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Rock Identification Method based on YOLOv8

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Abstract

The traditional rock identification methods mainly rely on the field survey and laboratory analysis of geologists. These methods are not only time-consuming and labor-intensive, but also limited by the experience and subjective judgment of geologists. With the rapid development of computer vision and deep learning technology, especially the continuous progress of target detection algorithm, automatic rock recognition technology based on image processing has gradually become a research hotspot. In this paper, a rock recognition system based on YOLOv8 is proposed. The system utilizes the efficiency and accuracy of YOLOv8 algorithm to realize the fast and accurate recognition of various rock types. By constructing a rock image dataset, training a deep learning model, and testing it in a real scene, the system achieves satisfactory recognition results. The research in this paper is of great significance for improving the efficiency and accuracy of rock identification and promoting geological exploration and resource development.

Keywords

YOLOv8; Rock Recognition; Deep Learning; Object Detection; Geological Exploration.

1. Introduction

Rock is the main material that makes up the crust of the earth, and studying its type, structure and distribution can better understand the evolution process of the earth, resource exploration and geological disaster prevention. Traditional rock identification methods mainly rely on geologists' field investigation, through naked eye observation, hand sample analysis and laboratory tests to determine the type of rock. However, these methods are not only time-consuming and labor-intensive, but also subject to many factors such as geologists' experience, environmental conditions and equipment performance, so they have certain limitations and subjectivity.

In recent years, with the rapid development of computer vision and deep learning technology, automatic rock recognition technology based on image processing has gradually shown its unique advantages. Deep learning algorithm can automatically learn the feature representation from a large number of data without manual design of features, and can process complex image data to improve the objectivity and accuracy of recognition. In particular, object detection algorithms, such as the YOLO series, have been widely used in many fields for their high efficiency and accuracy.

YOLOv8, as the latest member of the YOLO series, has introduced new Backbone and Anchor Free detection heads and new loss functions to further improve the detection speed and accuracy. Therefore, this paper applies YOLOv8 algorithm to the field of rock identification, aiming to develop an efficient and accurate rock identification system, which can provide strong support for geological exploration and resource development.

At present, there have been many researches on the characteristics and types of rocks. For example, Xu Shenglin[1] et al found that broadband electromagnetic sounding is one of the important methods

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to study the deep lithosphere of the earth, which has become an important support for geodynamics, resource exploration, geological disaster prevention and deposit genesis research in the study area. Yuan Ye[2] et al. explored the fracture characteristics of rocks under the action of cyclic stress and cyclic temperature, which is of great practical significance for ensuring the stability of the "two-carbon" project of compressed air energy storage in underground caverns. They also proposed a type I fracture test method of rocks under cyclic thermal action and discussed the feasibility of the test method. Wang Shiquan[3]Chen Hongcan[4] et al. studied the origin of the rocks and thus learned their implications for proto-Tethys Ocean subduction. Lu Xiaoyu[5] et al. studied the creep mechanical properties of single fissure rocks and found the damage evolution law. Liu Xin[6]cheng et al. studied the application of in-situ stress-rock mechanics analysis in horizontal well fracturing of low permeability tight sandstone gas reservoirs in the East China Sea. Zhao Chunchen[7] et al. studied the petrology characteristics of the Shanbei slope reservoir in Ordos Basin and analyzed its oil and gas exploration indication. Based on this, this paper carries out rock species identification through YOLOv8, aiming to provide reference for rock information processing.

2. Research Status at Home and Abroad

2.1 Status Quo of Rock Identification Technology

At present, rock identification technology mainly includes traditional methods and computer vision-based methods. Traditional methods rely on the expertise and experience of geologists to determine rock types through means such as naked eye observation, hand specimen analysis and laboratory testing. This method, while reliable, suffers from subjectivity and low efficiency. There are many methods to identify rock types, such as Tong Rongchao[8]'s hyperspectral method combined with machine learning, and Wang[9] Huaiyuan's image target detection technology.

