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Dynamic Segmentation ML Algorithm for Inferring Geothermal Reservoir Quality in Sandstones using Scanning Electron Microscope (SEM) Images: Case Study with Quantification of Quartz Overgrowths

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ABSTRACT

The abundance of diagenetic quartz overgrowths in sedimentary geothermal reservoirs can help infer the reservoir quality and improve the drilling success rate. The typical method for calculating the amount of quartz overgrowths involves a tedious process of manually examining Scanning Electron Microscope (SEM) images, particularly the cathodoluminescence (CL) and backscattered electron (BSE) images. This paper outlines an automated workflow to detect quartz overgrowths from SEM images using computer vision and machine learning techniques, which can dramatically cut the associated time and effort. The workflow was developed using SEM images available for public use.

The automated workflow consists of a dynamic segmentation algorithm incorporating noise suppression, multi-level auto-thresholding, and dynamic overlaying. As a result, the workflow can automatically infer mineralogy from lower-quality images with varying brightness and contrast values and noise levels. The algorithm can also handle overlay shifting in CL and BSE images. Random Forest was used to train the algorithm based on extracted SEM image features such as Gabor, Canny Edge, and Roberts Edge. The resulting ML model is then used to improve the prediction of the image segmentation more accurately as a mineralogy predictor.

The model training resulted in a 75% accuracy score, which is a promising start. The model can successfully differentiate between detrital quartz grains and their diagenetic quartz overgrowth; it can also identify porosity and the presence of other minerals. Furthermore, the detection capability was improved after training, particularly in reducing false positives in porosity detection. Further improvements can be made by applying morphology detection principles and expanding the model training to include different reservoirs.

1. INTRODUCTION

Permeability is an important property of sedimentary geothermal reservoirs because it determines the flow rate of fluids through the reservoir, affecting the amount of energy that can be extracted from the formation. A common problem in sedimentary geothermal reservoir is inadequate flow rate due to lower permeability than expected (Dillinger, et al., 2016)

Quartz overgrowth, also known as quartz cement, involves the precipitation of quartz minerals between the sand grains in a sandstone formation. Quartz overgrowths are the most abundant cement in sandstones and are among the most volumetrically significant diagenetic phase in sandstones (Goldstein & Rossi, 2022). Quartz overgrowths are known to reduce permeability in sedimentary geothermal reservoirs. This is because the precipitation of quartz minerals between the sand grains can cause a reduction in the size and connectivity of the pores, making it more difficult for fluids to flow through the rock. Additionally, the precipitation of quartz minerals can cause the rock to become more compact, which further reduces the permeability of the reservoir.

Overall, understanding the processes that lead to quartz overgrowth in sedimentary geothermal reservoirs is important for assessing the quality of the reservoir and determining the potential for extracting energy from the formation. Therefore, accurately determining the abundance of quartz overgrowth is key factor to consider when evaluating the potential of a sedimentary geothermal reservoir.

Currently, one of the most common methods for analyzing quartz overgrowth in sedimentary geothermal reservoirs is through the use of Scanning Electron Microscopy (SEM) images. In the case of analyzing quartz overgrowth, two type of SEM images are used, Cathodoluminescence (CL) and Backscattered Electron (BSE). Analysis is typically done by manually examining thousands of BSE and CL images to identify the presence of quartz overgrowth based on their characteristic shape, size, and composition. The manual examination can be time-consuming and labor-intensive, especially when dealing with large numbers of images. Additionally, manual examination can be subject to human error, which can introduce inaccuracies in the analysis.

This paper proposes an automated workflow using computer vision and random forest algorithms to de-noise the images, apply multi-level thresholding, train the machine learning (ML) model, and use it for quartz overgrowth on SEM images.

2. CONCEPTUAL BACKGROUND

2.1. Scanning Microscope Electron (SEM) Images

To achieve a comprehensive understanding of the reservoirs, two different imaging modes of SEM are utilized - SEM-BSE (Backscattered Electron) and SEM-CL (Cathodoluminescence). SEM-BSE images provide information about the elemental composition of the sample, with the contrast being based on the backscattered electrons collected by the detector. This mode can differentiate between quartz, which is usually depicted in grey, and pore space, which is usually black. On the other hand, SEM-CL images provide information about the surface topography and composition of the materials, with the contrast based on the secondary electrons emitted from the sample. In this research, SEM-CL is used to distinguish quartz overgrowths from its primary quartz.

