Automatic Detection and Classification Of Rock Microstructures Through Machine Learning

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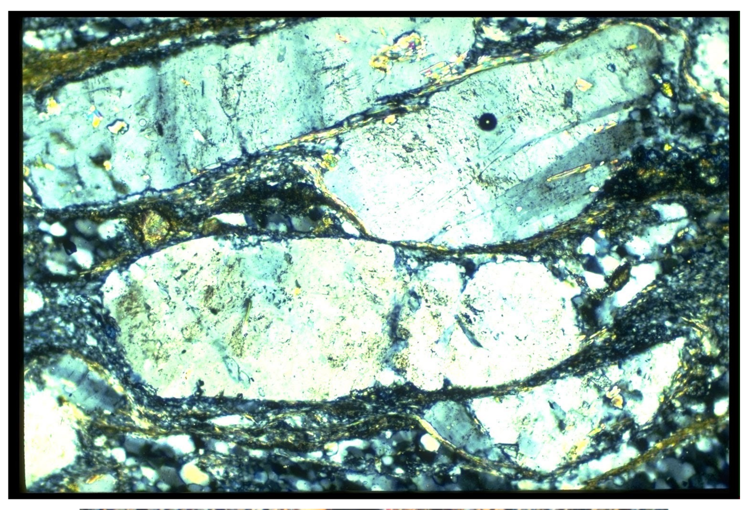
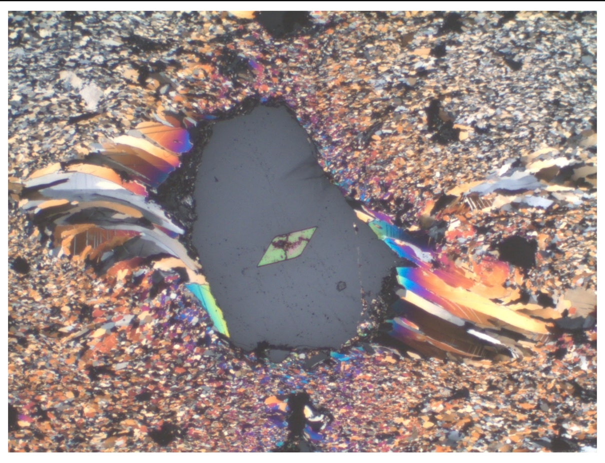
Introduction

Motivation and Dataset





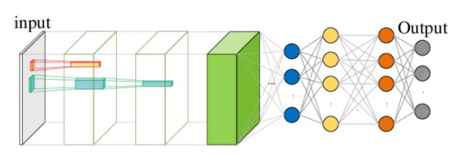
Geologists seek assistance in classifying microscope rock images

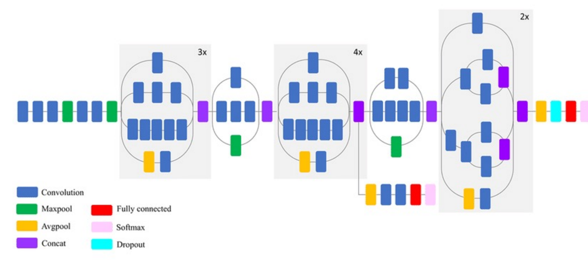
- Sigma clasts are a type of mantled porphyroclasts widely used as kinematic indicators in rock
- Want to automate classification of Sigma clast direction of rotation (CW or CCW)

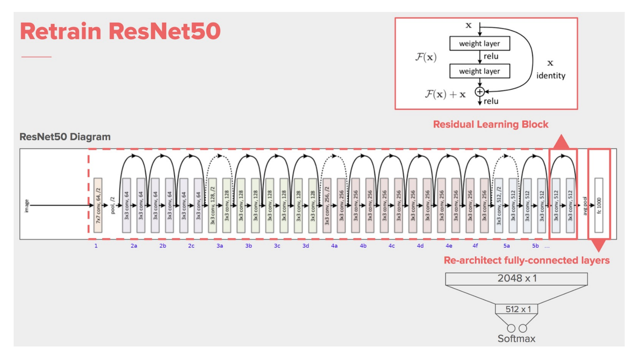
Challenge: Very limited dataset, difficult feature extraction

- Only ~ 100 positive examples
- Sigma clasts are notoriously difficult to classify, even for geologists

Machine Learning Methods







Machine Learning (ML)

- Use positive and negative examples to train models that can be used to predict whether a new image can be classified as a positive example

Convolutional Neural Networks (CNNs)

- CNNs are a type of ML models inspired by the brain.
- Used to extract features such as shape, color and texture to infer image labels.
- Requires thousands of examples!!

