Rock classification in petrographic thin section images based on concatenated convolutional neural networks

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Abstract
Rock classification plays an important role in rock mechanics, petrology, mining engineering, magmatic processes, and numerous other fields pertaining to geosciences. This study proposes a concatenated convolutional neural network (Con-CNN) method for classifying geologic rock types based on petrographic thin sections. Plane polarized light (PPL) and crossed polarized light (XPL) were used to acquire thin section images as the fundamental data. After conducting the necessary pre-processing, the PPL and XPL images as well as their comprehensive image developed by principal component analysis were sliced into small patches and were put into three CNNs, comprising the same structure for achieving a preliminary classification. Subsequently, these patches classification results of the CNNs were concatenated by using the maximum likelihood method to obtain a comprehensive classification result. Finally, a statistical revision was applied to fix the misclassification due to the proportion differences of minerals that were similar in appearance. In this study, there were 92 rock samples of 13 types giving 106 petrographic thin sections and finally 238,464 sliced image patches were used for the training and validation of the Con-CNN method. The 5-folds cross validation showed that the proposed method provides an overall accuracy of 89.97% and a kappa coefficient of 0.86, which facilitates the automation of rock classification in petrographic thin section images.

Keywords
Rock · Thin section · Classification · Convolutional neural network

Introduction
Rock classification is essential for geological research and plays an important role in numerous fields, such as rock mechanics, petrology, mining engineering, magmatic processes, and applications associated with geosciences (Izadi and Sadri et al. 2017; Li et al. 2017; Xu and Zhou 2018). This classification can be accomplished via the characterization of different minerals in rocks, which is performed by using various methods, for instance, polarized light microscopy, X-ray diffraction (XRD), X-ray fluorescence (XRF), atomic absorption spectrometry (AAS), electron micro probe analyzer (EMPA), scanning electron microscopy-energy dispersive X-ray spectrometry (SEM-EDX), and transmission electron microscope (TEM) (Izadi et al. 2017). Among these, the most acknowledged and widely used methodology is the manual analysis conducted by geologists on the images of petrographic thin sections, which is obtained by using a polarizing microscope. However, due to the inefficiency and subjectivity of manual analysis, it is necessary to develop automation methods by computer algorithms for the petrographic thin section image recognition. Based on the distinct optical properties of minerals (including color, cleavage, interference color, and extinction angle), the thin section image can provide abundant petrographic information. Despite the rapid development in technologies associated with computer image processing over the past decades, there have been additional studies trying to extract rock and mineral information from the thin section images automatically by computer algorithms, and
these approaches demonstrate a more enhanced, efficient, accurate, and objective methodology when compared to the traditional manual analysis (Reedy 2006). These related works can be divided into three categories: (1) pore information extraction, (2) mineral identification, and (3) rock classification.

Pore information extraction

A pore is the void space between minerals in a rock, which is critical for petroleum and gas exploration. It is common practice to extract pore information, such as the geometric shape, size, type, and coordination number. These parameters identify and measure the pore spot in thin-section images, which are impregnated with colored epoxy—usually blue, red, or the color different from other particles. Based on their unique color, pores can be identified by threshold methods in the RGB or HSV color spaces (Borajzani et al. 2016; Dong et al. 2019). Alternatively, it is possible to compare the optical feature of colorless epoxy in the pores with the counterpart at the margin of thin sections, including contaminants common in epoxy, to confirm the void space in the rocks. Pattern recognition and GIS-based methods are applied to extract the boundary and region of the pore as a polygon object, and, further, to calculate its shape, orientation, type, and spatial distribution (Li et al. 2008; Ghiasi-Freez et al. 2012; Asmussen et al. 2015; Berrezueta et al. 2019). Deep-learning methods classify the thin-section image pixel by pixel, performing image semantic segmentation, and creating the labeled output image in which each labeled pixel represents a mineral class or pore (Marques et al. 2019; Rubo et al. 2019). The extracted pore information can be used to estimate rock permeability and anisotropy in reservoir simulation, hydrology, and environmental engineering (Fauzi 2011; Peng et al. 2016; Rabbani et al. 2017).

Mineral identification

Similar to pore information extraction, the basic theory of mineral identification is that different minerals exhibit specific colors and textures due to their optical properties. Aligholi et al. (2017) summarized various image processing and pattern recognition techniques devoted to this field. Some other studies have used machine learning methods, such as artificial neural networks (ANN), support vector machine (SVM), U-Net (a kind of convolutional neural network, CNN), and instance segmentation to perform intelligent mineral identification using computer statistical analysis under human expert supervision (Baykan and Yılmaz 2010; Singh et al. 2010; Yesiloglu-Gultekin et al. 2012; Izadi et al. 2013; Xu and Zhou 2018; Rubo et al. 2019). After separating diverse mineral types, some reports have focused on extracting mineral grain geometric parameters, such as boundary, shape, size, and percentage (van den Berg et al. 2002; Hassanpour et al. 2009; Mingireanov Filho et al. 2013; Wen et al. 2019).