With the development of computer vision technology, automatic rock recognition technology based on image processing has gradually emerged. Scholars at home and abroad have done a lot of research on rock image preprocessing, feature extraction, classification and recognition, and have made remarkable progress. For example, the use of convolutional neural networks (CNN) for feature learning and classification recognition[10]

2.2 Application of Deep Learning in Rock Recognition

In recent years, the application of deep learning in the field of rock identification has become increasingly widespread. Deep learning algorithms can automatically learn feature representations from a large number of rock images without the need for manual feature design, and can process complex image data to improve the objectivity and accuracy of recognition. In particular, object detection algorithms, such as Faster RCNN, SSD and YOLO series, perform well in rock recognition.

YOLO series algorithms have gained wide attention in rock recognition for their high efficiency and accuracy. As the latest member of the YOLO series, YOLOv8 not only inherits the advantages of the previous generation algorithm, but also further optimizes the detection speed and accuracy. Therefore, this paper applies YOLOv8 algorithm to the field of rock recognition, aiming to develop a more efficient and accurate rock recognition system.

3. Design of Deep Learning Network Models

YOLOv8, Ultralytics' ingenious new generation of object detection algorithms, marks another milestone leap in the YOLO family of technologies. The algorithm is a significant innovation in its core architecture, integrating an innovative Backbone structure, Anchor-Free detection mechanism, and a well-designed loss function. In addition, YOLOv8 also introduces cutting-edge label allocation strategy and Loss calculation optimization scheme, which further improves the performance of the algorithm.

With its excellent performance, YOLOv8 achieves a significant improvement in accuracy while maintaining high-speed detection capabilities. It can not only efficiently complete the target detection task in complex scenes, but also expand the functional boundary to support multiple visual processing requirements such as instance segmentation and image classification, showing strong application potential and flexibility.

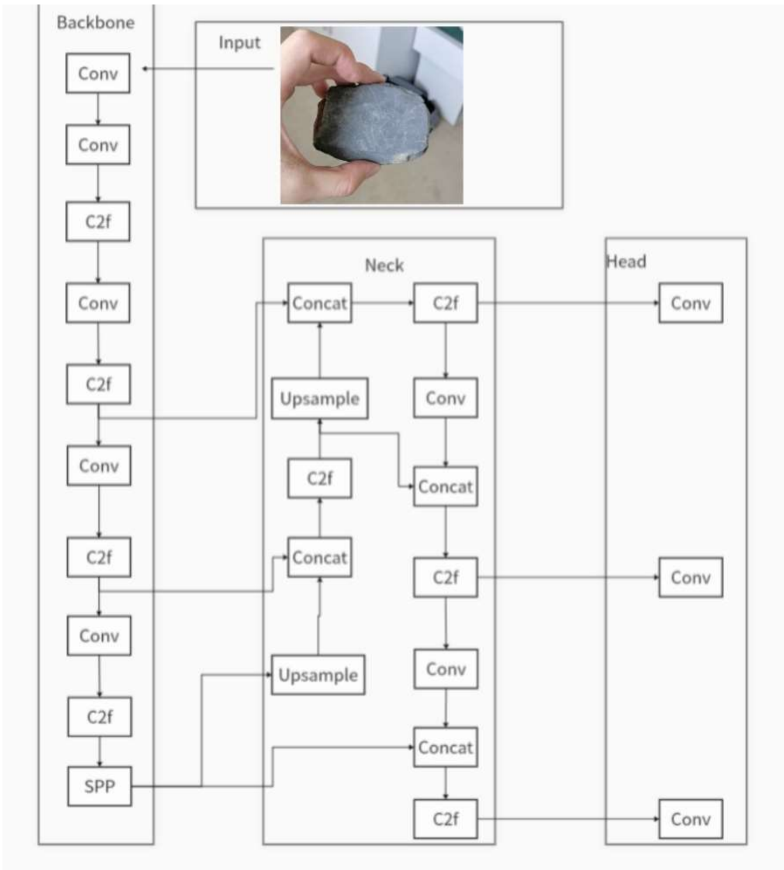

Figure 1. YOLOv8 network framework

In the YOLOv8 network architecture shown in Figure 1, the framework consists of three core components: Backbone backbone network, Neck layer and detection head. The workflow starts from the Input layer, which introduces the rock image to be detected into the network. Then, the Backbone is responsible for deep feature extraction of the input eye white image. Neck layer, located between Backbone and Head, plays the role of feature pooling and fusion, and provides support for subsequent decisions through further processing of the feature layer. As the decision-making core, the Head layer is responsible for outputting the final detection result based on the aforementioned processing results.

