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Convolutional Neural Networks for the Segmentation of Micro CT Images

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PRESENTED BY

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Personal Background

- Graduated from AHS in May.
- Entering UNM in August as a Computer Science Major.
- Spent summer of 2018 working on image segmentation with FIJI.
- Plan on pursuing bachelors degree while continuing work here at Sandia.

Outline

Catch-phrase: Computer vision for fracture detection; getting the computer to see what's right in front of it.

1. Introduction
2. Methodology Overview:
   1. Gathering image data
   2. Applying pre-processing/data augmentation
   3. Training the network
   4. Evaluating network performance
3. Overview of model architecture
4. Results
5. Discussion and future work
6. Conclusion

Introduction

- **Programmatic context:** Gypsum samples are created through 3D printing and then subjected to pressure. The samples are then captured with micro-CT scans, which are processed and then analyzed.
- **Question:** Can Convolutional Neural Networks (CNNs) be used to accurately process geological micro-CT scans?
- **Current gaps:** Image processing currently takes up a considerable amount of time due to the qualitative/subjective nature of image data.
- **Previous work:** Last year explored user-defined methods for image segmentation in FIJI.

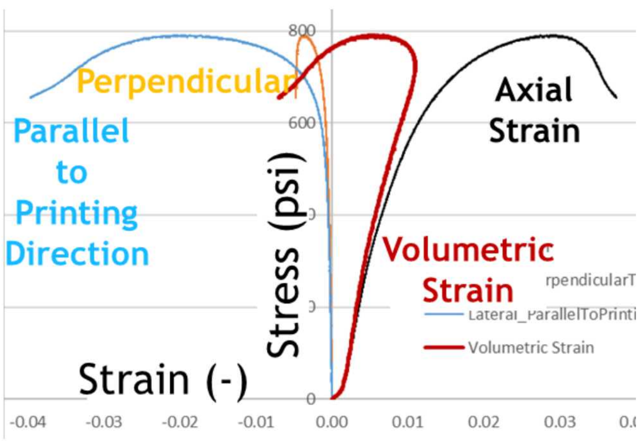
Introduction

Why 3D printing?

- 3D printing of fractured and porous analog geomaterials has the potential to enhance hydrogeological and mechanical interpretations by generating engineered samples in testable configurations with reproducible microstructures and tunable surface and mechanical properties.
- Overcome sample-to-sample variability for testing material response.

Gypsum powder-based 3D printing

- Print cylindrical core samples in three different directions to evaluate the impact of anisotropy on mechanical properties.



Mechanical testing and micro-CT scanning

- Printed samples were tested for compression strength and tested samples were 3-D imaged with micro-CT scanning.

Methodology

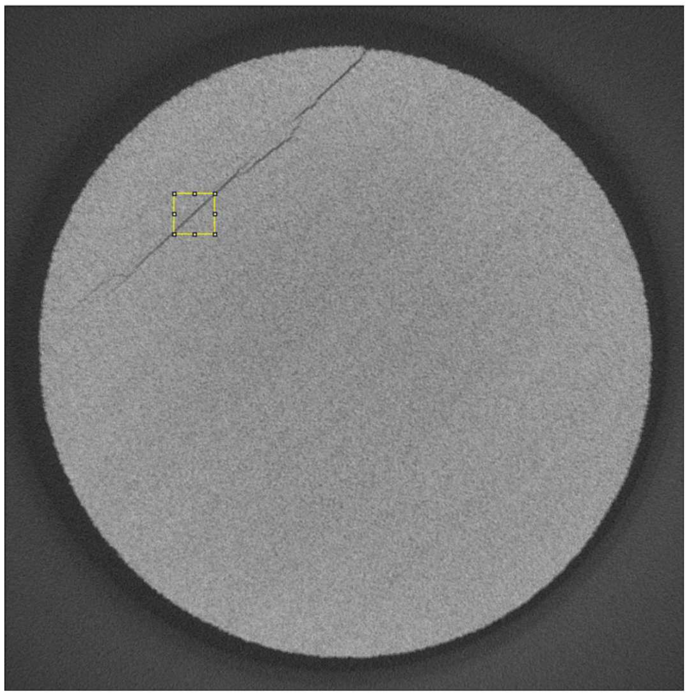
Methodology

1. Take 112x112 regions from original image datasets.
2. Scale down to 28x28 and create a corresponding label.
3. Repeat (1) and (2) to create a dataset.
4. Split dataset into training and validation.
5. Normalize training images and generate/add augmented images to the training set.
6. Train network using training set.
7. Evaluate network with the validation set.
8. Adjust hyperparameters and reevaluate (if need be).
9. Use network to generate predictions for entire images.