Rock classification

To classify the rocks into geologic types, it is necessary to develop effective methods for characterizing the thin-section image features. Marmo et al. (2005) used 23 texture features as an input to construct an ANN for classifying carbonate rocks into mud-stone, wackestone, packstone, and grainstone. Mlynarczuk et al. (2013) used 13 color features to classify nine kinds of rocks. After comparing different color-spaces and pattern recognition methods, they discovered that optimal outcomes were obtained when utilizing the methodologies of CIELab and nearest neighbor (NN). Joseph et al. (2017) calculated color histograms and edge features to detect quartz and accessory minerals in sub areas of igneous rock thin section images, and then the whole image was classified into diorite, tonalite, granite, and adamellite using an unsupervised method (called majority voting scheme) to synthesize the sub area detection results. Li et al. (2017) proposed a transfer learning method for sandstone classification to accommodate samples collected from separated regions. The transfer model refers to the generalization that what is learned in one environment can be used to improve another. The advantage of this method is that the well-trained model proposed in their study can be applied to any other untrained domain with little manual labeling effort, irrespective of the substantial differences among sandstones in diverse domains. Ładniak and Mlynarczuk (2015) designed an image database of microscopic rocks for visually searching similar images, which constitutes rock classification by the cluster method. With a similar purpose, some studies have classified rocks by image features rather than geologic types (Chatterjee 2013; Liu et al. 2016; Cheng et al. 2018). Given the current support of efficient computing equipment and big data, deep learning methods are applied in many fields. They have the potential to extract features and relations through training and learning from a large sample to provide a data-driven solution without the need for human involvement. Among them, CNN models are widely used in image classification, image recognition, and many other image processing fields based on two advantages. One is the convolution operation can maintain the local topological properties of images (LeCun et al. 2015). The other is today’s CNN models could have a deeper network architecture, which means the CNN model could have more expressive ability and thus able to deal with more complex objects and targets. In this study, a Con-CNN with concatenated structure is proposed for general geologic type rock classification by utilizing petrographic thin section images. A total of 2208 images, acquired from 92 rock samples of 13 rock types, were used for training and testing. The 5-
folds cross validation results showed that the overall accuracy was 89.97% and the kappa coefficient was 0.86.

Materials

This study covered a total of 13 rock types (andesite, granite, peridotite, gabbro, rhyolite, tuff, diorite, phonolite, basalt, syenite, limestone, sandstone, and schist) of 92 representative rock samples in igneous, sedimentary, and metamorphic categories. The majority of rock samples were obtained from the GeosecSlides and the Classic North American Rock Collection of Ward’s Science. The remaining samples were provided by the School of Earth Sciences, Zhejiang University. One hundred six thin sections made of these rocks were collected and 2208 digital images were taken under the AxioCamMR5 microscope. The number assigned to each material is shown in Table 1. All images were captured in RGB format at 2.5x optical magnification with a dimension of 2688 × 2016 pixels and 150 dpi resolution. The exposure parameter and white balance were automatically adjusted during the acquisition so that all image results could be displayed as close as possible to the microscopic observations. We used both plane polarized light (PPL) and crossed polarized light (XPL) to obtain the photographs and more comprehensive feature information. Considering that different minerals have diverse extinction properties, such as different extinction angles for clinopyroxene/orthopyroxene and bird-eye extinction featured by mica, we also captured these thin section images at multiple rotation angles.

| NO. | Type     | Sample | Thin Section | Image (PPL + XPL) |
|-----|----------|--------|--------------|-------------------|
| 1   | Andesite | 10     | 12           | 246 (123 + 123)   |
| 2   | Granite  | 9      | 14           | 280 (140 + 140)   |
| 3   | Peridotite | 11    | 11           | 220 (110 + 110)   |
| 4   | Gabbro   | 6      | 8            | 174 (82 + 82)     |
| 5   | Rhyolite | 9      | 10           | 200 (100 + 100)   |
| 6   | Tuff     | 7      | 7            | 166 (83 + 83)     |
| 7   | Diorite  | 3      | 4            | 100 (50 + 50)     |
| 8   | Phonolite| 9      | 9            | 174 (87 + 87)     |
| 9   | Basalt   | 5      | 5            | 100 (50 + 50)     |
| 10  | Syenite  | 8      | 8            | 160 (80 + 80)     |
| 11  | Limestone| 4      | 6            | 132 (66 + 66)     |
| 12  | Sandstone| 7      | 7            | 140 (70 + 70)     |
| 13  | Schist   | 4      | 5            | 116 (58 + 58)     |
| Total| 13      | 92     | 106          | 2208 (1104 + 1104) |

