[PS]An Approach in Caving Recognition by An Integrated Model of Computer Vision and Machine Learning for Any Drilling Environment*

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Abstract

Cavings are a valuable source of information when drilling which indicate that a failure has occurred downhole. This project is an integrated study of Machine Learning, Computer Vision, and Geology to recognize the presence of cavings in the shakers and how to link the morphology of cavings with borehole problems. The analysis can be transferred and applied to the Midland-Delaware (Permian) Basin and Fort Worth Basin or any unconventional reservoir.

The methodology involved developing a structured picture database of cavings from the Norwegian Continental Shelf which it is used to extract features such as Shape, Roundness, Color, and Size. Each picture will be converted into vectors that can be used to establish an array of features and labels; Algorithms written in Python can recognize the different characteristics of the caving and causal mechanisms. Also, MxN pixels of images will be the data points to cluster using k-means algorithm for the color feature which is used to correlate with the formation type. To extract the size feature, calibration was first done using a reference object, and OpenCV library is used to extract length and width of each object present in the picture.

Caving recognition was achieved by taking a picture of a new sample, this will enable a faster assessment of the drilling problem. A set of 25,536 pictures of cavings is being used for training and testing with nine different supervised Machine Learning algorithms and three different architectures of Neural Networks. Besides, features extracted from caving images can be successfully linked to cavings causal mechanisms; as a result, an integrated model between features, drilling parameters, and causal mechanisms, will suggest and implement remedial action in order to solve wellbore stability problems. This process is done automatically by the algorithm.

Selected References

Bestagini, P., V. Lipari, and S. Tubaro, 2017, A Machine Learning Approach to Facies Classification Using Well Logs: SEG Technical Program Expanded Abstracts, 2137-2142.

Sidahmed, M., A. Roy, and A. Sayed, 2017, Streamline Rock Facies Classification With Deep Learning Cognitive Process: SPE Annual Technical Conference and Exhibition.

An Approach in Caving Recognition by An Integrated Model of Computer Vision and Machine Learning for Any Drilling Environment

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Introduction

This project is an integrated study of machine learning, computer vision and geology to recognize the presence of cavings in the shakers and how to link the morphology of the caving present in the picture with borehole problems such as pore pressure.

The principal objective of this study is to bring a tool that can create a safer drilling environment by analysing pictures of cavings and recognizing the shape that an increased pore pressure creates downhole. There is change in the shape of the caving due to transport in the drillstring annular and thus, roundness needs to be considered.

The specific shape and edge definition that defines a problem related with pore pressure is concave-convex, the size of it can be millimetric or rather large with some centimetres. These features have been given to the different machine learning algorithms to learn how to recognize and differentiate different forms of cavings and what failure mechanism is causing them.

So far, the results show that the pictures need to have better resolution than the MNIST dataset, a 56x56 picture is being used instead of the traditional 28x28. This has been done to capture details in the shape and edges of the caving. The complete pre-processing, training, testing and validating is being performed in an INTEL i7-7700HQ 2.81 GHz with 16 GB RAM.

Background

The digitalization of the geological data and drilling operations are fields that are linked through the cycle of obtaining data to drill safer, faster and more economically.

In terms of machine learning, there has been a preference for using classifiers for facies prediction (Shashank et al., 2018 & Bestagini et al., 2017), deep learning cognitive process for rock classification (Sidahmed et al., 2017) and also for seismic trace editing where the interpretation plays a major role (Shen et al., 2018) but computer vision has started to be used more often only in the recent years, and regarding cavings it has been used for recognizing cuttings and cavings in 3D environments (Han et al., 2018) and caving depth prediction (Galvin et al., 2014).

Method

There are four main features that are needed to be recognized by the algorithms: Shape, Edge definition (roundness), Size and Colour. This features will be linked with the most common failure mechanisms (but not limited to): Pore pressure, Stress Anisotropy, Low mud weight, Presence of faults & Mud Chemistry.

Each picture has been converted into vectors that can be used to establish an array of features and labels; this has been used by the algorithms written in Python to recognize the different characteristics of the caving: morphology and causing mechanism. Supervised and unsupervised methods have been used to evaluate the best performance of the code, this includes the re-purpose of InceptionV3 for visual recognition.

