

Rock Joint Detection from Borehole Imaging Logs Using a Convolutional Neural Networks Model

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ABSTRACT: To map the rock joints in the underground rock mass, a method was proposed to semi-automatically detect the rock joints from borehole imaging logs using a deep learning algorithm. First, 450 images containing rock joints were selected from borehole ZKZ01 in the Rumei hydro-power station. These images were labeled to establish ground truth which was subdivided into training, validation, and testing data. Second, the YOLO v2 model with optimal parameter settings was constructed. Third, the training and validation data were used for model training, while the test data was used to generate the precision-recall curve for prediction evaluation. Fourth, the trained model was applied to a new borehole ZKZ02 to verify the feasibility of the model. There were 12 rock joints detected from the selected images in borehole ZKZ02 and four geometric parameters for each rock joint were determined by sinusoidal curve fitting. The average precision of the trained model reached 0.87.

KEY WORDS: rock joints, automated detection, borehole imaging, deep learning, YOLO model.

0 INTRODUCTION

Rock joints with various scales are developed inside the rock mass, which are often the weak parts of the rock mass to resist external forces. They can change the failure mechanism of the rock mass and lead to shear failure along the rock mass (Chen et al., 2011; Schepers et al., 2001). The crucial factor for stability analysis of rock mass is to calculate the parameters of these rock joints (Coli et al., 2008; Ballard, 1981; Myrianthis, 1975). Therefore, quick and accurate identification and characterization of the rock joint have important significance for various rock engineering practices, such as geohazard mitigation, underground mining, dam construction, and foundation works (Michalak et al., 2021).

Two primary approaches are available for measuring rock joints in rock masses: contact and non-contact measurements. Contact measurements, such as scanline surveys (Priest and Hudson, 1981) and window surveys (Kulatilake and Wu, 1984), are low-cost and straightforward but suffer from drawbacks including time-consuming procedures, labor-intensive requirements, and dependence

on operator experience. Furthermore, conducting surveys on steep outcrops or in adverse weather conditions poses high risks to engineers and geologists. To address these limitations, non-contact measurements, such as photogrammetry (Baltsavias, 1999; Chandler, 1999) and laser scanning (Chen et al., 2023; Fekete et al., 2010; Chang et al., 2005), have been developed. These methods automatically identify and characterize rock joints from high-resolution point clouds (Ge et al., 2022a, 2018; Dewez et al., 2016; Vöge et al., 2013), primarily suitable for surface outcrop surveys. However, they exhibit limitations in underground engineering due to poor lighting conditions and limited space.

To overcome these problems, a borehole imaging system was proposed. It not only carried an independent downward lens but also could capture 360° panoramic images of the borehole wall without omission (Wang et al., 2016; Li et al., 2013). Borehole imaging has been widely used in civil engineering, petroleum engineering, geological engineering, etc., and has become a helpful tool for underground exploration (Zou et al., 2020; Zohreh et al., 2014; Kabir et al., 2009). Assume that a rock joint is a plane and the borehole is vertical, the intersection between the rock joint and the borehole wall appears as a sinusoid on the expanded view of the borehole wall image captured by the borehole imaging system (Wang et al., 2017a).

There are two main methods to identify rock joints

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and calculate their parameters from the borehole images—manual interpretation and automatic identification. In the manual identification method, operators can subjectively select sinusoidal control points of the rock joints (peaks and low points) or input essential characteristic parameters. They then proceed to perform sinusoidal curve fitting to determine the geometrical parameters of the rock joints (Assous et al., 2014). However, the manual methods require huge work and are easily affected by subjective factors such as the experience and cognitive level of the operators, causing omission or misjudging of rock joints and low measuring accuracy (Dias et al., 2020; Zhou and Maerz, 2002). Therefore, the less subjective method was proposed. Many scholars have made great efforts to detect the rock joints from borehole images using image segmentation to improve the measurement automation level and accuracy, such as image color-space transformation (Wu et al., 2011), Hough transform (Ballard, 1981), image grayscale and gradient features (Wang et al., 2016), maximum gradient value (Wang et al., 2017b; Kabir et al., 2009), localization signal feature (Kun et al., 2020), covariance matrix and Canny detector (Ge et al., 2022b), etc. These methods have made successful attempts under certain conditions, but each method has its limitations. The computational cost for image color-space transformation and Hough transform methods is large (Wu et al., 2011). The image segmentation methods based on the features of grayscale-gradient-signal are complicated in the calculation and easy to ignore the lateral continuity of the borehole images (Zou et al., 2021). The automatic method using covariance matrix and Canny detector still needs to specify several parameter thresholds by operators for each case to improve the applicability of the algorithm, such as thresholds for bounding box height of rock joint region, thresholds for local maximum or minimum, and thresholds for Canny detector. Additionally, these methods make it difficult to capture hidden useful representations and fully explore the inherent relationship of input parameters. Deep learning has emerged as a promising solution to address the limitations of the aforementioned methods. Its strong feature extraction and data processing capabilities make it well-suited for rock mechanics studies and the management of geological hazards (Ma et al., 2021; Zuo et al., 2021). Deep learning has gained significant attention in recent research endeavors (Ge et al., 2025; Chen et al., 2024; Bui et al., 2020).