The SEM-CL and SEM-BSE images are overlaid to provide a complete understanding of the microstructure of the sedimentary geothermal reservoirs. This enables the researchers to differentiate various minerals present in the reservoir and study the distribution of quartz overgrowths, which play a crucial role in the permeability of the reservoir. The ultimate goal is to develop an automated workflow using computer vision and machine learning algorithms to analyze quartz overgrowths on SEM images.

2.2. Image Processing

To obtain accurate mineralogy analysis from Scanning Electron Microscope (SEM) images, a robust image processing workflow is crucial. The process begins with non-local means denoising to remove any unwanted noise from the SEM images. This is followed by the application of multi-level Otsu thresholding, which separates the images into different intensity levels and enhances their contrast. Finally, a dynamic overlaying algorithm combines SEM-CL and SEM-BSE images and achieves a more precise segmentation, differentiating porosity, quartz, quartz overgrowth, and other minerals. This algorithm accounts for lateral or horizontal shifting in some image pairs and inputs the necessary shifting values to achieve precise overlaying. With this comprehensive image processing workflow, the resulting mineralogy analysis is more accurate and reliable.

2.2.1. Non-local means Denoising

The non-local means filter is used in image processing to denoise an image by replacing the value of a pixel with an average of other pixel values selected by comparing small patches centered on the pixels (Buades, Coll, & Morel, 2011). The algorithm can restore textures better than other denoising algorithms and has two modes of computation - fast mode with uniform spatial weighting or slow mode with spatial Gaussian weighting. The noise standard deviation, sigma, can be subtracted when computing patch distances to improve image quality. Non-local means denoising is chosen because it still can preserve the various regions of different type of texture resulting in scanning images, including SEM images, while effectively cleaning the image up by assigning non-local weighted means for each similar texture or color image.

Figure 1: Comparison between the original image and non-local means denoised image.

2.2.2. Multi-Level Otsu Thresholding

Furthermore, multi-level auto-thresholding is applied to automatically adjust the image threshold level based on the images' characteristics between datasets and segment the images into several categories. This is important because different images may have different levels of brightness and contrast, and adjusting the threshold level can improve the accuracy of the analysis. A multi-level thresholding method based on a modified Otsu algorithm developed by Liao, et al. (2001) is performed in this study.

Otsu thresholding is a method of image segmentation that separates an image into two classes, foreground, and background. The method tries to find a threshold value that separates the image into two classes, maximizing the variance between the two classes. This threshold value is calculated based on the histogram of the image intensities.

Multi-level Otsu thresholding is an extension of the basic Otsu thresholding method. Instead of finding a single threshold value, multi-level Otsu thresholding tries to find multiple threshold values that can be used to segment an image into multiple classes. The algorithm calculates a threshold value for each class by maximizing the variance between the classes (Liao, et al., 2001). Multi-level Otsu thresholding was chosen due to the nature of SEM images that contain multiple regions with different intensity levels representing porosity, quartz, quartz overgrowth, and other minerals. Furthermore, the threshold difference that was observed between datasets can also be eliminated by multi-level Otsu thresholding.

2.3. Dynamic Overlaying

After multi-level Otsu thresholding has been applied to both SEM-CL and SEM-BSE images, those two images are overlaid to get a better segmentation that can differentiate porosity, quartz, quartz overgrowth, and other minerals. However, some BSE and CL image pairs do not overlay precisely. A lateral or horizontal shift of 5 – 10% might occur in some pairs. Therefore, we developed an algorithm that precisely overlays SEM-BSE and SEM-CL images by inputting lateral and horizontal shifting values in each pair (Figure 1). The final output of this process is then validated by manual observation of 30-pixel labeled JSON data of 200 CL images to obtain the full-image ground truth data.

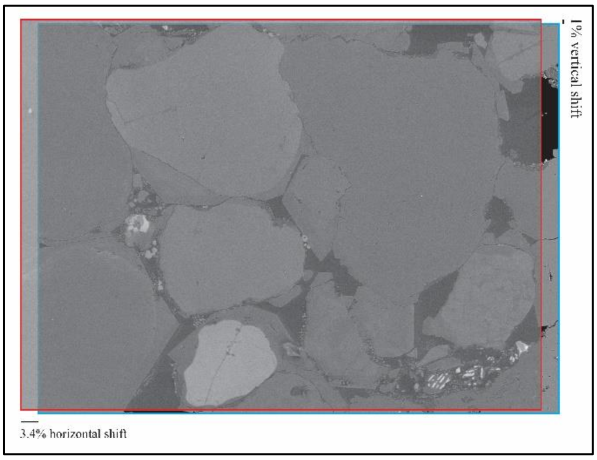


Figure 1: Comparison between the original image and non-local means denoised image.