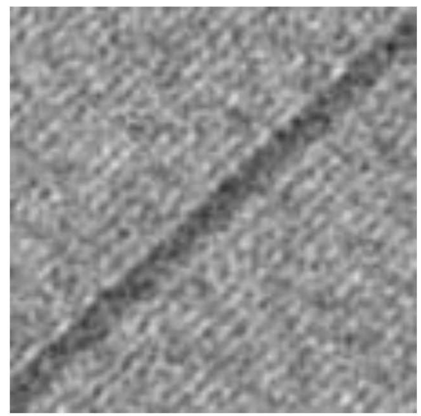
Assumptions/Limitations

- Network assumes label images are 100% accurate.
- Convolutions used within the network cause output maps have different dimensions than input; makes padding necessary.
- Pixel values are the only source of input.
- Training CNNs can take a considerable amount of time.

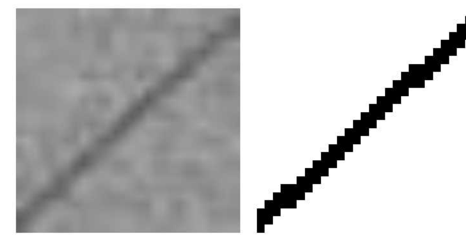
Methodology



Original Image



Selected Region



Scaled down region
and label

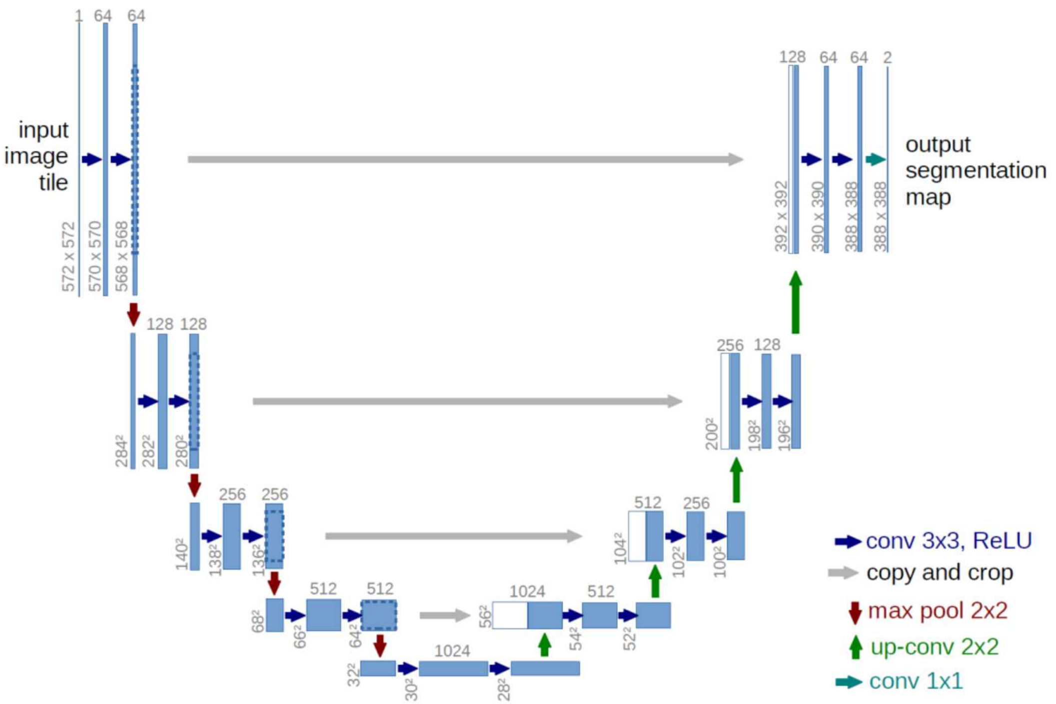
Methodology

Why CNNs?