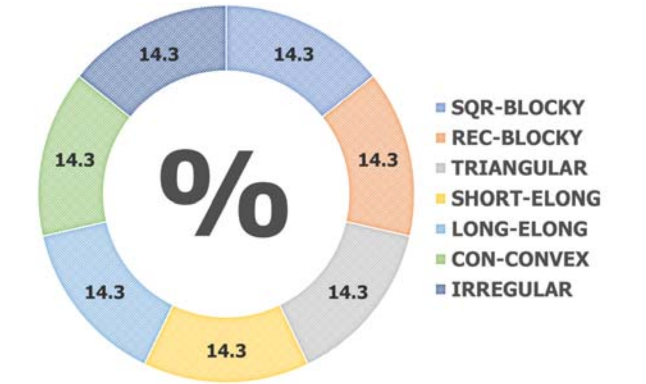
An MxN size image has been treated as MxN pixels, which RGB values are being used by the k-means algorithm to extract the color feature. With an array of data from the RGB code and the percentage of the dominant colors in the picture, a supervised method is used to correlate the data with the formation type, thus making possible to know the rock type of a new sample.

To extract the size feature, calibration was first done using a reference object which dimensions should be known and easy to find in the picture. Using Python with OpenCV library, the length and width of each object can be recognized within an exactitude of 1mm due to normal distortion effect. This feature has been used for pre-processing the images and make sub-classification of blocky and elongated shapes.

Photography Set-Up

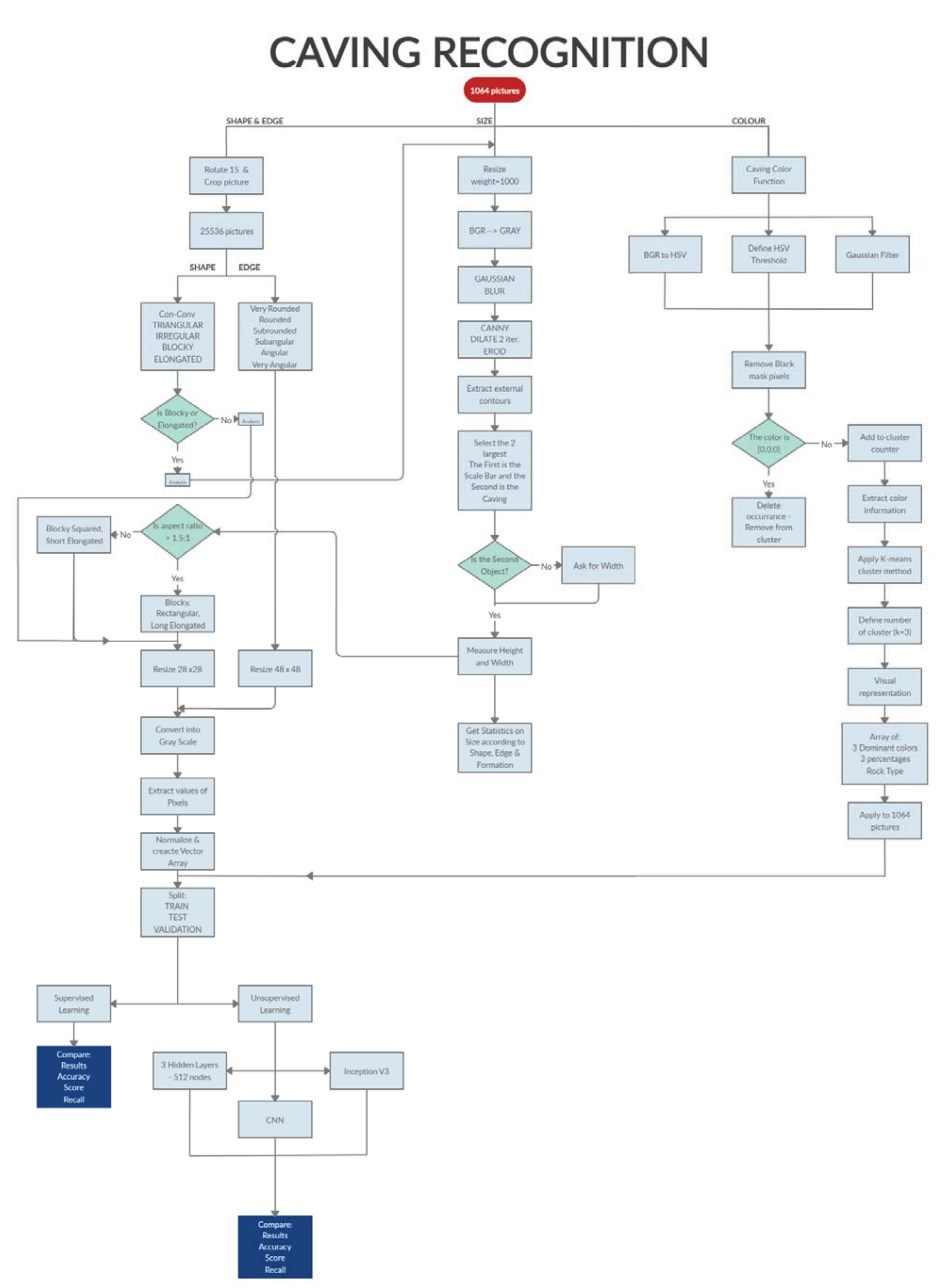
A standard dataset was built from scratch using a photobox with consistent light conditions through all the samples. It is important to have a template with the elements needed to guarantee the position of all the elements in the picture, including the position of the caving and the focus on it.