Methods

For all images, only the color and texture information were represented via pixel values and spatial arrangements. This is the fundamentals of object identification, classification, and image understanding performed by computers or humans. However, two special phenomena should be noted in petrographic thin section images: (1) the complex combination of the optical properties for minerals (PPL images show the shape, color, and cleavage, while XPL images show the extinction and interference of minerals, see Fig. 1), and (2) the distribution of minerals: some rocks are similar in composition and appearance but present different proportions of minerals. For instance, both granite and diorite contain quartz, feldspar, and mafic minerals such as biotite, amphibole, and magnetite, but the former contains greater quantities of quartz while the latter contains greater quantities of mafic minerals (see Fig. 2).

According to the special characteristics of petrographic thin section images shown above, a Con-CNN was proposed (see Fig. 3). The core technology of this method is the CNN for extracting particular image features. After using a large number of samples for learning and training (the details will be given in IV. EXPERIMENTS AND DISCUSSION), the CNN could establish an appropriate mapping relationship between the input image and the output category, which is the desired classification model. Con-CNN comprises three independent CNN branches to classify the input image into the corresponding geologic rock type, taking full advantage of PPL, XPL, and their comprehensive image of one petrographic thin section (the details will be given in the following Part I. Image Pre-process). The results of these three branches are concatenated by using maximum likelihood to arrive at a comprehensive classification result. For the final output, a statistical revision is performed to fix misclassifications due to the proportion difference of minerals that are similar in appearance. The entire Con-CNN method can be divided into five parts, which are detailed below.

Part I. Image Pre-processing

Before training and classification, two pre-processing steps need to be applied on the input raw data for more stable performance. First, the PPL and XPL original images were enhanced by the histogram equalization method (Krig 2014), increasing the intensity range by redistributing the pixel levels (Histogram Equalization is a classic computer image processing technique used to improve contrast in images. It accomplishes this by effectively spreading out the most frequent intensity values, i.e. stretching out the intensity range of the image). As a result, the image contrast enhanced and pixels clustered around the middle of the available range of intensities are avoided, yielding detailed information at the same
brightness level. Second, a composite image with six layers was created via layer stacking PPL and XPL (three layers: PPL$_R$, PPL$_G$, PPL$_B$, and the same for XPL). Then, the composite image was transformed by principal component analysis (PCA), which is a statistical procedure using an orthogonal transformation to convert the raw data into a set of values with linearly uncorrelated principal components (PC) (Krig 2014). The PCA transformation causes information to rapidly move forward to the PCs in front. Therefore, the first three PCs, representing most of the original information, were selected as the RGB layers for constructing a comprehensive image (CI), comprising a PPL and XPL fusion. In the end of the pre-processing steps, three images (PPL, XPL, and CI) needed to be normalized (stretch their pixel value to [0,1] based on their data range respectively) to keep the pixel values at the same quantity dimension.

Part II. Image slicing

In an image, pixel value and spatial arrangement combine to produce information. In other words, image features are represented by some adjacent local pixels, meaning that they are scale dependent. On a large scale, zooming in on parts of the image reveals more local details, allowing more discrimination between images. In contrast, zooming out to view the whole image results in more general characteristics but fewer details. Some petrographic thin section images are visually very similar. Therefore, the classification method should take full advantage of the image details. In this study, the original petrographic thin section image acquired from the microscope contained 2688 × 2016 pixels and was regularly sliced into 12 × 9 small patches with 224 × 224 pixels. Each patch was taken as an independent image for training and classification. Although the small patch image can better represent local details, the overall features of the original thin section image are fragmented and lost. This issue is considered in Part V below.

Part III. Convolutional neural network

A CNN was constructed as three independent models for the classification of each type (PPL, XPL, CI) of input image patch (as shown in Fig. 3). The proposed basic structure of the CNN refers to the classical model of LeNet (Lecun et al. 1998) and VGG16 (Simonyan and Zisserman 2014). The input patch is passed through five feature extraction blocks (FEB) with a classical architecture of CNN and three mapping blocks (MB) with a basic structure of fully-connected neural network, to be classified into one of 13 rock types. The FEB contains three computations: the first is a convolutional layer...
to extract the local image features, where convolutional filters with small receptive fields of $3 \times 3$ are applied with a stride of 1 pixel and no padding. The second is a pooling layer to gather the main information, where a $2 \times 2$ max-pooling operation is performed with a stride of 2 pixels following the convolutional layer. The third is an activation function to propagate the effective information to the next layer, where the pooling layer result is equipped with the widely used rectification non-linearity (ReLU) function. After 5 FEBs, the size of the input image gradually changes from $224 \times 224$ to $112 \times 112$, $56 \times 56$, $28 \times 28$, $14 \times 14$, and finally to $7 \times 7$. The MB contains two computations: the first is a fully connected layer, where all nodes between layers are connected—similar to a classic ANN—to establish mapping relations. The second is an activation function using the sigmoid function as common practice. Notably, the last MB is a SoftMax layer, which could map multiple values to the probability of belonging to a category.