- Extract features from data using convolutional filters; as a result are designed for processing data with a spatial relationship (i.e. images).
- Can learn abstract patterns in data.
- Capable of specialization.
- Once trained, a CNN is able to automatically generate predictions on raw data relatively quickly (meaning there is minimal input necessary from the user).
- Have proven effective in a variety of computer vision tasks, with examples including object detection for self-driving vehicles and the interpretation of biomedical image scans.

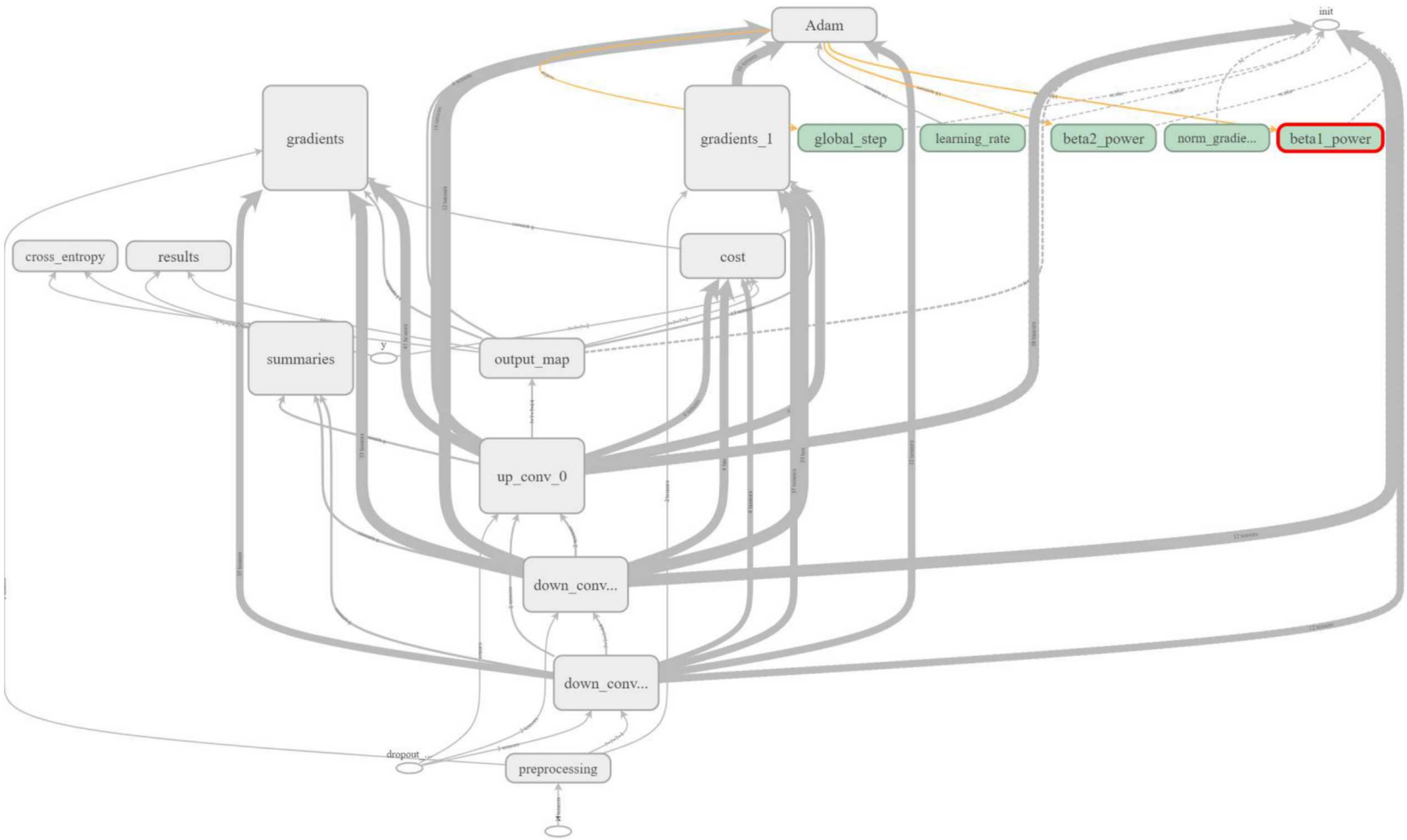
Encoder-Decoder Networks

- "Encoder" portion (left) of the network takes an input image and transforms it into a high-dimension feature vector.
- "Decoder" portion (right) takes the feature vector as input and uses it to construct a segmentation map of the original image.
- Segmentation map can be thought of as essentially an image where each pixel value corresponds to a probability.
- "Ground truth" label is compared against the output segmentation map to calculate error.
- Propagate backwards through network to determine how to best adjust parameters.