C2f module in YOLOv8 is similar to C3 module in YOLOv5 in its structural design. After its first two Conv convolution layers, C2f module adopts a Split layer for feature segmentation, which divides features into two parts, A and B. Part b Bottleneck module enters the bottleneck module for residual convolution operation. Generate output c; While part a is merged with subsequent Concat operations directly via residual concat. This process is repeated in multiple Bottleneck levels.

The core highlight of C2f module is its clever combination of module segmentation and multiple residual connections, which not only enhances the information flow within the network, but also realizes the effective fusion and enhancement of features by splicing features from different branches on different channel dimensions. This feature fusion strategy makes the spliced features more abundant and diverse, and significantly improves the model's ability to understand and detect complex scenes.

After deep processing and strengthening of features through the Neck layer, the detection head of YOLOv8 extracts three key feature layers from the network, the dimensions of which are

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(80*80*256), (40*40*512) and (20*20*512) respectively. These are fed into the Detect module and used to generate the final prediction results.

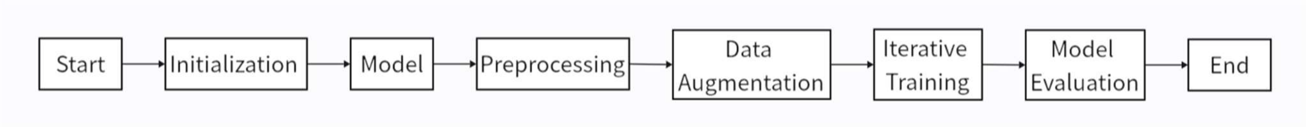

Figure 2. Model training process

Figure 2 shows the model training process. The process analysis is as follows:

(1) Initialization: Import PyTorch (torch), NumPy (numpy), os and other necessary graphics processing libraries, and load the specific modules and functions in YOLOv8 framework. In order to make full use of GPU acceleration capability, CUDA activation parameters were set, and random seeds were fixed to enhance the repeatability of the experiment. At the same time, the uniform size of the input image is determined, which is crucial for the subsequent data preprocessing. In terms of training parameter setting, key configurations such as training iterations (epochs), learning rate adjustment strategy and optimizer type are clearly defined. In addition, a small version of YOLOv8 pre-training Weights (yolov8_s.pth) is also downloaded for fine tuning during training. The path information of training set and verification set can be obtained by parsing COCO128.yaml configuration file, and the corresponding data set file can be read accordingly, which provides rich input data for the subsequent model training.

(2) Build the model: According to the constructed yolov8.yaml file, start to build the YOLO model and load data.

(3) Preprocessing: In the process of data loading, data preprocessing and data enhancement will be carried out on the data set. Before entering the model, the size of the picture is standardized and converted into 640*640 images, the image is optimized, and the image is re-encoded, and the data is converted into the format that the model can process.

(4) Data enhancement: in addition to the conventional rotation, translation of data enhancement methods. Mosaic and Mixup data enhancement strategies were also adopted. After using Mosaic data augmentation with 50% probability, add the policy of using Mixup data augmentation with 50% probability.

(5) Iterative training

Run the training task: set the learning rate, optimizer, iteration number and other parameters used in the current training according to the parameters of the initial configuration. Call the fit_one_epoch function to train and verify an epoch.

(6) Model evaluation

During the training process, the model is evaluated and the evaluation results on the verification set are recorded. The evaluation results are displayed and saved by the callback function, the current detection accuracy rate and average accuracy rate of each rock are fed back, and the weight file is saved at last.

