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

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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 related works presenting the evaluation results of the deployment of machine learning models 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 [2]. See the underpinnings of our approach in figure 1.

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 (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). 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 using the KNN trained with the four dominant colors in the CIELAB format (Fig. 3). It is required a greater number and variety of images taken from different angles and light effects to increase the recognition accuracy of different rock types in the field. However, 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.

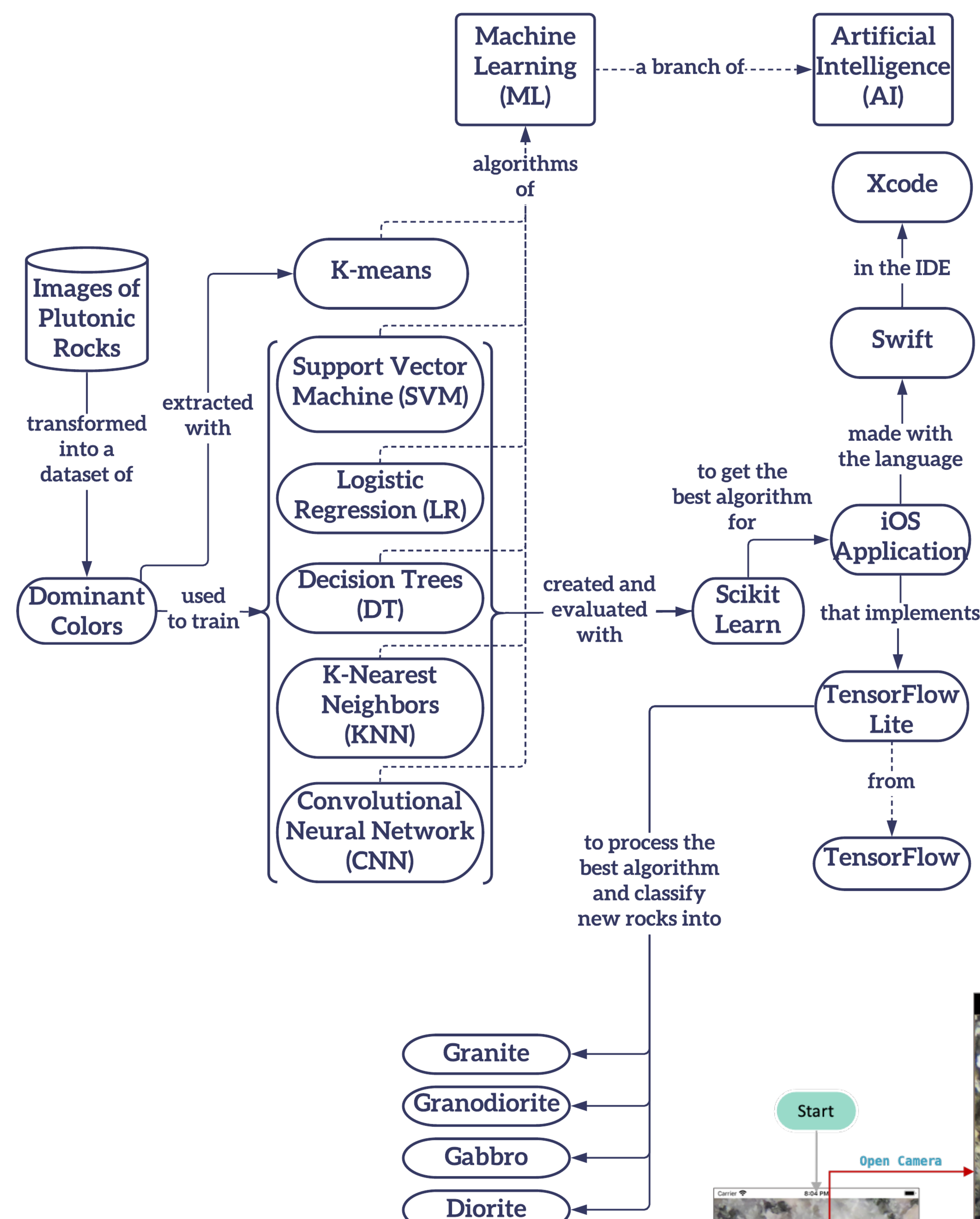

Figure 1. Underpinnings of our approach

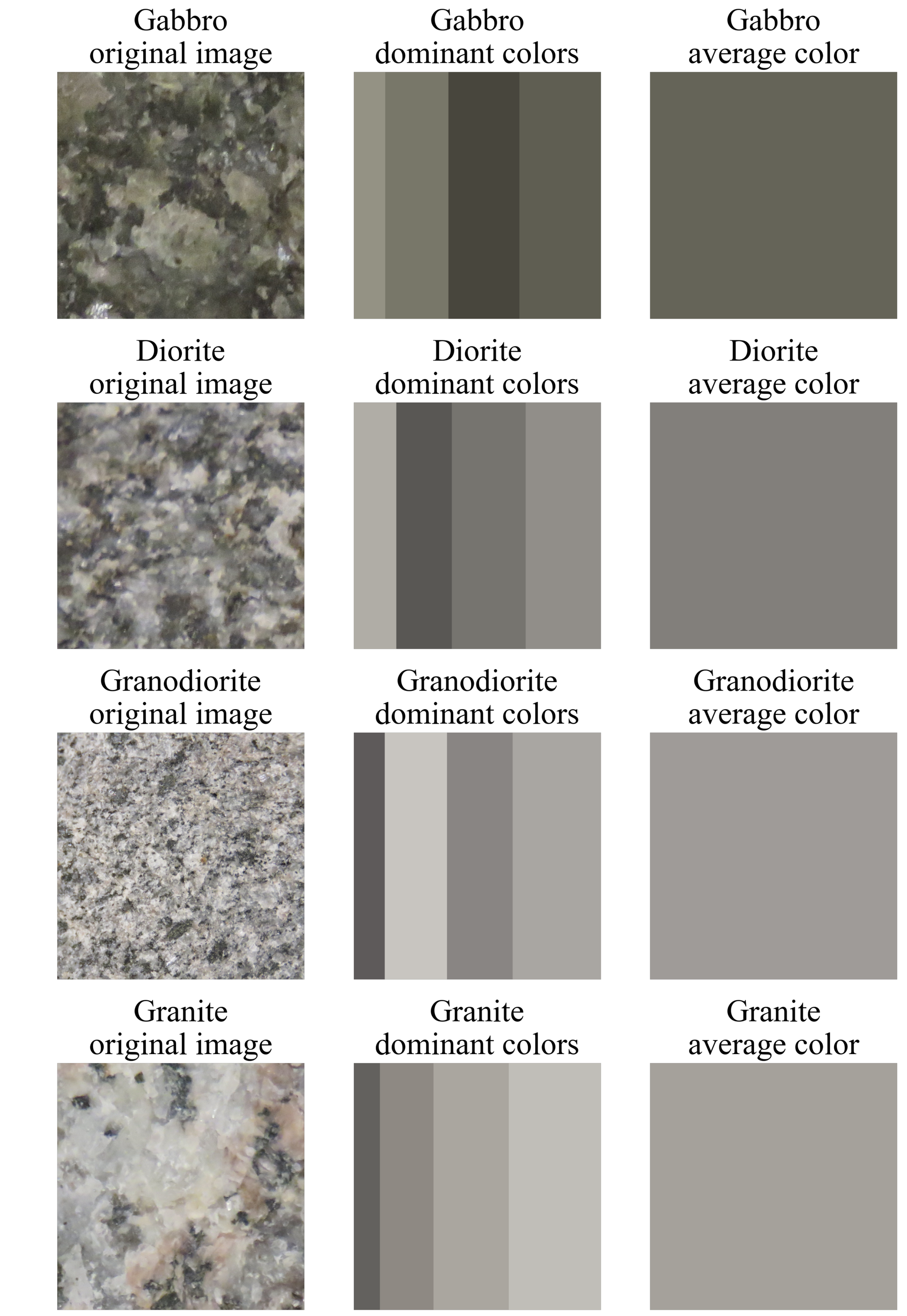

Figure 2. Dominant colors and average color of sample rocks in darkest to lightest order