Transfer Learning applied to Sigma Clasts Detection Problem

What is Transfer Learning?

- Typically, CNNs require hundreds and thousands of training examples to achieve useful prediction accuracy for a given problem
- Transfer Learning leverages CNN models trained with other data and does additional training with the data at hand
- On top of three widely-used Transfer Learning models, we train additional prediction layers on our sigma clasts data and observe the results.

Comparing Different Transfer Learning Approaches: InceptionV3, ResNet50, VGG19

	model	train_loss	train_acc	val_loss	val_acc	f1_score
0	InceptionV3_epochs132_train_acc-0.9939_val_acc-0.8250_Regularized-False.h5	0.031	0.994	1.806	0.825	[[metric, precision, recall, f1-score, support], [0.556, 0.833, 0.667, 6.0], [0.9, 0.643, 0.75, 14.0], [0.905, 0.95, 0.927, 20.0], [0.825, 0.825, 0.825, 0.825], [0.787, 0.809, 0.781, 40.0], [0.851, 0.825, 0.826, 40.0]]
3	ResNet50_epochs02_train_acc-0.8221_val_acc-0.8250_Regularized-False.h5	0.692	0.853	0.596	0.825	[[metric, precision, recall, f1-score, support], [0.667, 0.333, 0.444, 6.0], [0.733, 0.786, 0.759, 14.0], [0.909, 1.0, 0.952, 20.0], [0.825, 0.825, 0.825, 0.825], [0.77, 0.706, 0.718, 40.0], [0.811, 0.825, 0.808, 40.0]]
1	InceptionV3_epochs18_train_acc-0.9693_val_acc-0.7250_Regularized-True.h5	10.634	0.791	2.451	0.725	[[metric, precision, recall, f1-score, support], [0.333, 0.333, 0.333, 6.0], [0.818, 0.643, 0.72, 14.0], [0.783, 0.9, 0.837, 20.0], [0.725, 0.725, 0.725, 0.725], [0.645, 0.625, 0.63, 40.0], [0.728, 0.725, 0.721, 40.0]]
4	VGG19_epochs14_train_acc-0.9939_val_acc-0.6250_Regularized-False.h5	0.180	0.982	2.622	0.625	[[metric, precision, recall, f1-score, support], [0.3, 1.0, 0.462, 6.0], [1.0, 0.5, 0.667, 14.0], [0.923, 0.6, 0.727, 20.0], [0.625, 0.625, 0.625, 0.625], [0.741, 0.7, 0.618, 40.0], [0.857, 0.625, 0.666, 40.0]]
2	ResNet50_epochs20_train_acc-0.9264_val_acc-0.6250_Regularized-True.h5	2.903	0.779	5.850	0.625	[[metric, precision, recall, f1-score, support], [0.6, 0.5, 0.545, 6.0], [0.667, 0.429, 0.522, 14.0], [0.615, 0.8, 0.696, 20.0], [0.625, 0.625, 0.625, 0.625], [0.627, 0.576, 0.588, 40.0], [0.631, 0.625, 0.612, 40.0]]
5	VGG19_epochs35_train_acc-0.5215_val_acc-0.6000_Regularized-True.h5	1.231	0.521	1.211	0.600	[[metric, precision, recall, f1-score, support], [0.0, 0.0, 0.0, 6.0], [1.0, 0.286, 0.444, 14.0], [0.556, 1.0, 0.714, 20.0], [0.6, 0.6, 0.6, 0.6], [0.519, 0.429, 0.386, 40.0], [0.628, 0.6, 0.513, 40.0]]