2.3. Random Forest Algorithm

The Random Forest (RF) algorithm is a popular method for solving a range of problems, as it does not require data preprocessing. The algorithm is based on combining multiple decision trees to average out individual mistakes, reducing the risk of overfitting (Figure 2). The trees in a random forest are built by introducing random variations in the data used to train the tree and selecting the best feature to split a node. The final prediction is based on a weighted vote across all the trees in the forest.

In recent years, machine learning algorithms, specifically RF, have been applied in geological image analysis, including SEM image analysis for reservoir characterization. In rock image segmentation, there are two main categories: mineral phases segmentation and microstructure segmentation. Wu et al. (2019) proposed a SEM segmentation workflow that involves feature extraction and a random cluster forecast to locate organic matter and pores in samples.

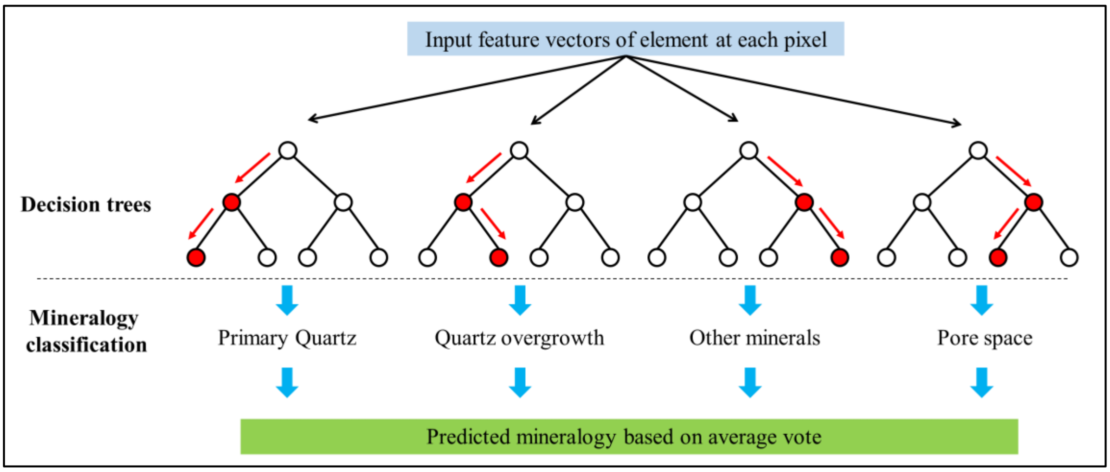


Figure 2: Comparison between the original image and non-local means denoised image.

3. METHODOLOGY

Dataset given in this project includes four datasets of SEM images (BSE, CL and MM) and a 30-pixel labelled JSON of 200 CL images as the ground truth data. This dataset is available for public use in https://doi.org/10.22008/FK2/5TWAZK .

The detailed methodology that our team employed is summarized in Figure 3. In summary, we implement a dynamic segmentation algorithm that includes noise suppression, multi-level auto-thresholding, and dynamic overlay. The algorithm can automatically infer distinct mineralogy from noisier, lower-quality images with varying degrees of brightness/contrast values much better than hard-coded thresholds. The algorithm can also account for overlay shifting due to misalignment between CL and BSE. We also implement full-image supervised training instead of only 30-pixel matching, so our ML optimizer can eliminate internal cracks and false detections.