4. Experimental Process and Analysis

4.1 Experimental Process

4.1.1 Evaluation Index

The evaluation indicators use the mAP formula, which is the average accuracy.

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$$mAP = \frac{\sum_{i=1}^{c} AP_i}{C} \tag{1}$$

In the formula, C is the number of identified ore categories, and AP is the average accuracy rate corresponding to each ore.

4.1.2 Experimental Design

This paper designed the experiment, used YOLOv8 official model network for training, trained 300 rounds of iterations, and finally took the model weight file with the highest mAP value as the final result of the experiment.

Table 1. Label ids

ID	Name	Number of tags
1	Serpentine marble	1082
2	magnetite	1152
3	magnesite	1101
4	diorite	1032
5	coal	1061
6	basalt	1201
7	Dolomite schist	1098
8	Syenite	996
9	quartz	1169
10	Seric schist	1201
11	pyrite	1138
12	granite	1086
13	obsidian	1102
14	hematite	1183
15	slate	1044
16	dolomite	1582

Figure 3 shows an example of rocks in the data set. Various rocks have different appearance. For example, SLATE is different from other rocks by its stratification and peeling properties and variable colors; Granite, on the other hand, shows medium coarse-grained, blocky and bright light tones; Basalt has deep color and prominent porosity structure; Diorite is characterized by neutral composition and dark gray to light green tones.

Figure 3. Example of rock species

Table 2. Server environment configuration table

Configuration name	Parameters
Operating system	Windows 11
CPU	12th Gen Intel(R)Core(TM)i7-12700H
GPU	NVIDIA GeForce RTX 3060 Laptop GPU
RAM	32G
Video card driver	30.0.15.1274

4.1.3 Setting Network parameters

The pre-training weight uses the heavy file yolov8.pth, and the input image is 640 pixel value in height and 640 pixel value in width. Number of batches =16. Each training iteration number is set with a 50% probability of enhancement using mosaic data and a 50% probability of enhancement using mixup data. Of the set total epochs, mosaic data enhancement will be enabled for 80% of Epochs.

The maximum learning rate of the model is 0.01, the minimum learning rate is 0.01 of the maximum learning rate, the optimizer uses sgd, and the weights are saved every 10 rounds of training.

4.2 Analysis of Experimental Data

Table 3. Accuracy rate of each ore in YOLOv8 experiment

Rock type	Identification accuracy (%)
1	86.76%
2	91.42%
3	94.22%
4	86.54%
5	89.21%
6	83.55%
7	91.03%
8	86.67%
9	84.82%
10	85.34%
11	82.54%
12	86.31%
13	88.22%
14	87.89%
15	90.66%
16	

