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 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 [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

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.

2. Deployment of the iOS application

The best model was deployed after validation on an iOS application that classifies the extracted colors in new images of the four rock types.

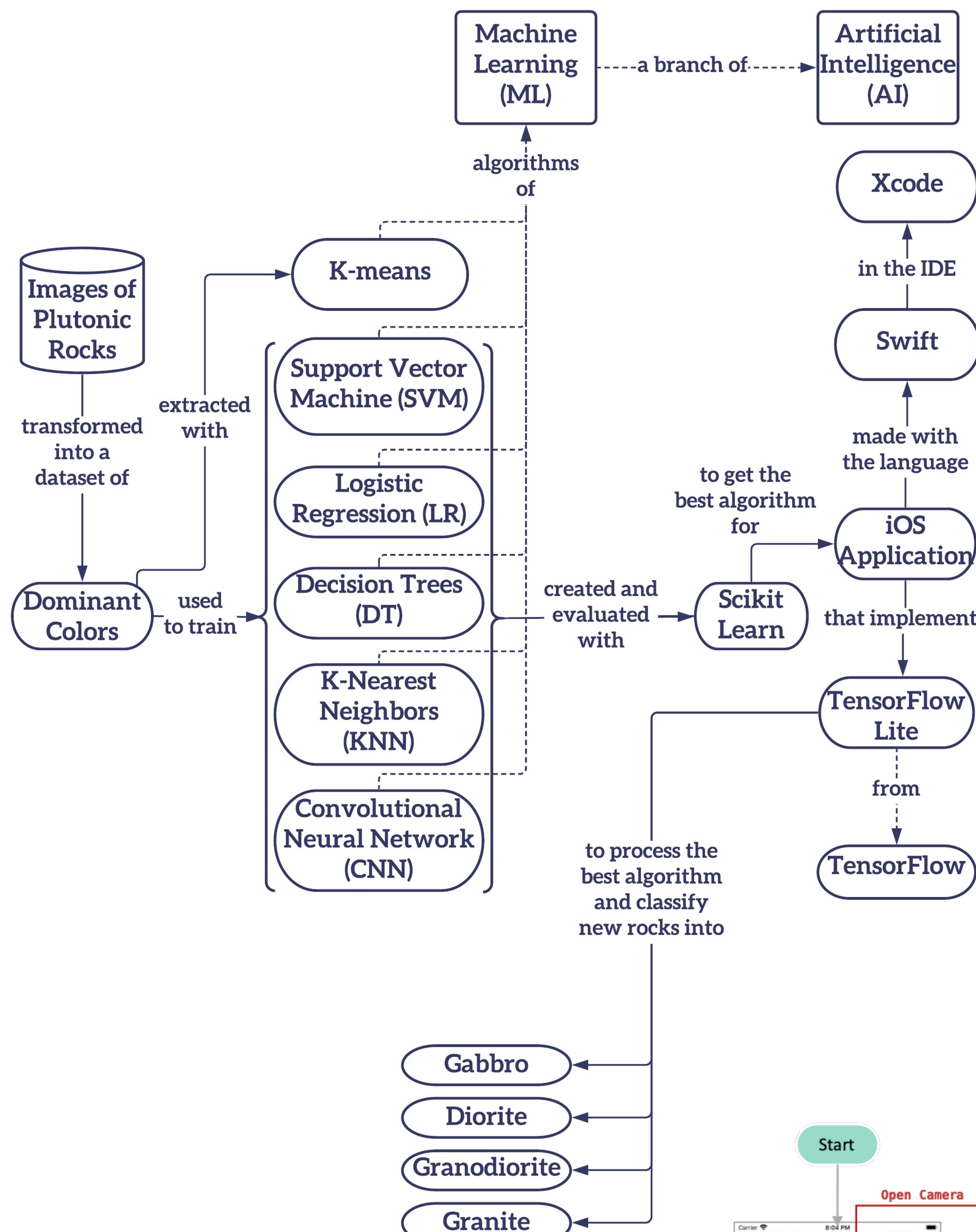

Figure 1. Underpinnings of our approach

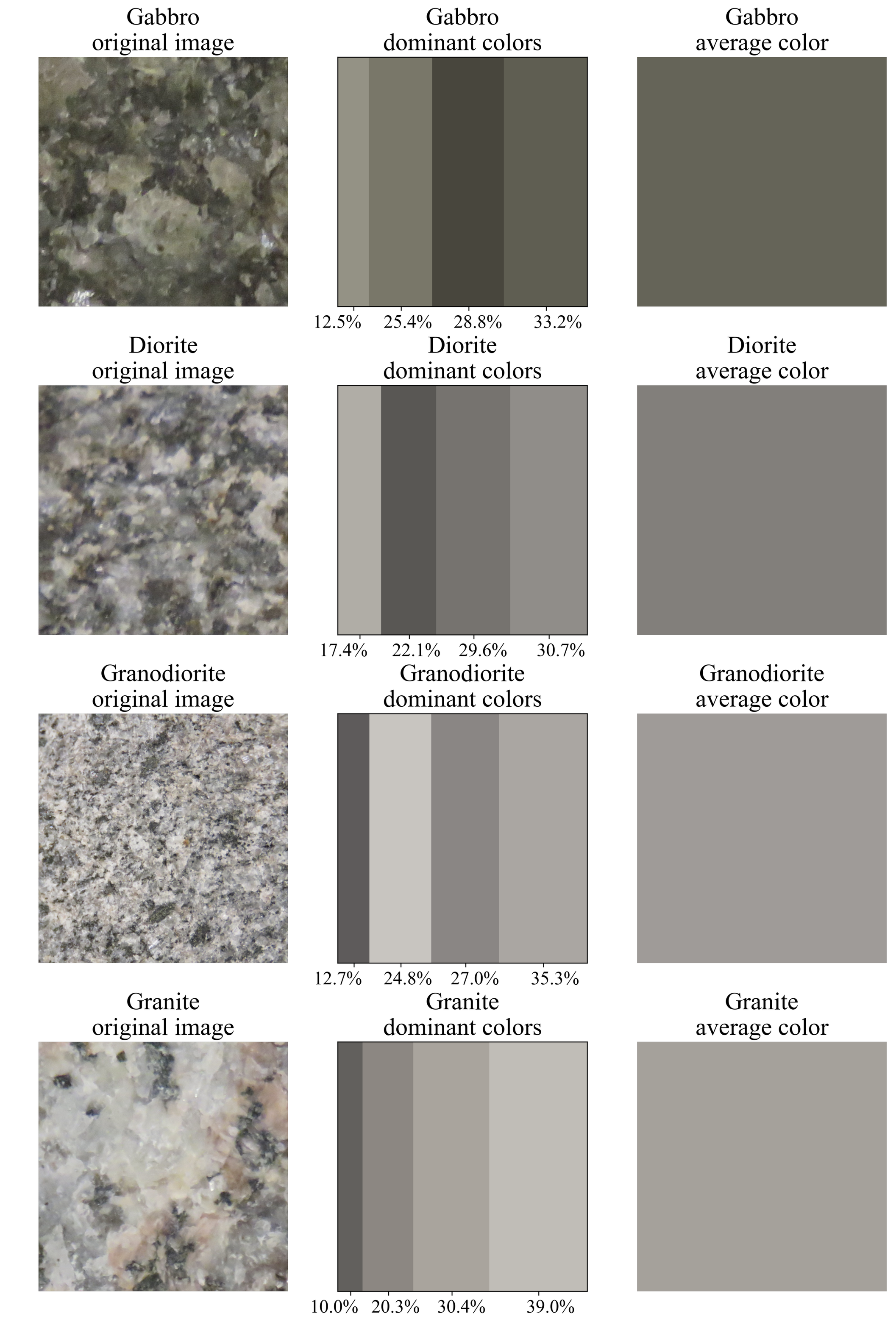

Figure 2. Sample rocks with their dominant colors in percentage order and their average color