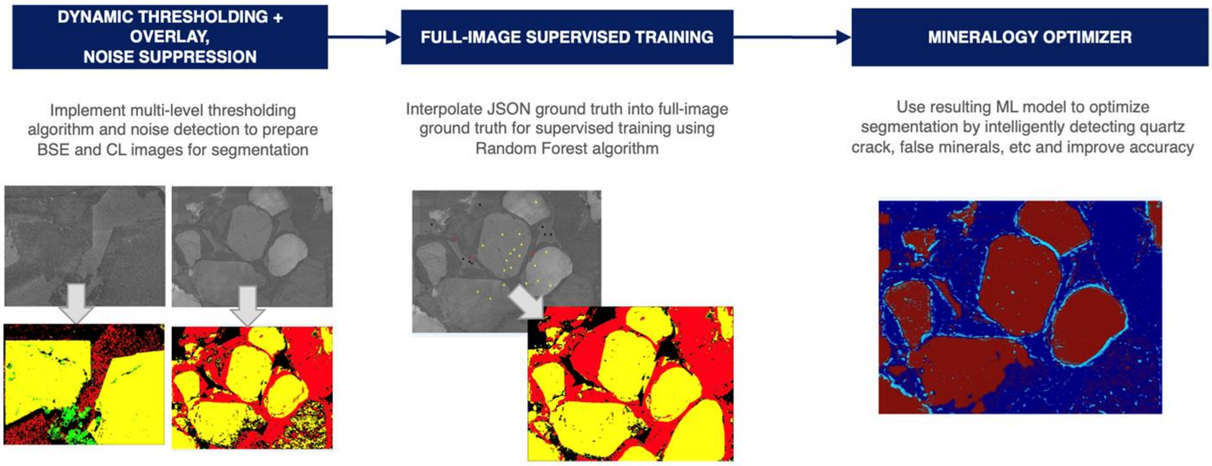


Figure 3: An overview of the methodology behind the mineralogy optimizer

3.1. Data Cleaning and Preparation

SEM data cleaning and preparation is a crucial step in analyzing sedimentary geothermal reservoirs. The SEM images need to be cleaned and prepared for analysis to ensure accurate results. This includes removing noise and artifacts from the images to enhance image quality. Non-local means denoising is implemented to clean both SEM-BSE and SEM-CL images.

3.2. Image Segmentation and Dynamic Overlaying

Cleaned SEM-BSE and SEM-CL images are then dynamically segmented using multi-level Otsu thresholding using four channels that can infer multi-level and notable bins from varying degrees of brightness and contrast. BSE segmentation is first commenced. The segmentation process in BSE classifies 3 categories of Quartz, Pore, and Other minerals. Before performing the CL segmentation, BSE and CL need to be overlayed on top of each other, and this is where the dynamic overlay comes into play to correct the alignment shift that often occurs differently on different runs. The x-shift and y-shift ask for user input since overlay shifting is the fastest to be figured out by examining one of the images outside the system. Then, CL segmentation is implemented and aimed to primarily detect Quartz Overgrowth.

3.3. Features Extraction

<u>Texture filtering</u>

Gabor filters are widely used for feature extraction, texture analysis, and pattern recognition in image analysis. They are particularly useful for analyzing images with complex textures and structures, such as those found in geological and geothermal reservoirs. Gabor filters are designed to capture an image's frequency and orientation information. The parameter of the Gabor filter plays an important role in deciding the output image. Gabor Filter selects the phase, size, frequency, the orientation of the resulting image as a parameter. The Gabor filter operates by convolving the input image with a small window that moves across the entire image. The output of the Gabor filter at each position in the image is proportional to the intensity of the corresponding frequency and orientation information in the image (Figure 4). Several sets of Gabor parameters are iterated to get the best Gabor feature for the images.

