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

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INTRODUCTION

Plutonic rocks are formed when magma cools and solidifies below the Earth's surface [1]. 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 [2]. 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. This research extracts dominant shades and colors from plutonic rock images to train several machine learning algorithms and deploy the best model in an iOS app for the automatic classification of four classes of plutonic rocks in order from darker to lighter: gabbro, diorite, granodiorite, and granite.

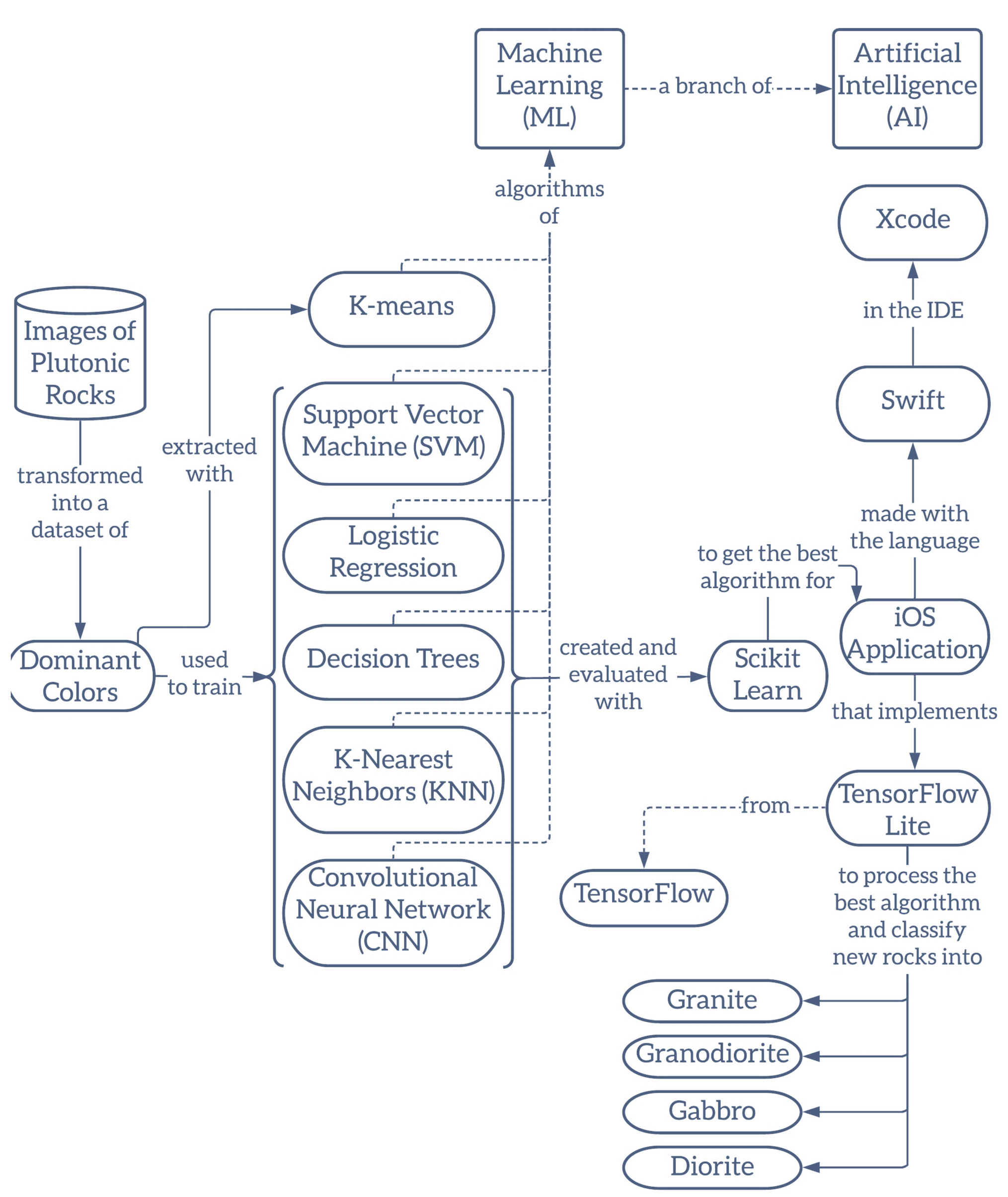

Figure 1. Underpinnings of our approach

Author	Year	Dataset	Algorithm of extraction	Extracted features	Dataset for training	Best trained model	Results	Results in the field
E. Vázquez and H. Alférez [3]	2021	7846 patches from 71 images of six plutonic rock types (diorite, gabbro, granite, granodiorite, monzodiorite, and tonalite)			50% of the patches	4-layer structure CNN	Accuracy: 95%, Precision: 96%, Recall: 95%, F1-score: 95%	Android application accuracy results: 70% for gabbro, 28.5% for diorite, 100% for granodiorite, and 28.5% for granite
Fan et al. [4]	2020	3,208 images of 28 rock lithology categories			80% of the images	SqueezeNet	Model accuracy: 94.55%	Android application accuracy: 94.55%
Fan et al. [5]	2020	3,795 images of 30 different rock types			80% of the images	ShuffleNet	Model accuracy: 95.30%	Android application accuracy: 97.65%
Ran et al. [6]	2019	14,589 patches from 2,290 images of six rock types (granite, limestone, conglomerate, sandstone, shale, mylonite)			60% of the patches	3-layer structure CNN	Model accuracy: 97.76%	
Zhang et al. [7]	2019	481 images of four minerals (K-feldspar, perthite, plagioclase, and quartz)	Inception-v3 CNN model	High-level features (such as chromatic aberration and texture)	90% of extracted features	Stacking model (LR, SVM, and MLP)	Model accuracy: 90.9%	
Maitre et al. [8]	2019	3,192 sub-images of the view taken to a surface with 27 mineral grains species	Simple Linear Iterative Clustering (SLIC) algorithm	Color and Peak intensity of super-pixel histograms	70% of extracted features	Random Forest (RF)	Model accuracy: 89%	
Cheng and Guo [9]	2017	4,200 images of three feldspar sandstones rock types (coarse, medium granular, and fine)			75% of the images	6-layer structure CNN	Model accuracy: 98.5%	

Table 1. Related work

METHODOLOGY

We used pictures from plutonic rocks that were classified by using petrography and chemistry data to train the models [3].

1. Color extraction

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 (see Fig. 2).

