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


Sarah Hernández[1]; Germán H. Alférez, Ph.D.[1]; Benjamin L. Clausen, Ph.D.[2]; Ana M. Martínez, Ph.D.[2]

[1] School of Engineering and Technology of Montemorelos University; [2] Department of Earth and Biological Sciences of Loma Linda University

1170469@alumno.um.edu.mx; harveyalferez@um.edu.mx; bclausen@llu.edu; anmartinez@llu.edu


## INTRODUCTION

Plutonic rocks are formed when magma cools and solidifies below the Earth's surface. 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. 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. See the underpinnings of our approach in figure 1.

## METHODOLOGY

We used pictures from plutonic rocks that were classified by using petrography and chemistry data to train the models [2].

### 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).

### 2. Model training and evaluation

The data of the four dominant colors in 283 images 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).

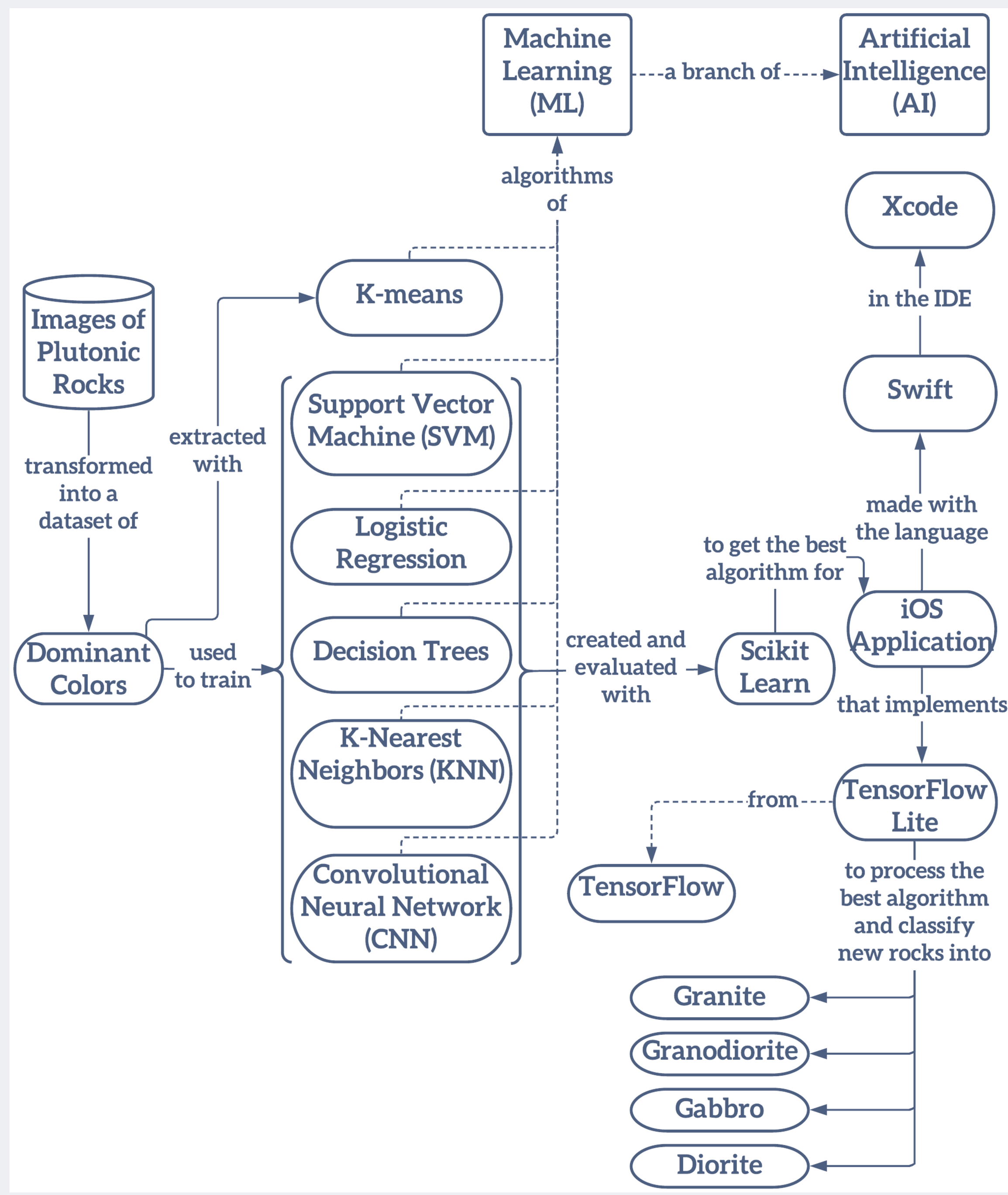


Figure 1. Underpinnings of our approach

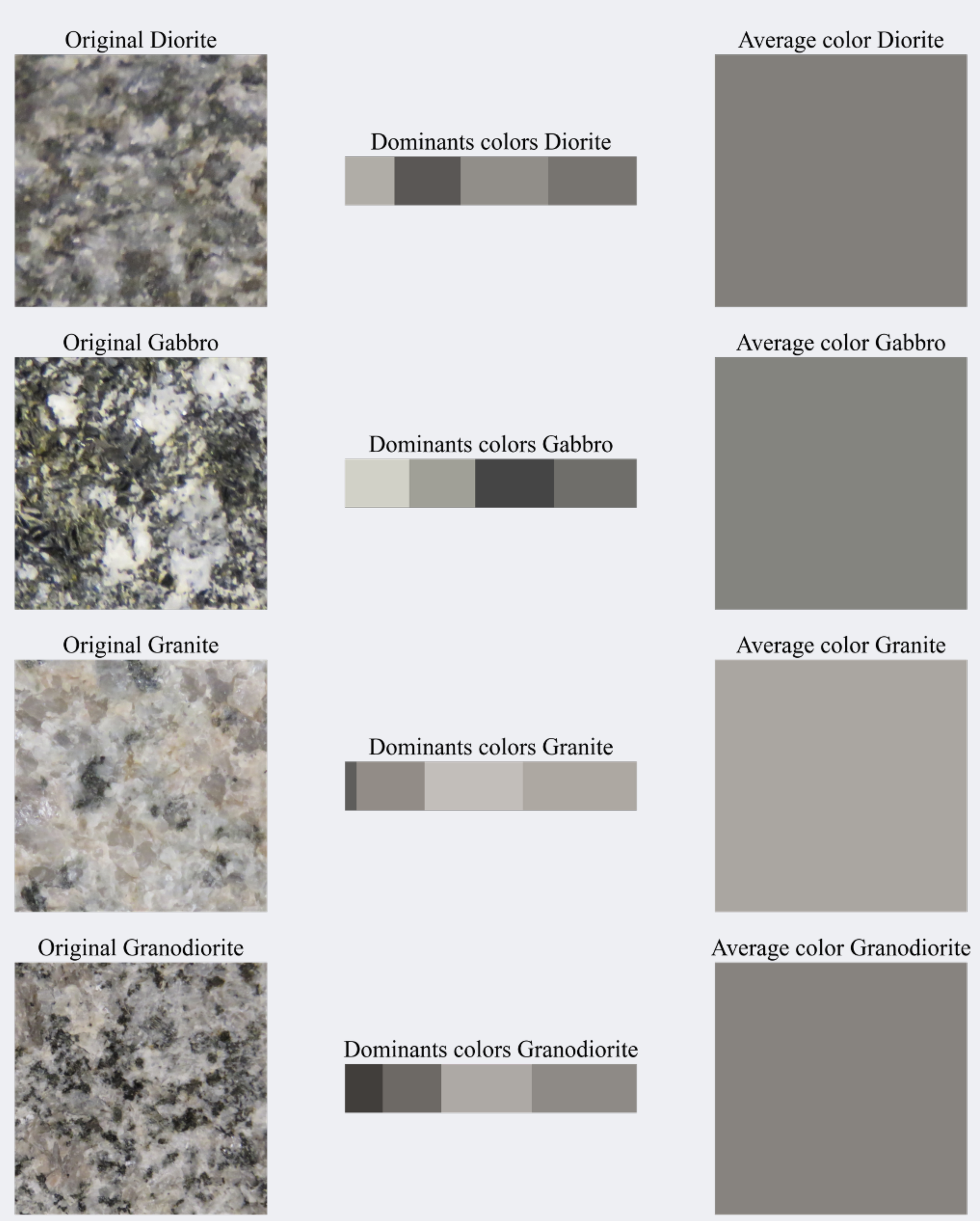


Figure 2. Dominant colors in sample images

The experiments were executed first with the dominant colors in RGB and then in CIELAB. The best results during validation were for the