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Crack Density and Length Detection using Machine Learning

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Abstract **-** This study presents a comprehensive approach for detecting and analyzing microscopic cracks in rock samples using computer vision techniques and machine learning algorithms. The proposed methodology involves image segmentation, crack detection, length, and density prediction, utilizing a combination of image processing techniques and linear regression modeling. Microscopic rock images captured at various temperatures were analyzed to detect and measure cracks accurately. The developed system demonstrated effective crack detection and length measurement capabilities, aided by image segmentation, edge detection, and feature extraction methods. Moreover, the application of linear regression facilitated the prediction of crack parameters, exhibiting a clear relationship between crack characteristics and temperature variations. The findings contribute to a deeper understanding of crack formation mechanisms in rocks under different temperature conditions, offering valuable insights for geological studies and infrastructure integrity assessments.

Keywords**: Crack detection, Canny Edge Detection, Image Segmentation, Linear Regression, Image Segmentation, Crack length, Crack density**

1. Introduction

Rocks are fundamental components of the Earth's crust, serving as building blocks for mountains, cliffs, and landscapes. Despite their apparent solidity, rocks are subject to various geological processes that can lead to the formation of cracks and fractures. One significant factor influencing the behavior of rocks is temperature variation. Temperature fluctuations can induce thermal stresses within rocks, leading to cracking and fracturing over time. Understanding the relationship between temperature and rock cracking is crucial for numerous scientific disciplines, including geology, civil engineering, and environmental science.

Measuring crack formation and propagation in rocks at different temperatures provides valuable insights into the underlying mechanisms of rock degradation. By examining microscopic images of rock samples captured at various temperature levels, researchers can gain a deeper understanding of how temperature influences the development and propagation of cracks. Moreover, accurate measurement and analysis of cracks can inform predictive models for rock behavior under different environmental conditions. This knowledge is indispensable for mitigating geological hazards, assessing infrastructure stability, and predicting geological phenomena such as landslides and earthquakes.

The ability to predict temperature-induced rock cracking has significant implications for a wide range of applications. In civil engineering, understanding how rocks respond to temperature changes is essential for designing durable structures and ensuring their long-term stability. By incorporating temperature-dependent crack measurements into engineering models, engineers can optimize construction materials and techniques to withstand environmental stressors effectively. Similarly, in geology and environmental science, predictive models of rock cracking at various temperatures can aid in interpreting geological formations, predicting erosion patterns, and assessing the impact of climate change on landscapes.

Advancements in computer vision and machine learning have revolutionized the field of rock analysis, enabling researchers to automate the detection and measurement of cracks in microscopic images with unprecedented accuracy and efficiency. By leveraging image processing techniques such as segmentation, edge detection, and feature extraction, coupled with machine learning algorithms for crack length and density prediction, researchers can extract valuable quantitative data from complex rock images. These data-driven approaches facilitate comprehensive analysis and interpretation of rock properties, paving the way for deeper insights into the relationship between temperature and rock cracking.

We present a systematic approach for detecting and analyzing cracks in rock samples at various temperatures using computer vision and machine learning techniques. We demonstrate how image segmentation, crack detection algorithms, and linear regression modeling can be employed to quantify crack parameters and predict temperature-dependent crack behavior. By integrating these methodologies, our research contributes to the advancement of predictive models for rock cracking, providing valuable tools for geological studies, infrastructure design, and environmental monitoring. Through our analysis, we aim to enhance understanding of the complex interplay between temperature and rock integrity, offering valuable insights into the behavior of geological materials in changing environmental conditions.

2. Literature Review

Talab Ahmed et. al [1] propose a method for crack detection in images using the Otsu method and multiple filtering techniques, aiming to improve the accuracy of crack detection in various types of images. The paper utilizes the Otsu method for crack detection in images, which is a widely used thresholding technique that automatically determines the optimal threshold value for image segmentation and refers to [2]-[6]. Multiple filtering techniques are employed in the proposed method to enhance the accuracy of crack detection. These filtering techniques may include but are not limited to median filtering, Gaussian filtering, and morphological filtering . The combination of the Otsu method and multiple filtering techniques allows for improved crack detection in various types of images, making the method more robust and effective

Jing Yu Armstrong, et. al [7] characterises fractured coal samples based on micro-CT data and takes inspiration from [8]-[13]. It models the coal samples. It is simple to observe the permeability of cracked coal based on geometrical features.

Wang Gang et al. [14] used fractal theory and CT 3D reconstruction to describe the coal's microstructure. The writers investigate [15]–[19]. Using a 3D box dimension based on 3D data, the volume fractal dimension may be computed. It was noted how porosity and permeability related to fractal dimensions.

