Photomicrograph Rock Images Classification with Convolutional Neural Networks

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Abstract: Several attempts were carried out to check if a small CNN model, based on the LeNet-5 model could classify rock images. 239 rock thin-section images including three rock types "metamorphic", "sedimentary", "volcanic" were selected from a dataset, wich contained 2568 images, found on an online science database (Science Data Bank). The model has been trained and validated, after that the performances were evaluated with Accuracy, Loss, Confusion Matrix and "Accuracy per Fold". The model revealed a good performance notwithstanding the database shortness.

1 Introduction

Rock type classification is really important in geology and all his applications, the actual main way to classify is to use tools such as magnifying glass etc. This way of classification is time-consuming and costly so a Convolutional Neural Network (CNN) based approach could be the solution. CNNs have big advantages in image processing fields, in fact, they are widely used in image classification problems. Studies were carried out on how to optimize the "Figure Detection" parameters of CNNs [2]. CNNs have been widely used in early years for "medical purposes" [1], for "autonomous" driving [5], for "face recognition" [9], in "natural language processing" [4], for "remote sensing" [11], and for the classification of rocks [7], also combined with transfer learning [8]. Gao et al. [3] showed how a CNN with "hidden layers" outperforms a "Shallow Neural Network" in the classification of rock sections. In this report we used a CNN to classify a photomicrograph rock images dataset acquired from Nanjing University of China, containing 3 rock classes: metamorphic, volcanic and sedimentary. In the Section 2 introduces Dataset details and CNN architecture. The Section 3 includes the model results and performances. Lastly the Section 4 contains an overall about the model and how it could be improved.

Metamorphic	Sedimentary	Volcanic
76	87	76

Table 1: Description of the Dataset.

2 Methods

2.1 Dataset

The dataset used is a photomicrograph rock dataset acquired from Nanjing University of China [10] that includes three rock types:metamorphic, sedimentary, and volcanic rocks. From the original 2634 microscopic images contained, 239 have been selected, Table 1 shows the images distribution.

2.2 Model Architecture

We took inspiration from the LeNet-5 Architecture [6], invented by Yann LeCun in 1998. The structure forsees an initial Conv2D Layer (16, 4, activation='relu') followed by a Max Pooling2D Layer, another Conv2D Layer (7, 4, activation ='relu') followed by a Pooling2D Layer. Finally a Flatten Layer followed by a Dense Layer (100, activation='relu') and the last Dense Layer (3, activation='softmax').

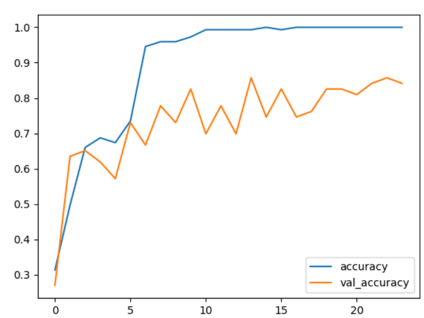

Figure 1: Accuracy,notice how after 10 epochs, the accuracy rises to max.

2.3 Environment and Training

We used Tensorflow as deep learning framework. The total 239 images were divided into training and testing datasets: 210 for training (and validation) and 29 for test. The input image had a 384×306 resolution (resized from the initial 1280x1024, using os and cv packages), the number of training epochs was 100, an early stopping callback with the following parameters was used: (monitor= valaccuracy, patience=10, mode="auto") to stop the training when the validation accuracy dropped. K-Fold Cross Validation has been set to 3 folds as optimizer we choose ”Adam” and as loss function ”SparseCategoricalCrossentropy”. At the end of training a function to extract the mislabeled images from the confusion matrix was added. All the experiments were executed on Google Colab Jupyter Notebook, running Python 3 using the ”base” resources: 12.7GB RAM, 15GB RAM GPU (used for acceleration).

3 Results

The performance of the model has been compared using an accuracy vs validation accuracy graph (Figure 1), a loss vs validation loss graph (Figure 2), a confusion matrix (Figure 3) and with ”score per fold” (Figure 5).

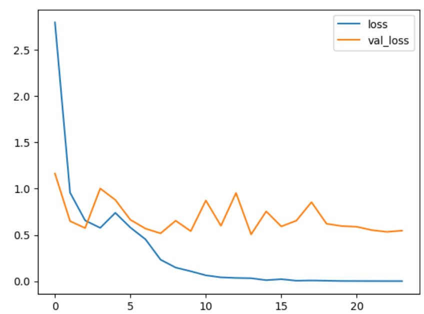

Figure 2: Loss, after 16 epochs validation loss reaches a plateau.

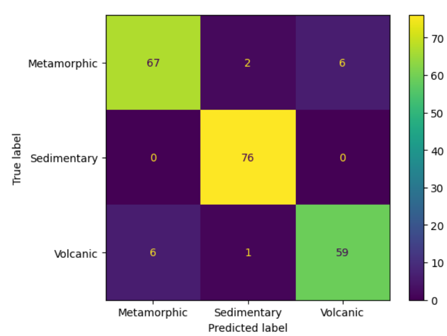

Figure 3: Confusion Matrix: Metamorphic and Volcanic are the most mislabeled classes.

As can be seen the validation accuracy remains stable at around 0.80, while the accuracy per fold got an average of 87%. The Confusion Matrix shows clearly that the the most common mispredicted label is between Metamorphic-Volcanic (labels 0-2) & Volcanic-Metamorphic (labels 2-0), this could have been caused by the similarity between the thin rock section images (Figure 4).

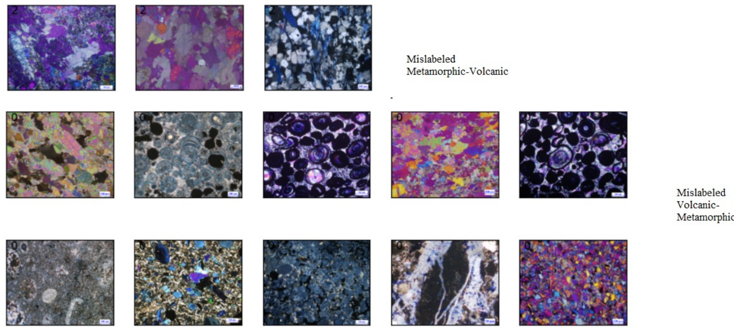

Figure 4: Mislabeled images, Metamorphic-Volcanic & Volcanic-Metamorphcic, notice the similarity.

4 Conclusions

CNNs models are an excellent tool for photomicrograph rock images classifications, the 80% average of accuracy despite the small amount of images in the dataset (reduced due to low computing power available) is a good start. Next step to improve performances could surely be the enlargement of the dataset, and the enhancement of the computational power provided to the CNN.

```
Score per fold
------------------------------------------------------------------------
> Fold 1 - Loss: 1.61591374874115 - Accuracy: 88.7499988079071%
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> Fold 2 - Loss: 0.5691907405853271 - Accuracy: 81.25%
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> Fold 3 - Loss: 0.19602708518505096 - Accuracy: 91.13923907279968%
------------------------------------------------------------------------
Average scores for all folds:
> Accuracy: 87.04641262690227 (+- 4.21314741943439)
> Loss: 0.793710524837176
------------------------------------------------------------------------
```

Figure 5: Accuracy per Fold, for every fold the accuracy is greater than 80%.

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