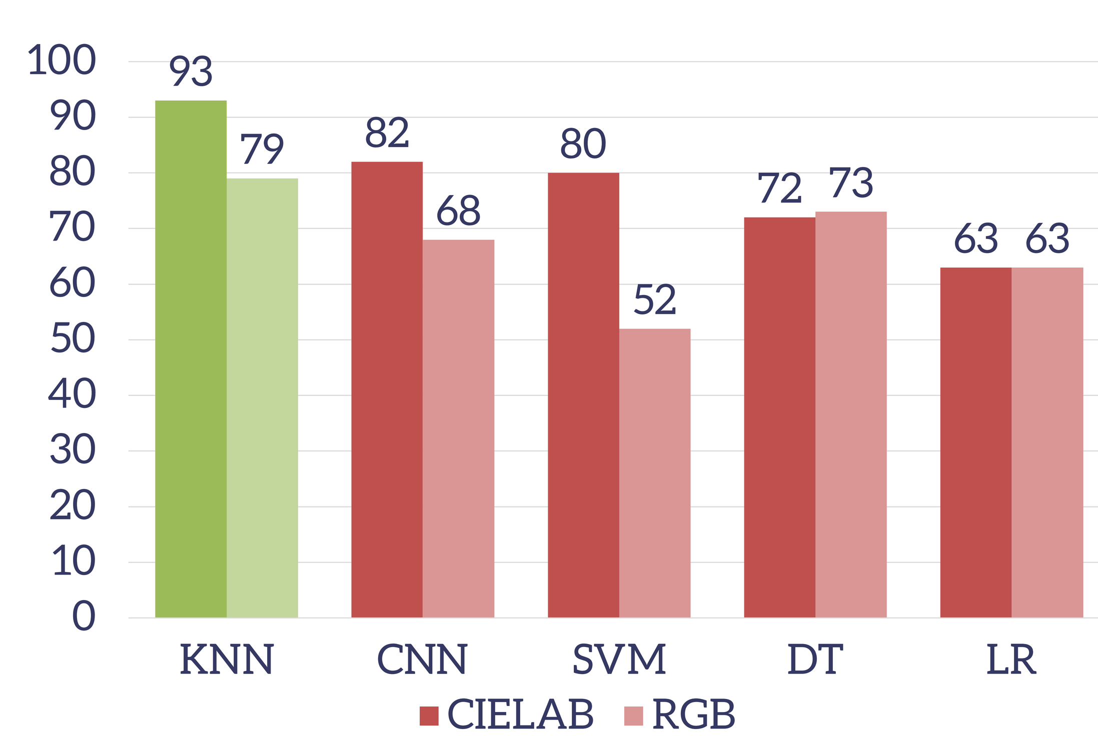

Figure 3. Accuracy of the models trained with the RGB and CIELAB. dominant colors data

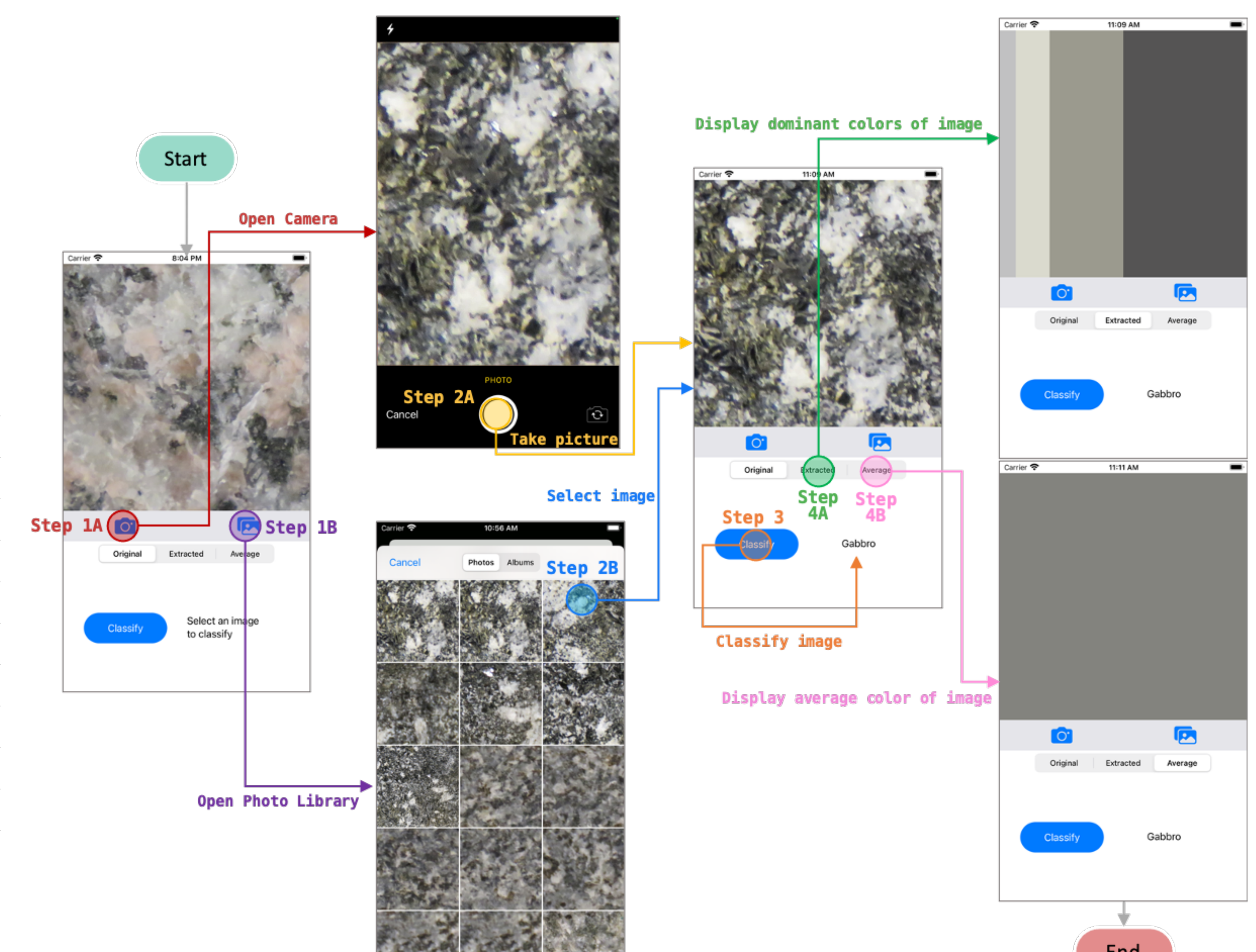

Figure 4. Application workflow

RESULTS

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). These results are better than those obtained in [3,4] in which feature extraction was applied to classify mineral samples. Moreover, they are similar to other works [5,6,7,8,9] in which machine learning was applied for rock classification. 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 [5, 6, 7]. KNN was the model deployed in the application (Fig. 4).

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 additional crystal shape extraction to the dominant colors.

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