CNN was used to classify igneous rocks from the thin section images in Seo Wanhyuk, et. al. [4]. The images were segmented into small patches and classification performed on the segmented images individually. The classification scores for all subimages were summed up to give an overall classification value.The truly classified images showed well-perceived mineral grains.

Su Cheng et al.'s Con-CNN approach [5] for categorising geologic rocks according to their petrographic thin sections. Images were taken using two types of light: cross-polarized light (XPL) and plane-polarized light (PPL). Principal Component Analysis was used to separate images into patches. A full classification result was obtained by combining the patch classification results using the highest likelihood method. An accuracy rate of 89% was attained overall.

This study applies the U-Net architecture, designed for biomedical image analysis, to texture-based feature extraction and object segmentation problems in SEM images of shale. Through the addition of a revised weight function and a local variable weight based on spatial data in training, the U-Net is able to distinguish between clay aggregates, matrix mineral particles, and organic materials with great success. Tensorflow validation yields an astounding 91.7% average IOU for the model. The process, which is applied to 300 SEM tiles of Devonian Duvernay shale, successfully separates the clay aggregates, highlighting the viability, economy, and promptness of texture-based deep learning for the extraction of geologic features and providing insightful information for geoscientists. Chen, Zhuoheng et. al [6] present work on this.

3. Methodology

For the purpose of achieving the goal, microscopic rock images were used. The images were captured at various temperatures - 100K, 200K, 300K, 400K, 500K and Room Temperature. 15 images at both 10x and 4x levels of magnification were captured and used for training the model.

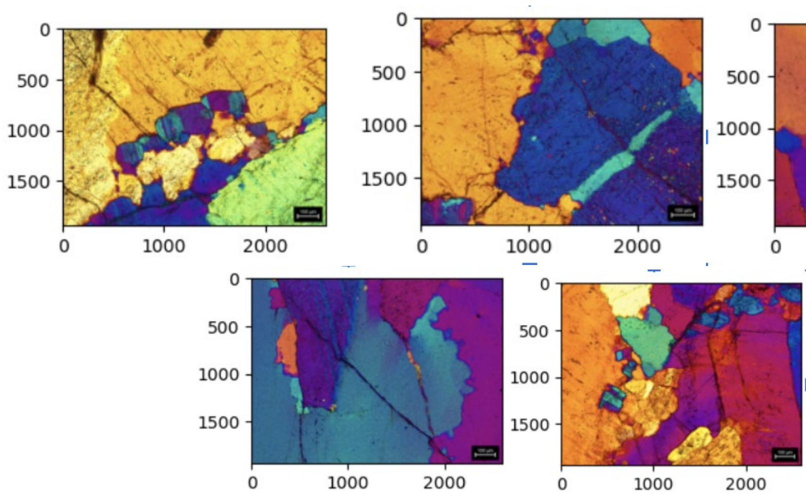

Fig 1: Microscopic images of rocks at Room Temperature, 100K, 200K, 300K, 400K and 500 K

Fig 1 shows the microscopic image of the rock at 5 different temperatures. There were multiple pictures like this that were fed into the model for prediction and training purposes. There are a lot of minute cracks seen in the rock sample images which are quite difficult to distinguish and measure manually. A Computer vision program is required to detect the cracks and measure its length accurately.

The entire work can be divided into two main categories :

1. Cracks detection
2. Cracks length and density prediction

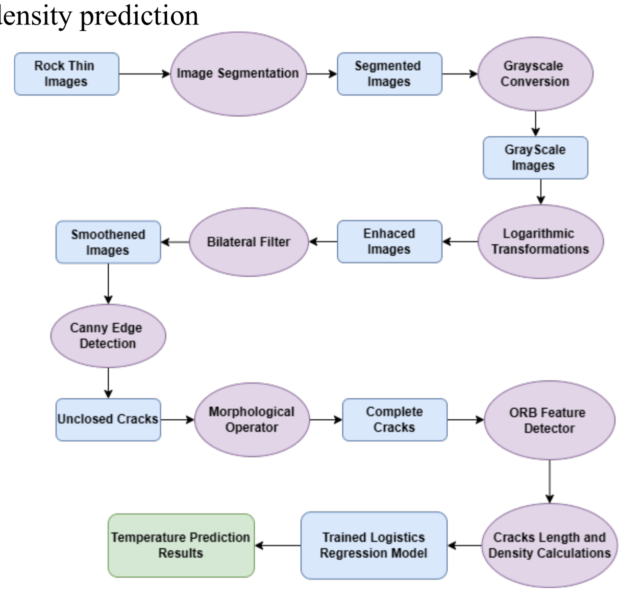

Fig 2 : Methodology Flowchart

The entire methodology can be broadly split into four parts: Image Segmentation, Crack Detection, Calculation of Crack Length and Density and Prediction of Crack Length and Density. Fig 2 depicts the flow of steps that are followed for crack detection and prediction.