Ronneberger, Olaf; Fischer, Philipp; Brox, Thomas (2015). "U-Net: Convolutional Networks for Biomedical Image Segmentation". arXiv:1505.04597

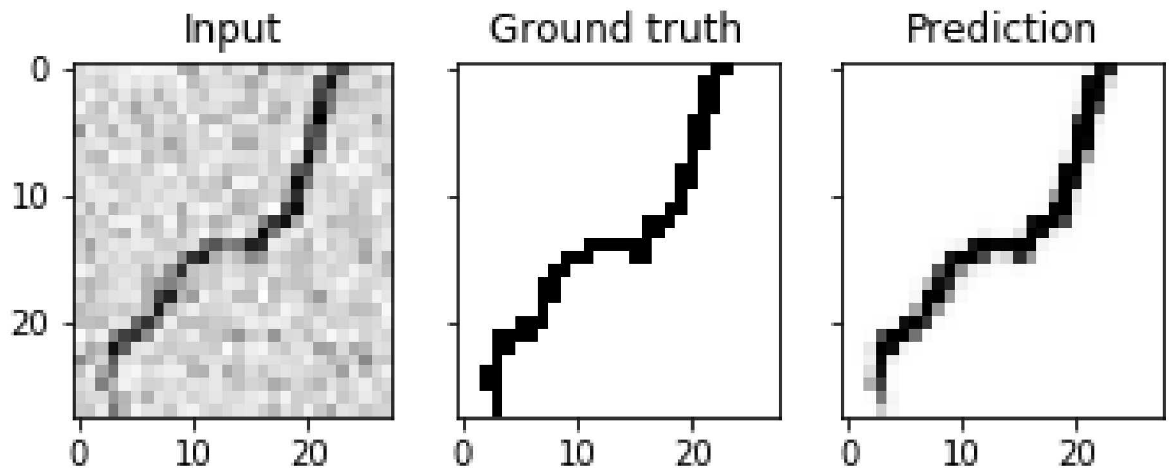
Overview of Model Architecture



Graphic created using TensorFlow
Abadi et al. TensorFlow: Large-scale machine learning on heterogeneous systems, 2015. Software available from tensorflow.org.

Results

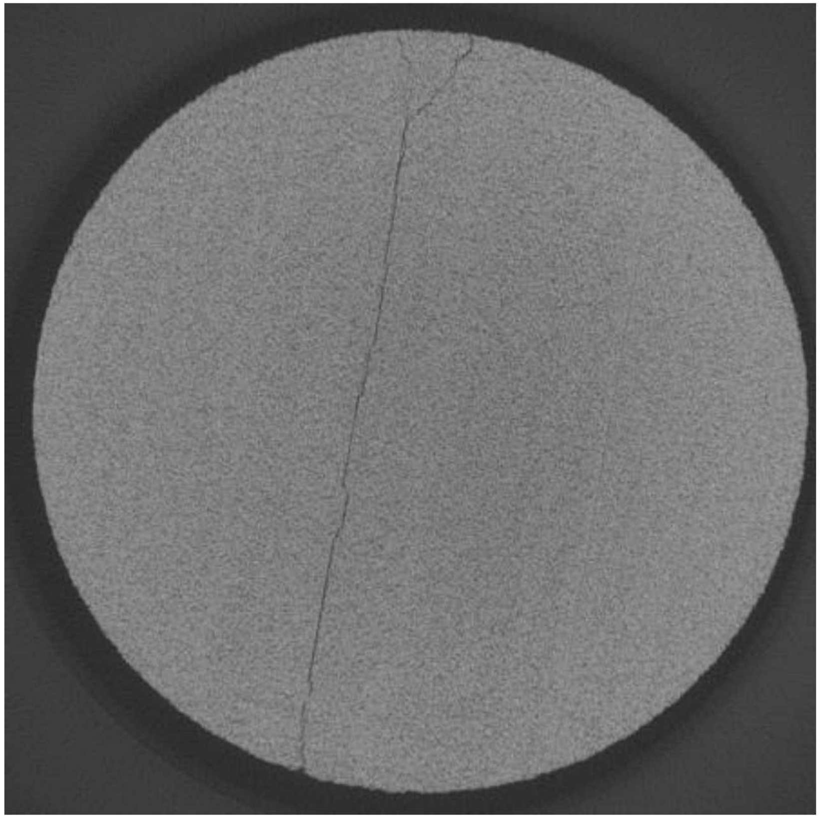
- Achieved an error rate of 1.44% on the validation set.
- Results indicate the network is able to successfully detect a variety of fracture features.
- However, the current model has a tendency to generate false positives and fails to capture particular microfracture regions.