Part IV. Concatenation

For one petrographic thin section, three types of images (PPL, XPL, and CI) have been used as input data for the CNN to classify the studied material. Each classification result has the probability of belonging to one of the 13 rock types. Here, the concatenation was applied to integrate these three CNN classification results. More specifically, these results were weighted and averaged to obtain the final outcome. Through many experiments, we suggest that the weights are 0.4 for PPL, 0.4 for XPL, and 0.2 for CI. For instance, if the granite probability from the PPL image is 0.92, from the XPL is 0.87, and from the CI is 0.89, then the final probability of belonging to granite is $0.92 \times 0.4 + 0.87 \times 0.4 + 0.89 \times 0.2 = 0.902$. After the concatenation, the final rock type is set as the one with the highest probability, using the maximum likelihood principle.
Part V. statistical revision

As described in Part II, the original petrographic thin section image was sliced into small image patches for classification. For one petrographic thin section, 324 image patches (the PPL image was sliced into 12 × 9 = 108 patches, and the same was done for XPL and CI) were classified. After each patch was classified, the mode number of rock types was calculated to determine which rock type was the majority among the 324 (108 × 3 = 324) classification results. Then, the majority rock type was uniformly assigned to all small image patches belonging to the same petrographic thin section. This revision restored the overall statistical characteristics of the original image to some extent and avoided the issue of information fragmentation and loss due to image slicing.

Experiments and discussion

To evaluate the proposed Con-CNN model, a test experiment was implemented with the PyTorch deep learning framework (Paszke et al. 2019). Petrographic thin sections for a total of 92 rock samples of 13 types were prepared. A total of 2208 images, acquired with a microscope for accurate rock type information, were sliced into 238,464 small image patches. All the image patches were used as training and validation samples and entered the Con-CNN for modeling. To obtain the general performance of the Con-CNN model, a 5-folds cross validation was applied by randomly dividing all image samples into 5 groups, 4 groups used for training and the other one used for validation. This experiment was repeated five times by switch training group and validation group to obtain the average evaluation result. For each experiment in cross validation, the model tended to converge after about 20,000 iterations. Table 2 shows the average classification performance of the Con-CNN model, which presented an overall accuracy of 89.97% and a kappa coefficient of 0.86.

Three comparison experiments were implemented. The first only used the PPL image for training and classification to compare whether more image information could improve the result (Only PPL vs. PPL + CPL + CI as input). The second augmented the image input data by random rotation and translation, which are widely used methods to expand training samples in machine learning for imaging studies. (In this study, two augmented images of rotation and translation were acquired from each original image so that there were 4416 more augmented images than the original dataset of 2208 images.) to compare whether data augmentation could im-
prove the result. The third one replaces the CNN of the architecture proposed in this paper (Part III. Convolutional Neural Network of chapter II. METHOD) by a deeper CNN of ResNet-50 (He et al. 2015) to compare whether a deeper CNN could improve the result. These three experiments were conducted through a five-fold cross-validation with the same materials. Figure 4 shows their receiver operating characteristic and area under the curve results.

The results show that none of the three comparison experiments work as well as the original method detailed in Section III. This may have been caused by the inability of the PPL image to fully reveal the optical characteristics of minerals in petrographic thin sections, thus affecting the rock classification, in the first comparison. A possible explanation for the results of the second comparison is that the data augmentation did not conspicuously improve the classification results. We believe that this is because the color and texture of the petrographic thin sections are relatively uniform, random, and stable, meaning that some samples could express their complete features, in contrast to the general photograph with a special direction. Therefore, using random rotation, translation processes to expand the training group of samples could not provide new information. For the third comparison a deeper CNN did not significantly improve the classification accuracy, suggesting that the mapping relationship between petrographic thin section images and geologic rock types might be relatively simple and constructed through a CNN with relatively few layers.

Conclusions

In this study, a Con-CNN method was proposed for rock classification based on petrographic thin section images. Two images were acquired with PPL and XPL, respectively, and their comprehensive image was fused by the PCA method. Subsequently, this original image was divided into small patches and then were put in the CNN for classification. After the concatenation of the CNN results and the statistical revision process had been completed, the suggestion of the final rock type was successfully obtained. The experiments showed that the Con-CNN method could effectively extract petrographic thin section images and establish the mapping relationship between the image of a particular rock type and its geologic characteristics via learning from samples. Further, this method exhibited good performance supporting the use of Con-CNN as an automated solution for rock classification in petrographic thin section images.

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Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

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