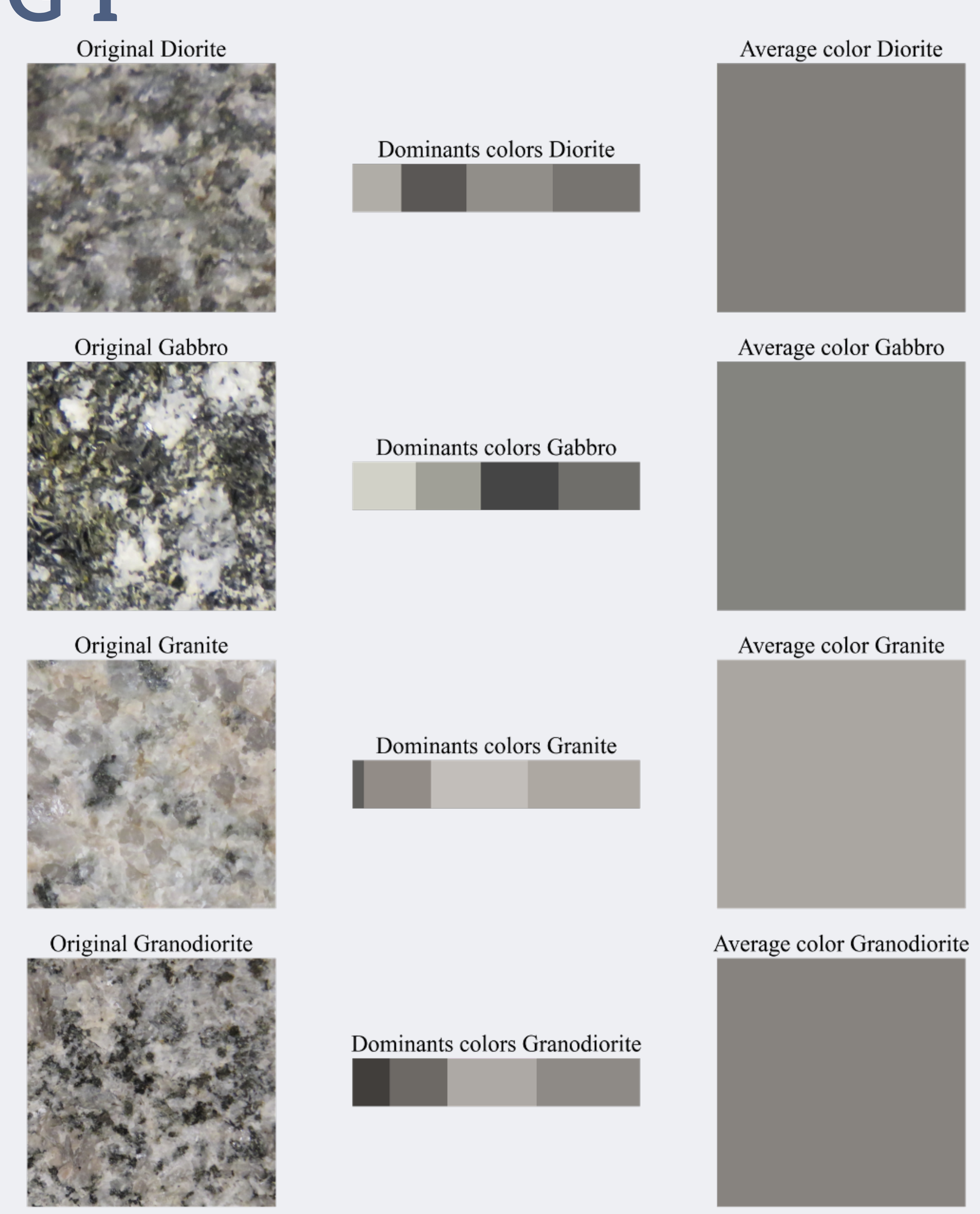

Figure 2. Dominant colors in sample images

2. Model training and evaluation

The data of the four dominant colors were used to create and evaluate several machine learning models with the following algorithms: Logistic Regression (LR), K-Nearest Neighbors (KNN), Decision Trees (DT), Support Vector Machine (SVM), and Convolutional Neural Networks (CNN). The best results during validation were for the model generated with the K-Nearest Neighbors trained with 283 images in the CIELAB color space (see Fig. 3). Results gave accuracy, precision, recall, and F-score average values of 93%.