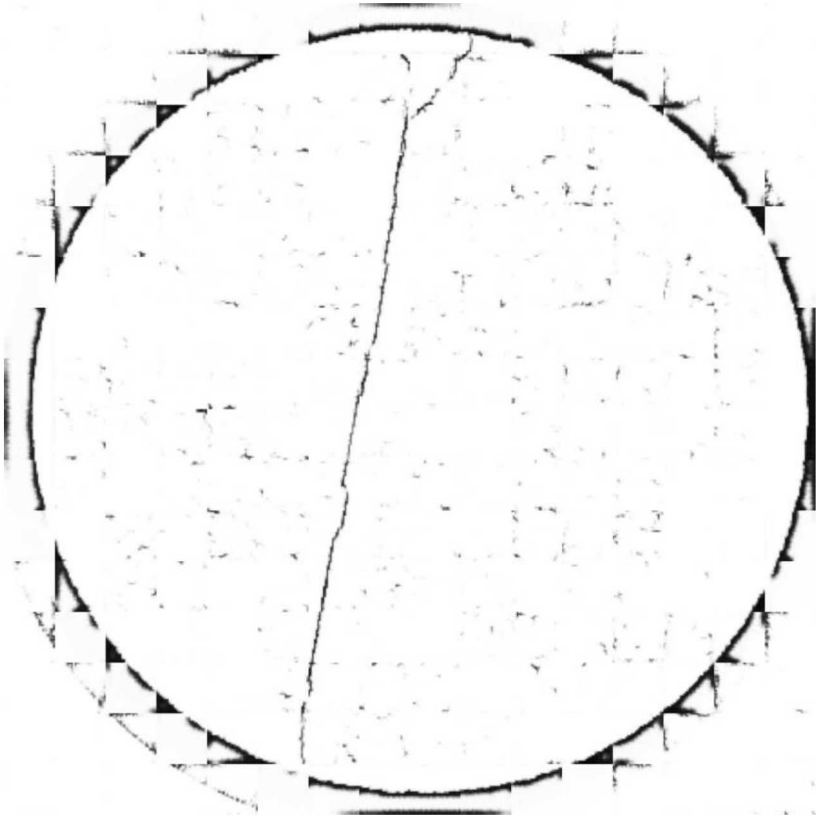


Error: 1.02%

Results

- Result of prediction over an entire image
    1. Image was decomposed into 28x28 regions (originally 112x112).
    2. Images were padded.
    3. Network used to generate corresponding prediction images.
    4. Prediction images reassembled to create wholistic prediction.





Discussion

- Results indicate the model is able to identify general fracture features, but generates false positives and underrepresents microfractures.

- Potential improvements and future work:
  - Use non-scaled images for training.
  - Explicitly include more microfracture regions in the training set.
  - Test alternatives for padding.
  - Add in non-pixel information for training the network (e.g. connectivity).
  - Compare different methodologies.

Conclusion

- Potential Applications:
  - If results can be improved could potentially serve as a replacement for current image processing software.
  - Research regarding the effects of stress on geological samples.
  - Research regarding the structure of geological samples.

- Major takeaway: Learned many of the fundamentals behind convolutional neural networks and related concepts. In the future will hopefully be able to continue to explore machine learning and develop more effective models.

Thank you!