AUTOMATIC CLASSIFICATION OF PLUTONIC ROCKS WITH MACHINE LEARNING APPLIED TO EXTRACTED SHADES AND COLORS ON iOS DEVICES

By Sarah Hernandez, Germán Alferez, Benjamin Clausen, and Ana Martinez

INTRODUCTION

Lightness and color are properties used for the classification of plutonic rocks; however, these attributes can be difficult to describe because perceived rock colors depend on the observer’s experience [1]. Moreover, although the classification of plutonic rocks can be done using data from various instrumental techniques, these approaches tend to be expensive and time-consuming. Also, there are no works presenting the implementation of machine learning on iOS devices. This research extracts dominant shades and colors from plutonic rock images to train several machine learning algorithms and deploy the best model on an iOS app for the automatic classification of four classes of plutonic rocks in order from darker to lighter: gabbro, diorite, granodiorite, and granite.

METHODOLOGY

We used pictures of plutonic rocks that had been classified using petrography and chemistry data to train the models (You can find this data through the link in the references). Our methodology is based in three main steps: **Color extraction, Model training, and Deployment of the iOS application**.

Figure 1 introduce the underpinnings of our approach.

**First,** The dominant colors of plutonic rock images were extracted with the K-means algorithm by grouping the image pixels according to the RGB and CIELAB color spaces. K-means is an algorithm of machine learning which is a branch of Artificial Intelligence.

In figure 2 we can see the dominant color extraction of 4 sample images of Gabbro, Diorite, Granodiorite, and granite. The second column shows their extracted dominant colors ordered from less to greater presence in the image. The third column shows the average pixel color of each sample.

The data of the four dominant colors in 283 images were used to create and evaluate five machine learning models with the following algorithms: a Convolutional Neural Network (CNN), Decision Trees (DT), K-Nearest Neighbors (KNN), Logistic Regression (LR), and Support Vector Machine (SVM). The experiments were executed first with the dominant colors in RGB and then in CIELAB. The best model was deployed after validation on an iOS application that classifies the extracted colors in new images of the four rock types.

RESULTS

The best results during validation were for the model generated using the K-Nearest Neighbors algorithm trained with the four dominant colors in the CIELAB format as you can see in Figure 3. These results are better than those obtained in **[3,4]** *(the works of 3 and 4 cited in the references)* in which feature extraction was applied to classify mineral samples. Moreover, they are similar to other works **[5,6,7,8,9]** *(cited in 5,6,7,8,9 references)* in which machine learning was applied for rock classification.

The model generated with K-Nearest Neighbors was deployed in the application which you can appreciate in figure 4. In addition, the training time of 0.068 seconds, the execution time of 339.87 milliseconds, and the file size of 0.018 MB obtained in this approach were better compared to the results of the works in 5, 6, and 7 references in which machine learning models were deployed in Android applications.

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**[5]** E. Vázquez and H. Alférez, “Using Deep Learning for Automatic Classification of Plutonic Rocks with Mobile Devices”, 2021.

**[6]** G. Fan, F. Chen, D. Chen, and Y. Dong, “Recognizing Multiple Types of Rocks Quickly and Accurately Based on Lightweight CNNs Model,” *IEEE Access*, vol. 8, pp. 55 269–55 278, 2020. DOI: 10.1109/access.2020. 2982017.

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**[9]** G. Cheng and W. Guo, “Rock images classification by using deep convolution neural network,” *Journal of Physics: Conference Series*, vol. 887, p. 012 089, 2017. DOI: 10.1088/1742-6596/887/1/012089.

CONCLUSIONS

The dominant colors approach can be useful in classifications where color is important to differentiate images. CIELAB color format is an excellent option to do this. In addition, feature reduction can be applied when a quicker and lighter solution is needed. Although the images are not as many as in other papers, the results are very promising and can be improved with techniques such as data augmentation and extracting crystal shapes from rock images in addition to the dominant colors.

In this research work, five machine learning algorithms were trained with just the four dominant colors extracted from images of plutonic rocks. The best model was found with the KNN algorithm trained with the dominant colors in the CIELAB color format of 283 images. The KNN model has an accuracy, precision, recall, and F-score values of 93%.

As future work, the datasets for training and validation will be extended with a larger number of plutonic rock images taken in the field, rather than in the lab. Also, images will be taken under different conditions – different distances, angles, and lighting effects, e.g., blue vs. cloudy sky, with weathering or alteration, shadows, vegetation, and moss.