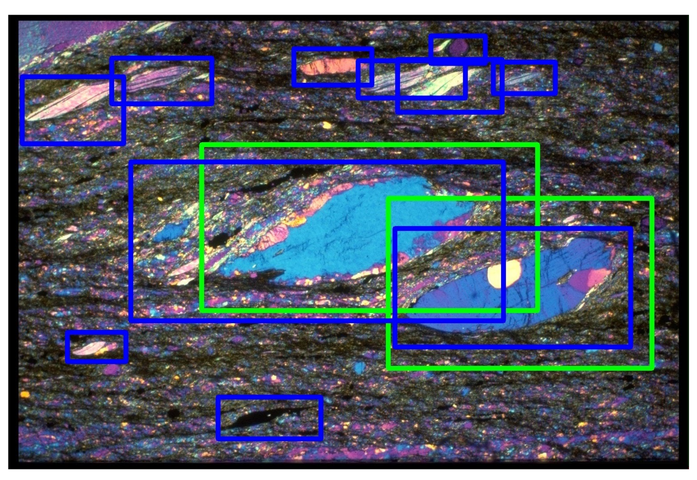
Experimental Setup

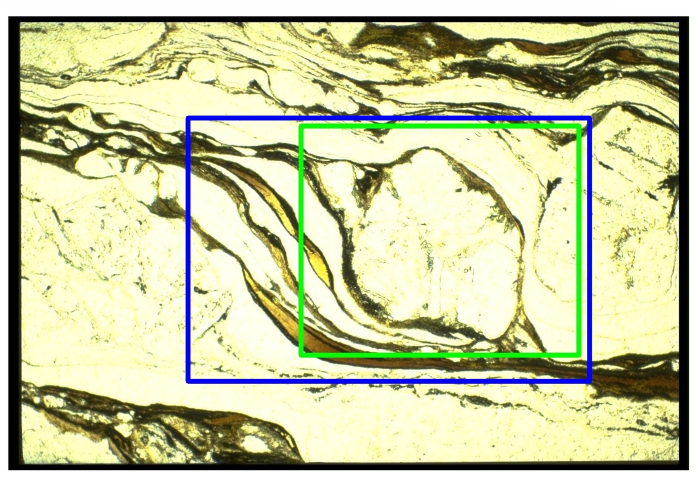
- Train/Validation Split = 0.8 on total of 100 images
- Epochs = 50
- Optimizer = Adam
- Loss = categorical cross entropy
- Iteration step size = 1e-4
- Activation = Relu, softmax for last layer

Through hyperparameter tuning, we are able to optimize prediction accuracy on our data set.

Current Areas of Work

Detecting Multiple Objects in an Image



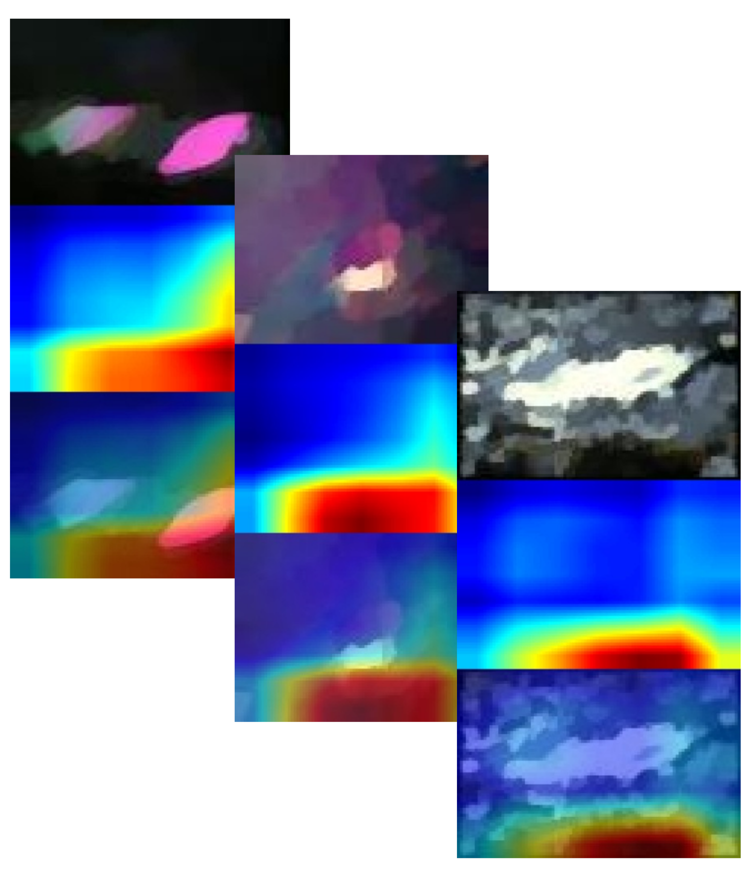


- YOLOV3 is the third iteration of CNN based object detection architecture, able to output real time bounding boxes around Sigma clasts

Blue – ground truth labels
Green – predicted labels

- Initial implementations of YOLO show the ability to distinguish multiple sigma clasts in a single image: not possible through Transfer Learning
- In the future: fine tune this approach using tail detection.

Efficient Exploration of Models through Visualization



Understand Model Prediction Accuracy

- In order to prioritize the exploration of possible new models with different settings, we are developing a computational experimentation environment to visualize different CNN network layers, classification heatmaps, and comparative metrics.
- We propose heatmaps that show where the CNN model is ''looking'' for sigma clasts, to compare and distinguish where some models are underperforming