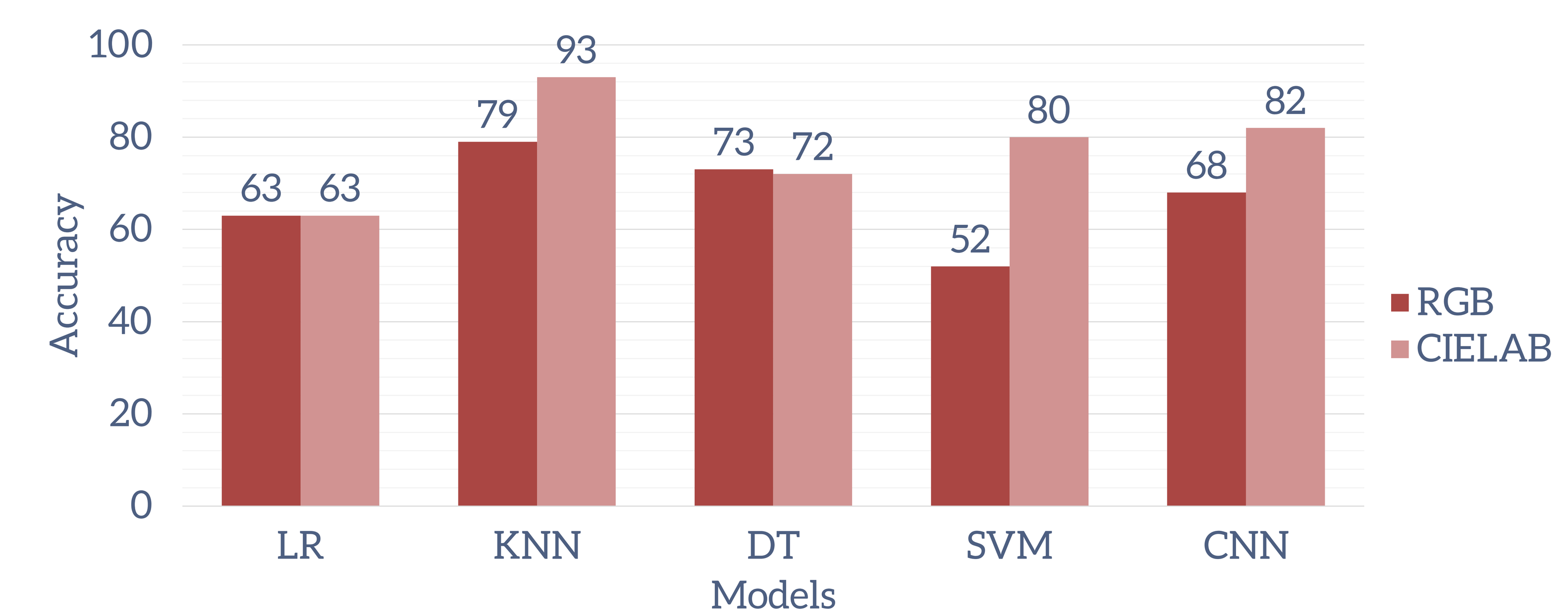

Figure 3. Accuracy of the models in RGB and CIELAB formats

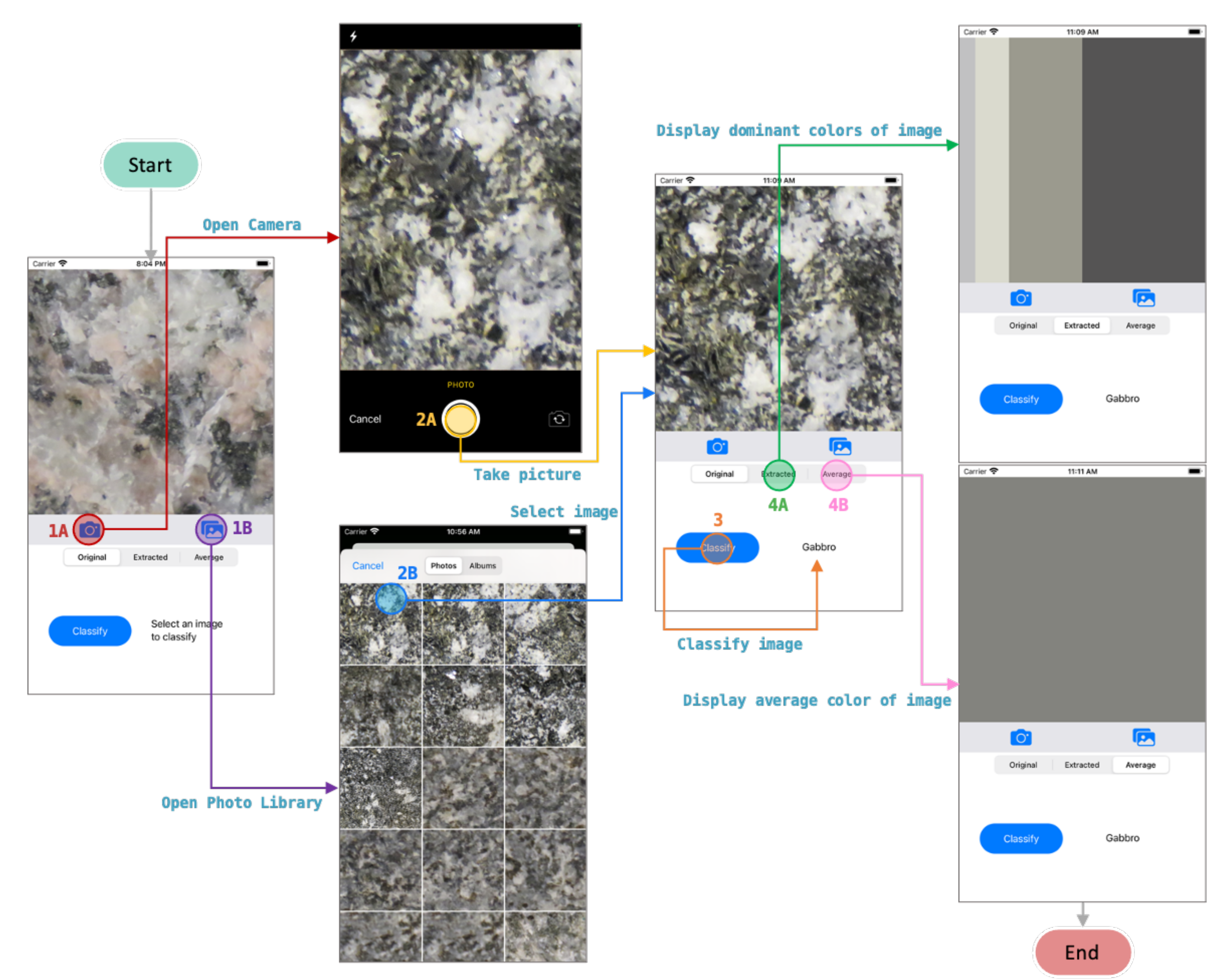

Figure 4. Application workflow

RESULTS

The KNN model was deployed after validation on an iOS application that classifies the extracted colors in new images of the four rock types (see Fig. 4). The application was tested in the field with 34 images, and the following average accuracy results were obtained: 70% for gabbro, 28.5% for diorite, 20% for granodiorite, and 85.7% for granite.

Class	Taken images	Correctly classified	
		Images	Percentage
Granite	7	6	85.7%
Granodiorite	10	2	20%
Gabbro	10	7	70%
Diorite	7	2	28.5%
Total	34	17	50%

Table 2. Accuracy results of application evaluation

CONCLUSIONS

The high accuracy when classifying gabbro samples was because they are noticeable darker than samples of the other 3 classes. Similarly, granites were noticeably lighter. In contrast, diorite and granodiorite share characteristics of the other rock types closest to them in the dark-light sequence; therefore, it is more difficult to automatically classify them based on their dominant colors.

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