model generated with the KNN trained with the four dominant colors in the CIELAB format (see Fig. 3).

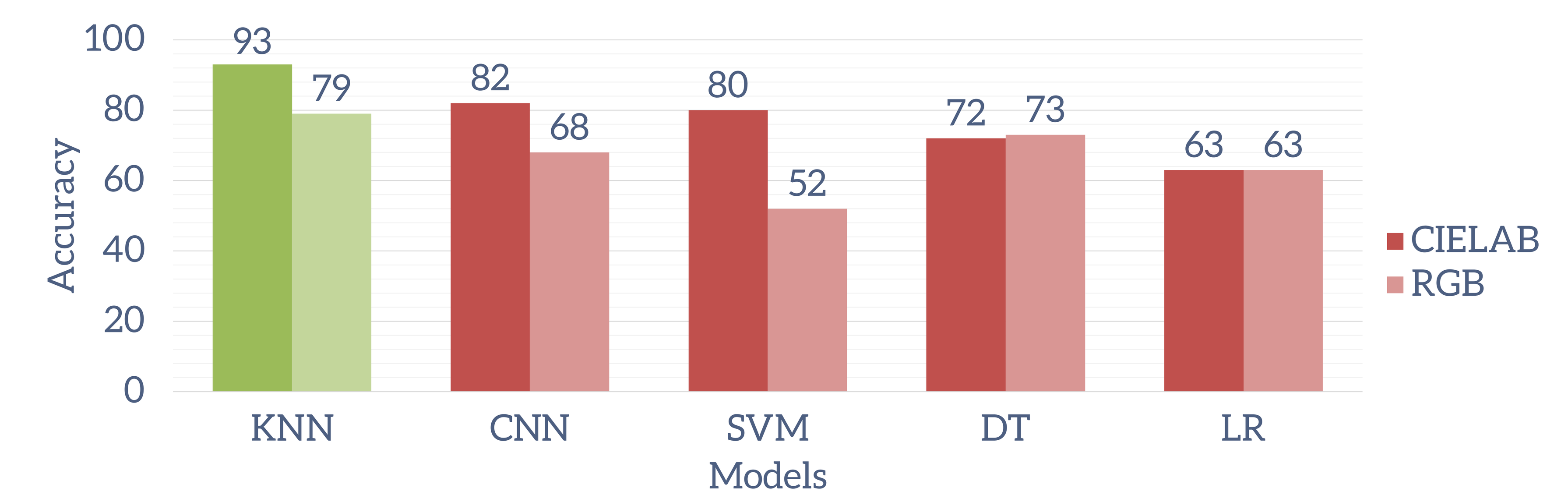


Figure 3. Accuracy of the models in RGB and CIELAB formats

These results are better than those obtained in [3,4] in which feature extraction was applied for classification of mineral samples. Moreover, they are similar to other works [5,6,7,8,9] in which machine learning was applied for rock classification on Android devices. There are no works presenting the implementation of machine learning on iOS devices.

### 3. Creation of the iOS application

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).

