security Administration, Minority Serving Institutions Partnership Program DE-NA0003948.

References

[1] M. Cordts, M. Omran, S. Ramos, T. Rehfeld, M. Enzweiler, R. Benenson, U. Franke, S. Roth, and B. Schiele, "The Cityscapes Dataset for Semantic Urban Scene Understanding," in *Proc. of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2016.

[2] Badrinarayanan, Vijay, et al. "SegNet: A Deep Convolutional Encoder-Decoder Architecture for Image Segmentation." *ArXiv.org*, ArXiv, 10 Oct. 2016, https://arxiv.org/abs/1511.00561.