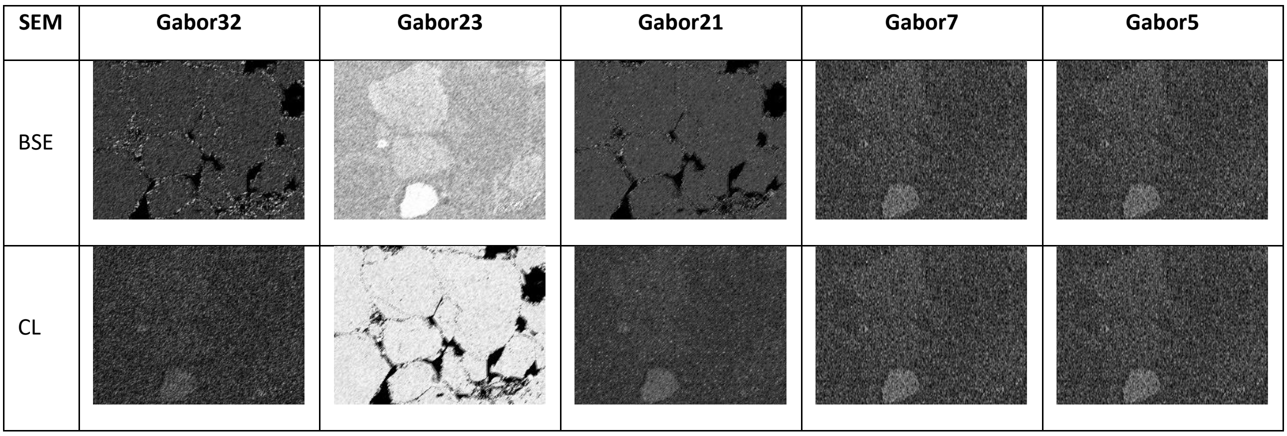


Figure 4: Gabor filter features with various parameters

Edge enhancing filters

Edge-enhancing filters are a type of image-processing technique used to highlight the boundaries between objects in an image. These filters are widely used in computer vision, image analysis, and pattern recognition to extract important features and information from images. There are several types of edge-enhancing filters, including Canny edge, Roberts edge, Sobel edge, Scharr edge, and Prewitt edge filters.

The Canny edge filter uses a multi-step approach to detect edges in an image, including noise reduction, gradient calculation, non-maximum suppression, and thresholding. The Roberts edge filter is a simple, two-step process that uses a convolution operation and thresholding to detect edges. The Sobel edge filter is similar to the Roberts filter, but it uses a 3x3 convolution kernel and calculates gradient magnitude and orientation to detect edges. The Scharr edge filter is an improved version of the Sobel filter, with a more accurate gradient calculation. The Prewitt edge filter uses a 3x3 convolution kernel to detect edges. Still, it differs from the Sobel and Scharr filters in that it calculates the gradient using a combination of positive and negative weights.

In this research paper, these edge-enhancing filters are applied to SEM images to extract important information about the microstructure and mineralogy of sedimentary geothermal reservoirs (Figure 5). By highlighting the edges in SEM images, these filters provide valuable information about the distribution and shape of mineral phases and pore spaces, which is critical for characterizing and understanding geothermal reservoirs.

Gaussian Filter

Gaussian Blur is a widely used image processing technique that reduces image noise and detail by smoothing the image. It works by convolving the image with a Gaussian kernel, a two-dimensional probability distribution with a peak at the center. The Gaussian kernel spreads the intensity values of the pixels over a larger area, which reduces the prominence of sharp edges and detail, and smooths out the noise. The size of the Gaussian kernel determines the extent of smoothing and the strength of the blur effect. By adjusting the standard deviation of the Gaussian kernel, the user can control the degree of smoothing. The Gaussian blur filter is widely used in image processing applications such as denoising, edge detection, and feature extraction. In the context of this research paper, Gaussian Blur is used as a pre-processing step to prepare the SEM images for further analysis and to remove small-scale noise and unwanted detail.

Statistical Filter

Statistical filters in image features are techniques used to extract information about the distribution of image intensity values. Mean, and variance features are two of the most commonly used statistical filters in image processing. The mean feature provides information about the average intensity of the pixels in an image. By calculating the mean value of the pixel intensities, the filter can provide a summary of the image'. Variance, on the other hand, provides information about the dispersion of the intensity values. It measures the spread of the intensity values and provides an idea of how much the intensities deviate from the mean. A high variance indicates that the intensity values are spread out over a wide range, while a low variance indicates that the intensity values are mostly clustered around the mean.

In image processing, mean and variance features are used to extract information about the texture and smoothness of the image. For example, a high mean value with a low variance indicates a smooth and homogeneous texture, while a low mean value with a high variance indicates a rough and heterogeneous texture. In addition, these statistical features are also useful for image segmentation, where the goal is to separate different regions of the image based on their intensity values. The mean and variance features can be used to identify different intensity distributions in the image and to differentiate between different regions.

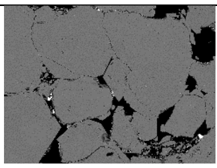
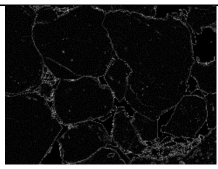
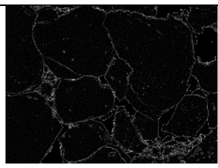
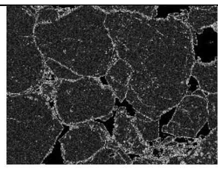
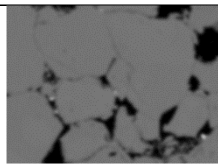
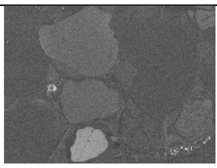
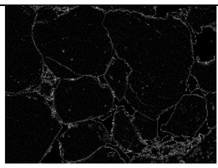
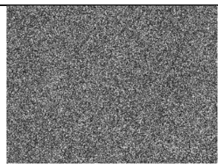
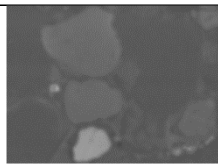
SEM	Original	Prewitt	Sobel Edge	Variance	Gaussian
BSE					
CL					

Figure 5: Edge enhancing and statistical filter features.