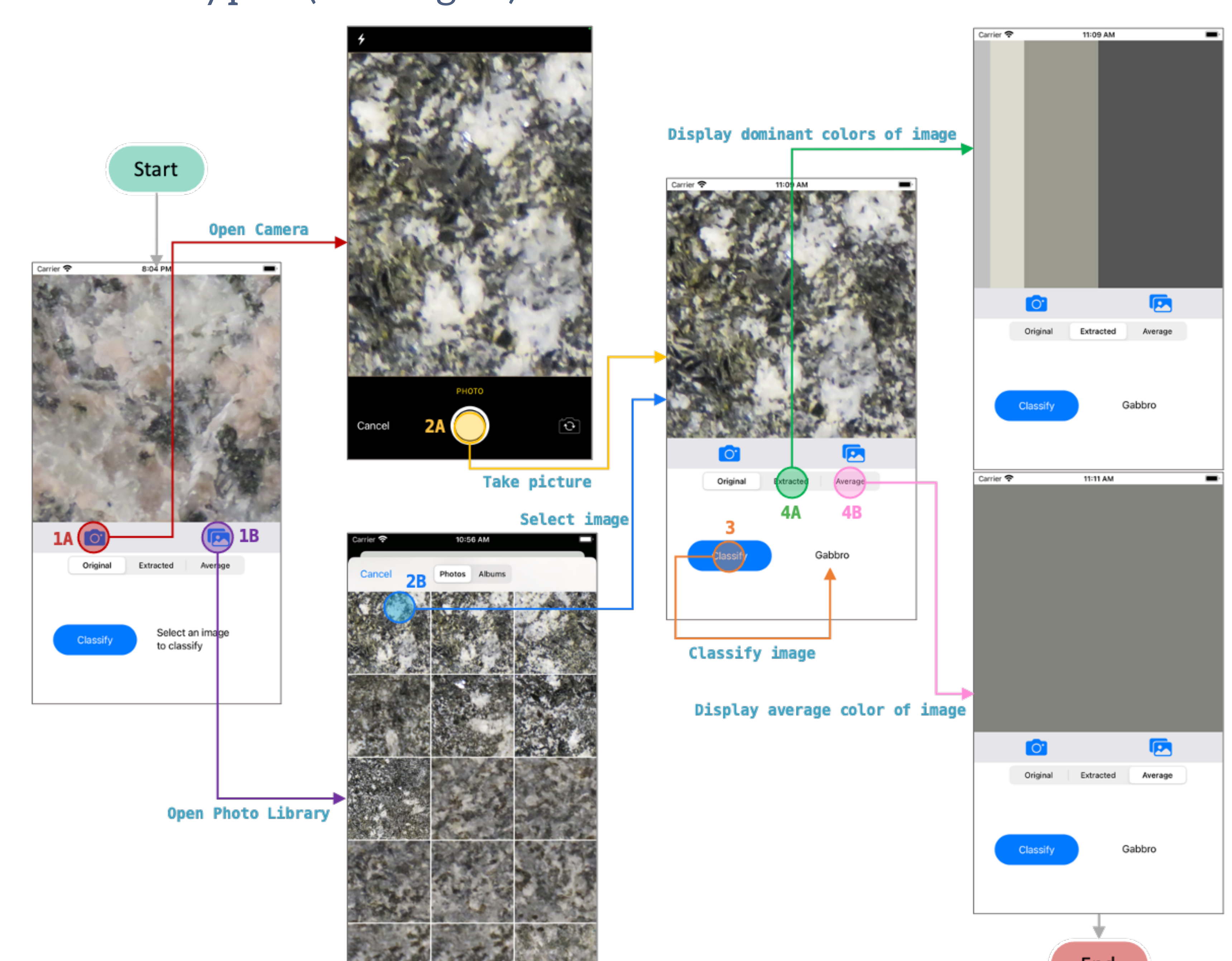


Figure 4. Application workflow

## RESULTS

The application was tested in the field with 34 images (see Table 1).

| Class | Taken images | Correctly classified | |
|---|---|---|---|
| | | Images | Percentage |
| Granite | 7 | 6 | 85.7% |
| Gabbro | 10 | 7 | 70% |
| Diorite | 7 | 2 | 28.5% |
| Granodiorite | 10 | 2 | 20% |

Table 1. 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.

## REFERENCES


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