Generated Dataset



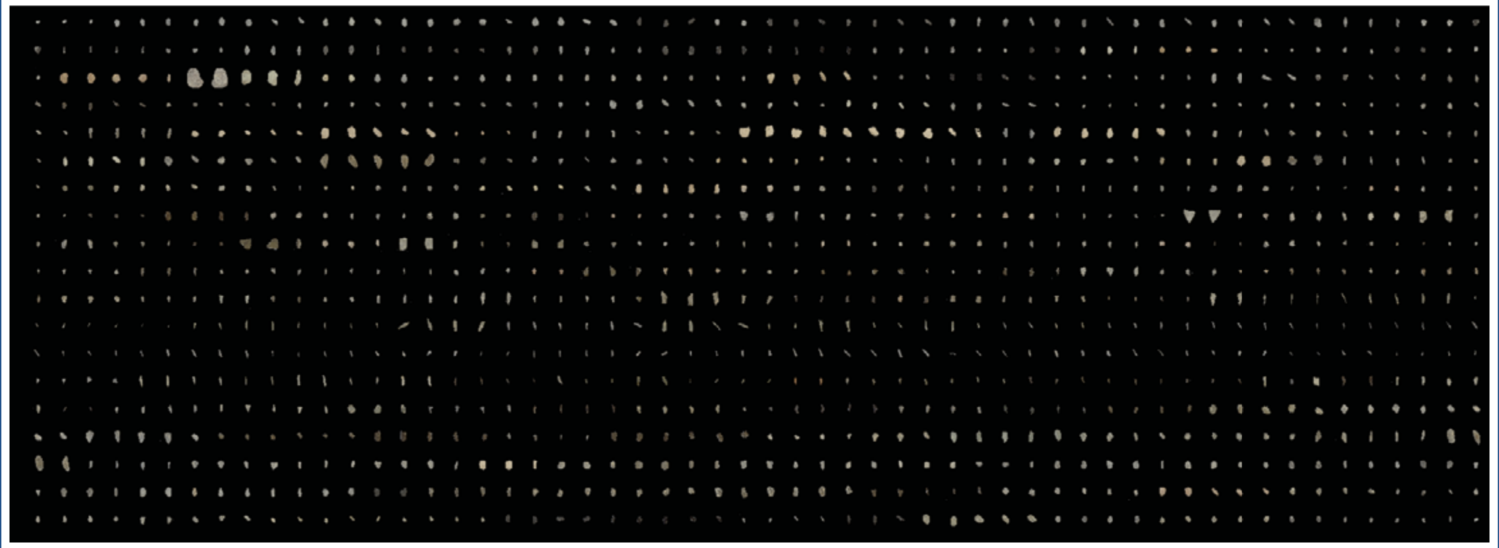
The basic dataset consist of 1,064 pictures of different cavings. To show the real colour of the caving, it was cleaned using olive oil to remove the drilling mud. In a real scenario, this might not be possible but the study focuses more on the shape of the caving, which is independent of the colour.