3.4. Machine Learning Model Building

After building full-image ground truth data using the image segmentation method and extracting several features of the input images, as mentioned in the previous section, we combined those ground truth data and image features into a single dataframe. Then, this dataframe will be divided into training and test data. The training data will be used to build the machine learning model using RF and will be validated using the testing data. The resulted model, will then be saved into pickle that later will be ready to use to predict mineralogy on another SEM images input.

A Machine Learning (ML) model can be used on the features that have been extracted and preprocessed in a previous section of the research. Using an ML model allows for analyzing a large amount of data in a relatively short amount of time. This research paper uses the Random Forest algorithm as the ML model. Random Forest is an ensemble machine-learning technique known for its robustness and versatility in handling various problems. The algorithm is based on combining multiple decision trees to reduce the risk of overfitting the data. During training, the random forest creates tens to hundreds of individual decision trees using random variation in the data and feature selection. Once the random forest is trained, it can make predictions based on the target classes based on a weighted vote across all decision trees. This approach has been reported as effective for various applications of machine learning algorithms in geological image analysis, including SEM image analysis for reservoir characterization.

5. RESULTS AND DISCUSSION

The result of the automated workflow is shown in Figure 4. The full model training resulted in 75% accuracy score, which is a promising start. We recommend further improving the ML model with more data training; however, we will need an HPC cluster run to run the training due to the large size. Nevertheless, we noticed a notable detection improvement after training, which is false porosity detection associated with internal cracks being reduced using the mineralogy predictor. We recommend improving the predictor by applying morphology detection principles.

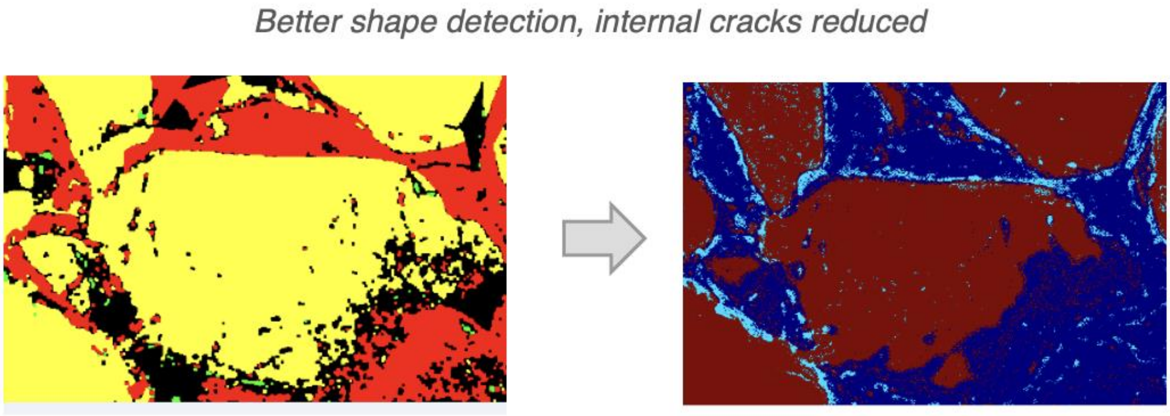


Figure 4: False porosity detection associated with internal cracks is reduced using the mineralogy predictor

Some parameters, such as overlay shifting, need information from the user. We have designed the program to capture input in plain English, which can be used with little to no coding experience. We recommend further developing the interface into a web app to be even easier to use.

6. CONCLUSION

The automated workflow to detect and classify mineralogy from SEM images and calculate quartz overgrowth percentages is useful for accelerating the time and reducing the error associated with inferring geothermal reservoir quality. Further improvements on the dynamic segmentation ML algorithm, such as by incorporating morphology detection principles, can further increase the accuracy of the workflow.

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