With the improvement of the computer vision and artificial intelligence (AI), several deep learning algorithms, including SPP-NET (He et al., 2015), Fast R-CNN (Girshick, 2015), YOLO (Redmon et al., 2016), and SSD (Liu et al., 2016), have been proposed and widely applied in image recognition with the advancement of computer technology (Zhang et al., 2018; Agostinelli et al., 2014). YOLO, a real-time object detection neural network, surpasses traditional two-stage algorithms like RNN networks by conducting region detection and recognition simultaneously via one fully connected layer in a single iter-

ation, leading to faster and more accurate predictions (Redmon et al., 2016).

This study aimed to develop an approach to detect and characterize the rock joints from borehole imaging logs using a deep learning algorithm. Images sequences with joint labels and bounding boxes were carefully selected from the borehole ZKZ01 in Rumei hydropower station to create the ground truth for prediction network training, and then YOLO (a deep learning model) was used to generate a prediction model to determine the rock joints from the images of another borehole ZKZ02 by learning the ground truth. Following the rock joint detection, the characterization of the rock joint was conducted to measure the orientation (dip angle and dip direction), depths, and apparent aperture of the detected rock joints. A manual survey of the rock joints was performed to verify the robustness of the proposed deep-learning model.

1 GEOLOGICAL SETTINGS

Two boreholes—ZKZ01 and ZKZ02—were selected as the study case in Rumei hydropower station, which is located in Southeast Tibet, China with a longitude of 98° 21'3"E and a latitude of 29°37'4"N (Figure 1a). The imaging logs from borehole ZKZ01 were utilized for creating the ground truth (learning samples) to train the deep learning model, while borehole ZKZ02 was used to verify the trained detection model.

The study area belongs to a mountain-canyon area, where situated in the upper reaches of the Lancang River in Rumei Town, Tibet. The elevation in the study area undulates between 2 000 and 3 500 m. The slopes on both banks of the Lancang River are very steep, showing a v-shaped valley in the cross-section of the river. There are many gullies with steep slopes on both banks, and most of them spread perpendicularly to the river channel. The lengths of most of these gullies are less than 500 m except a few gullies with lengths over 1 000 m. Due to the effect of the high *in-situ* stress and strong weathering, the rockmass in the study area is extremely fractured, and many unloading fissures can be observed at the outcrop (Figure 1b).

The main strata exposed in the study area are Zhuka Formation of the Middle Triassic (T_2z), followed by the widespread surficial deposits of Quaternary strata which are discontinuously distributed on both banks of the Lancang River with different causes, such as deluvium (Q^d) on the left bank southeast of the study area, deluvium and alluvium (Q^{d+al}), eluvial deluvium (Q^{edl}), proluvium (Q^p), and eluvial deluvium and alluvium (Q^{edl+al}). Several faults with different scales are observed in the study area (red lines shown in Figure 1a), and the longest one is Zhuka fault (f4) which is a northwest-trending fault. Two boreholes (ZKZ01 and ZKZ02) were drilled close to the river, and borehole imaging was conducted in two boreholes to capture the images of borehole walls. The total depth of borehole ZKZ01 reaches 187.2 m, while borehole ZKZ02 is 241.5 m deep. As shown in Figure 1a, the

positions of the borehole ZKZ01 and ZKZ02 are very close with a distance of approximately 100 m. Therefore, the geological conditions of the two boreholes are similar to a great extent, especially the discontinuity pattern.