Flowchart



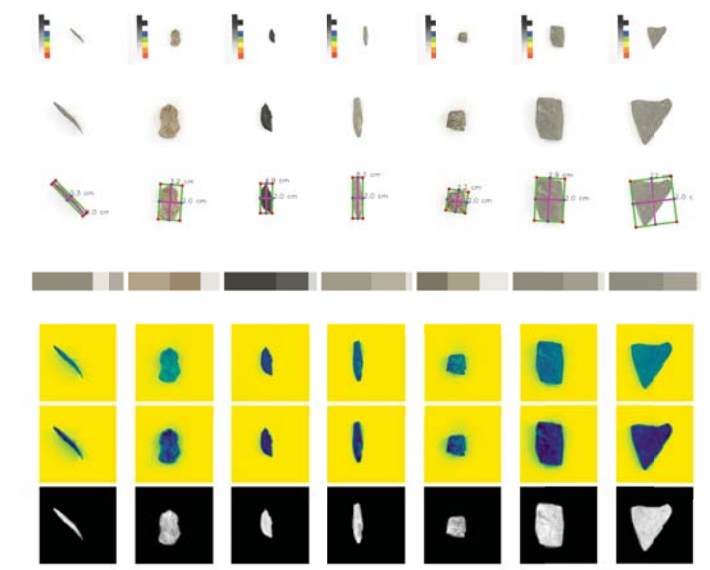
The process of extracting the features of each caving can be summarized in three fronts: Shape & Edge, Size and Colour. The first two are within the interest of the project and the last two are used to help recognize the correct caving.

Complete Dataset



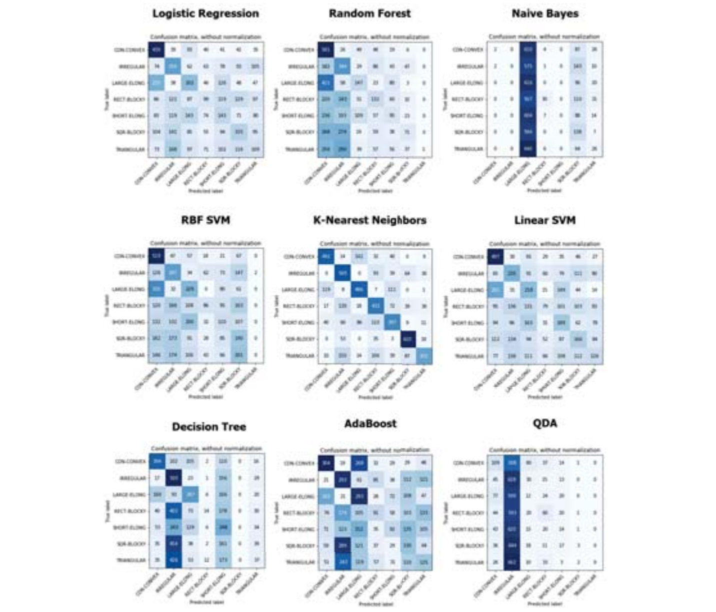
1,064 pictures have been catalogued and labelled. Present in the database there is: Limestone, Shale, Sandstone among others. The samples were cleaned with olive oil and dry at normal conditions.

Feature Extraction



Each picture is cropped within the desired area, resized and turn each pixel into values to get the following array: 1,064x3,136 (rows x columns). Where each row is a picture and each column is a feature with a value between 0-255 as an 8-bit grayscale picture. Feature extraction also includes the size of the caving and the most dominant colours using K-means clustering.

Preliminary Results



From the first results with supervised learning, Nearest Neighbors gives the best results so far. With an accuracy of 65% (recall 64% and score 64%), all the algorithms need to be optimized. Another method of improvement is by using more pixels but with higher computational cost or by using Harmonic Neural Networks instead of Convoluted Neural Networks.

Conclusions and future work

A set of 25,536 pictures of cavings from the Norwegian Continental Shelf is being used for training and testing with 9 different supervised ML algorithms and 3 different architectures of Neural Networks.

Next steps include using Harmonic Neural Networks to reduce the training time and also the size of the dataset as it contains 24 rotated pictures per sample. The comparison between neural networks architectures will be used as a platform to process the data for edge definition. The study need to define the optimum size reduction of the pictures (number of pixels to be vectorized) as it directly impacts on computing time.

Features extracted from caving images can be successfully linked to cavings causal mechanisms; as a result, an integrated model between features, drilling parameters and causal mechanisms, will suggest and implement remedial action in order to solve wellbore stability problems. There is also a strong connection between the shape and the physical problem the well is experiencing with the formation that produces the caving, that interaction is being told by looking at the shape of the caving and not so much to the color of it.

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