3.1. Image Segmentation

First, following the divide and conquer approach, each image is segmented into smaller images. The OpenCV library has many functions that can help achieve this goal. Each image is first converted from the BGR (Blue, Green, Red) format to the RGB(Red, Green, Blue).

Upon iterating through the height and width of the original image, segmentation is done by extracting smaller images of size 250X250 pixels. Further processing is done on each sub-image separately. Further processing shall be done on the individual segmented images.

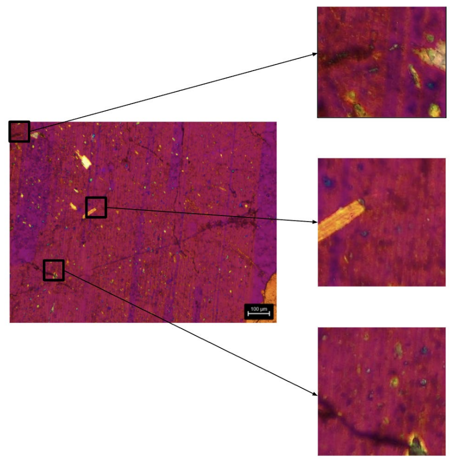

Fig 3 : Segmented parts of the image

One rock image is segmented into almost 90 sub-images of size 250 x 250 pixels. The smaller sub images of a microscopic image are highlighted in Fig 3. These are later converted to grayscale before sending it into the model.

3.2. Crack Detection

All the segmented images for each individual rock image are required to calculate the crack length and density for that particular rock sample.

To make computations simpler and smoother, gray scale conversion of coloured images is necessary. To further enhance the image and contrast, logarithmic transformation is done that expands the darker pixels. The natural logarithm of the pixel values of the grayscale image is calculated first, and then it is normalized to the range [0, 255].

Bilateral filter is used to smoothen the image. This reduces the noise but keeps the edges intact which is what we need.It replaces the intensity of each pixel with the weighted average of nearby pixels. Bilateral filtering preserves edges while smoothing the image, and it takes into account both spatial and pixel intensity differences.

The Canny Edge Detection Algorithm is then used to detect edges. The bilateral image undergoes application of the Canny edge detection technique. By computing gradients and ignoring non-maximum pixels, it may identify edges in a picture. A multi-stage method is used to identify a variety of edges in pictures. It consists of five steps: edge tracking using hysteresis, non-maximum suppression, gradient calculation, noise reduction, and double threshold.

Initially, the Gaussian filter is employed to eliminate the noise, serving as a secondary filtering layer in this case. Secondly, the Gaussian filter's derivative is computed throughout both dimensions. Points contributed by non-maximum edges are suppressed. The pixels that are higher than the gradient magnitude are then preserved using the Hysteresis Thresholding technique.

The edges detected through this algorithm often leave gaps in edges which may lead to incorrect length and density measurements. To fill such gaps, Morphological closing operator is used. Erosion operation followed by dilation operation is performed which fills the gaps between the edges. A kernel of size 5x5 is used.

To find features (edges) in an image, we utilise the ORB feature detector. With numerous improvements, ORB is a combination of the FAST keypoint detector and the BRIEF descriptor. It first finds keypoints using FAST, and then it finds the top N points among these using Harris corner measure. One key characteristic of BRIEF is that every bit feature has a mean that is close to 0.5 and a significant variance. The primary focal points, which indicate significant spots or characteristics within the image and are identified by the ORB feature detection technique, are stored in a file.

The resulting images received after applying canny edge detection and following the other steps is seen in Fig 4. The cracks in each sub image are highlighted in the images displayed on the right.

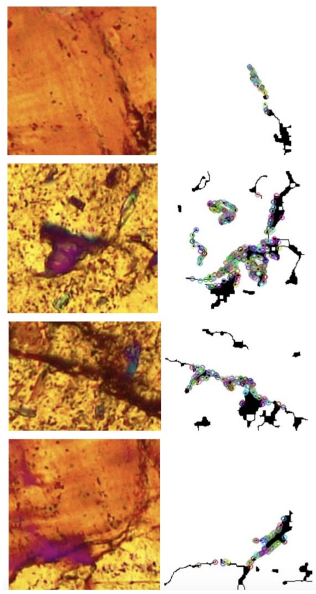

Fig. 4. Segmented Image and Edges Detected from Feature Images

3.3. Calculation of Crack Length and Density

The lengths of the edges are calculated for each segmented feature image and summed up for all the images.