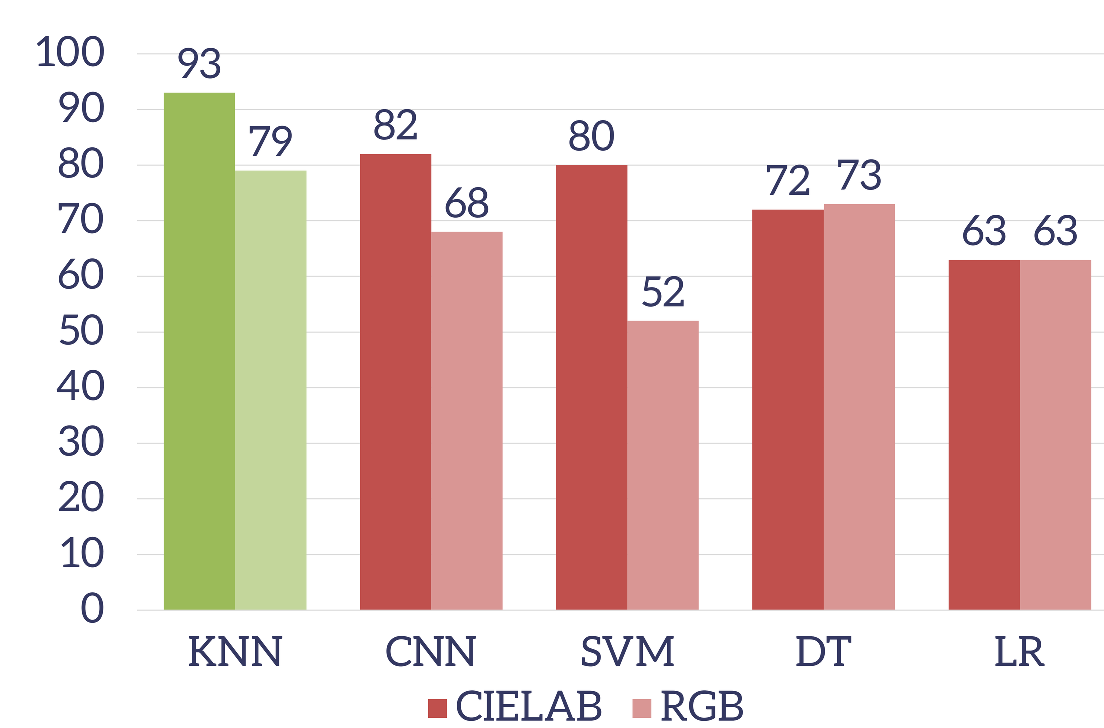

Figure 3. Accuracy of the models trained with the RGB and CIELAB dominant colors data

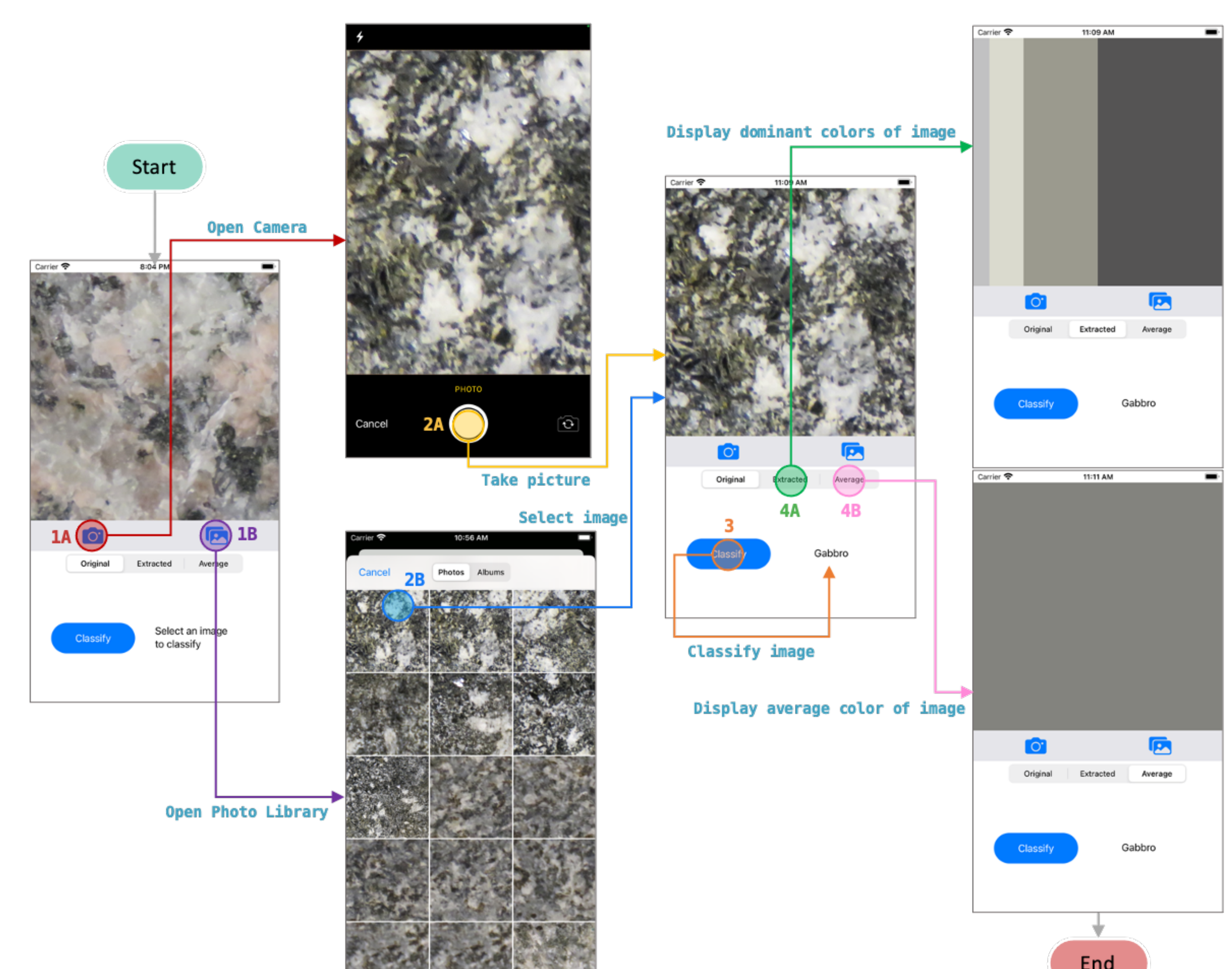

Figure 4. Application workflow

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 (Fig. 4). The iOS application was tested in the field with 34 images (Table 1).

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

Table 1. Accuracy results of application evaluation

CONCLUSIONS

The high accuracy when classifying gabbro samples is due to the noticeable darker color of the samples than 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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