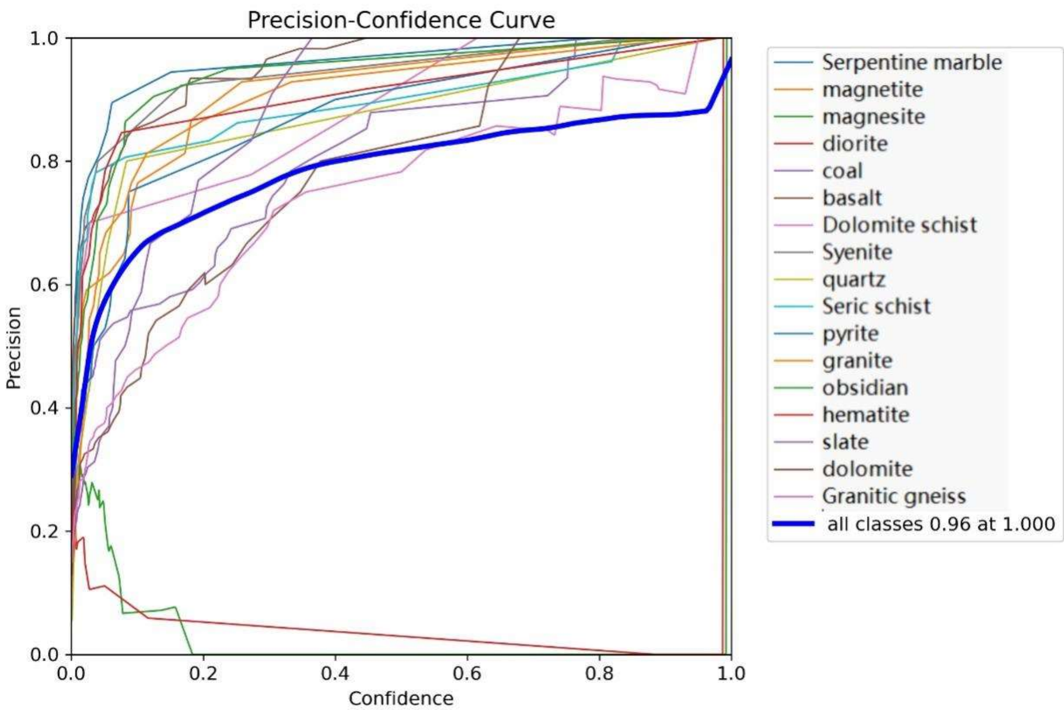

Figure 4. Confidence curve of each ore

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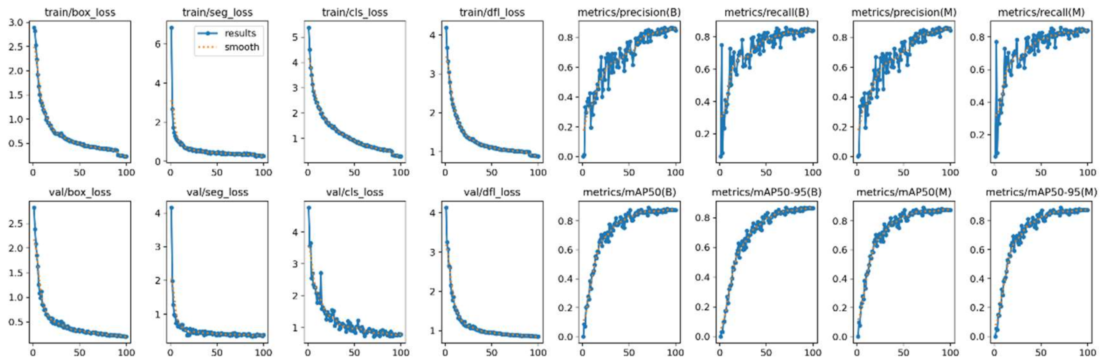

Figure 5. Iteration curve of loss and accuracy

Figure 5 shows the loss curve of YOLOv8 obtained in this experimental environment. According to the following information, the YOLOv8 model showed good performance changes during the first 20 rounds of training. With the increase of the number of training rounds, all the losses showed a decreasing trend, indicating that the model was gradually optimizing its forecasting ability. At the same time, the accuracy was gradually improved, indicating that the accuracy of the model in identifying the target was continuously enhanced. When the number of training rounds reached about 50, the model began to converge, meaning that it had been able to fit the training data better. To sum up, YOLOv8 showed a steady performance improvement in the front-wheel training and stabilized after about 50 training rounds. After 100 rounds of iterations, the final accuracy rate reached 82.20%.

Figure 6. Recognition effect drawing

As shown in Figure 6, this study successfully realized the accurate identification of different types of rocks by applying the YOLOv8 model. With its powerful feature extraction capability and efficient target detection mechanism, this model has demonstrated excellent performance in a variety of complex rock samples. The experimental results show that YOLOv8 not only has a fast recognition speed, but also has a high accuracy, which fully proves its advantages in the field of rock recognition.

5. Conclusion

To sum up, this study verifies that YOLOv8 can perform the task of rock identification excellently in practical applications, and provides strong technical support for the research and practice in related fields. This study not only demonstrates the advanced nature of YOLOv8 model in object detection, but also lays a solid foundation for subsequent rock identification and classification research.

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