After processing all segmented images, the density of the cracks is calculated by dividing the total crack length by the area of the original image (calculated at the beginning of the code). This gives an indication of how much of the image is covered by the edges relative to the total area of the original image.

3.4. Predicting Crack Density and Length

Predicting the crack parameters at any given temperature is an interesting task to do. Here we have done this using Machine Learning. Linear Regression model is used to make the predictions .Linear regression is a very popular Machine Learning algorithm. It statistically predicts unknown variables. It makes predictions for continuous variables unlike classification algorithms which make predictions on discrete variables. A linear relationship between one dependent variable and several independent variables is the underlying assumption of linear regression.

The crack lengths and densities measured above are split into a training and testing set of ratio 4:1. The model is obtained by training on the training set and tested against the test set. Performance metrics used are Mean Squared Error and R2 score . All the results can be seen in the Results section 4.

4. Results

The crack lengths and densities of rocks at 6 different temperatures were known. This was then fed into the model which is used to model how the crack length and density would change as the temperature rises or falls. Following is the graph for temperature dependence of crack lengths :

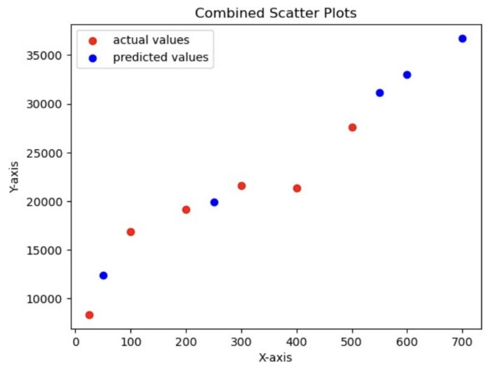

Fig. 5. Segmented Image and Edges Detected from Feature Images

Fig. 5 shows the relationship between the crack length and change in temperature. From the data point we had, it was seen that the length of the cracks were increasing as the temperature increased. After feeding this information to the model it is observed that the predicted values for the unknown temperatures seem to be following a similar trend. The cracks increase in the rocks as the temperature rises and so do the crack lengths.

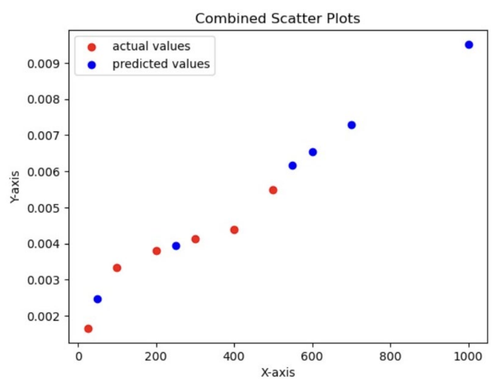

Fig. 6. Segmented Image and Edges Detected from Feature Images

The data showed that the higher the temperature rose, the crack density also increased. The proposed model is able to predict the crack densities for other unknown temperatures as observed in Fig 6. The red points on the graphs are the values that were known previously and the points in blue depict the unknown predicted crack densities.

Table 1: Crack Density and Length Measurements

Temperature	Average Density (px^-1)	Average Length (px)
25	0.006562	33066.033
50	0.008329	41969.44
100	0.010377	52287.02
200	0.012758	64287.86
250	0.013695	69008.32
300	0.014469	75909.15
400	0.015714	76178.73
500	0.019888	100210.56
550	0.021744	109566.62
600	0.023085	116326.37
700	0.025768	129845.81

In table 1, all the values both real and predicted have been recorded. It can be observed that as the temperature increases, the density and length of the cracks in the rocks also increases. It shows the same pattern as is seen in Fig 5 and Fig 6.
In table 1, average density and crack length is taken as the average value for all the microscopic rock images for a particular temperature is considered to give a more general idea.

5. Conclusion

After a very long process of researching various methods for analysing cracks in rocks at different temperatures, we conclude that crack lengths are directly proportional to the temperature of the rocks. As the crack density is directly proportional to crack length with the constant being the area of the rock surface, we see that the crack density is also directly proportional to the temperature. As the temperature increases, we see that the crack density of the rocks also increases.

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