The main type of groundwater in the study area is fissure water in jointed rockmass zones, such as water flowing along bedding or faults and pore water in Quaternary loose accumulation layers. The fissure water commonly found inside slopes is mainly retained in bedrock fissures or rock joints and fault zones. It is recharged by atmospheric precipitation and snow melt water. The pore water is mainly retained in Quaternary loose accumulation layers, usually at the gentle slope of the slope surface, which is greatly impacted by the season and mainly discharged to nearby valleys or gullies.

The study area is characterized by a plateau mountain climate and a subtropical monsoon climate with a low average annual temperature of nearly 4.8 °C. The average frost-free period in this study area is around 115 days each year. The mean annual rainfall is about 350–450 mm per year, and the rainfall is primarily concentrated between June and September. July and January have the maximum and minimum rainfall throughout the year, respectively.

2 METHODOLOGIES

The main steps of the proposed method included: rock joint detection and rock joint characterization, and Figure 2 illustrates the outline of the workflow. In the rock joint detection, borehole image logs of rock joints were labeled to establish the ground truth, followed by the ground truth partition: training data (60% of the ground truth), validation data (10% of the ground truth), and test data (30% of the ground truth). The feature extraction network and the detection network were used to build the YOLO framework, and the ground truth was inputted into the YOLO network for training and testing the model to predict the bounding box containing the rock joints and the possibility. In the rock joint characterization, we fitted the upper, median, and lower sine curves of the detected rock joints within bounding boxes, and geometric parameters of rock joints (dip direction, dip angle, depth, and apparent aperture) were calculated.

2.1 Data Description and Ground Truth

The data set used for ground truth was collected from the ZKZ01 borehole images log which were captured by an SR-DCT (W) borehole imaging system. In total, 450 rock joint images with pixel sizes of 85 × 71 were selected from the image logs. The manual labeling was performed to generate the ground truth of rock joints, based on a MATLAB APP—Image Labeler. The ground truth was defined as a collection of selected images with the correct location and labels for rock joints, which is important for enhancing the performance and accuracy of the deep learning model (Arras et al., 2022; Han et al., 2021). The creation of ground truth data requires experienced experts based on their professional background,

which is easily affected by personal subjective impressions. Therefore, much attention was needed pay to the production of the ground truth. The selection of images was guided by the following criteria, designed to ensure that the dataset comprehensively represents the variability of rock joints within the borehole while maintaining high-quality data for model training.

(1) High-resolution images with clear visibility of rock joints were prioritized. This includes images free from significant blurring, excessive noise, or other distortions that could hinder the accurate detection and analysis of rock joints.

(2) To capture the diversity of rock joint characteristics (e.g., orientation, spacing, aperture), images were selected to include a wide range of joint features. This was done to ensure the model's ability to generalize across different joint configurations.

(3) Images that were representative of the geological context of borehole ZKZ01 were selected. This involved choosing images that displayed identifiable geological formations and transitions, contributing to the understanding of the spatial distribution of rock joints.

The rock joints were manually marked in the images by specifying the regions and labels of rock joints. Figure 3 displays the typically labeled joint images for five types of rock joints, along with red rectangles representing the bounding boxes containing the rock joints in the images.

The borehole ZKZ01 in Rumei Hydropower Station was used to create the ground truth data for training the deep learning model, while the images from another new borehole ZKZ02 were used to verify the trained prediction model. 450 images were initially selected from the ZKZ01 borehole images to represent the ground truth and then randomly classified into training data (270 images, 60%), validation data (45 images, 10%), and test data (135 images, 30%). Among them, the training data and the validation data were inputted to train the YOLO model. The test data was only designed to generate the P-R curve to evaluate the performance of the trained model. Furthermore, the proposed deep learning model was applied to a new borehole ZKZ02 to further verify the accuracy and efficiency of the rock joint detection model.

Additionally, to increase the diversity of training data, data augmentation was carried on based on the original 450 images (only training data was processed for data augmentation, and the test data and validation data were not processed at all). There were many ways for data augmentation, such as flipping the images horizontally, flipping the images vertically, cropping the images randomly and so on (AbdElNabi et al., 2020; Loey et al., 2020; Shorten et al., 2019). In this study, randomly flipping the images and associated box labels horizontally were used to enhance the training data. The principle of the randomly flipping the images enhancement algorithm is to increase the diversity of the training data by randomly flipping the image horizontally or vertically during the training process. This method can help the model to better learn features from different angles and directions.

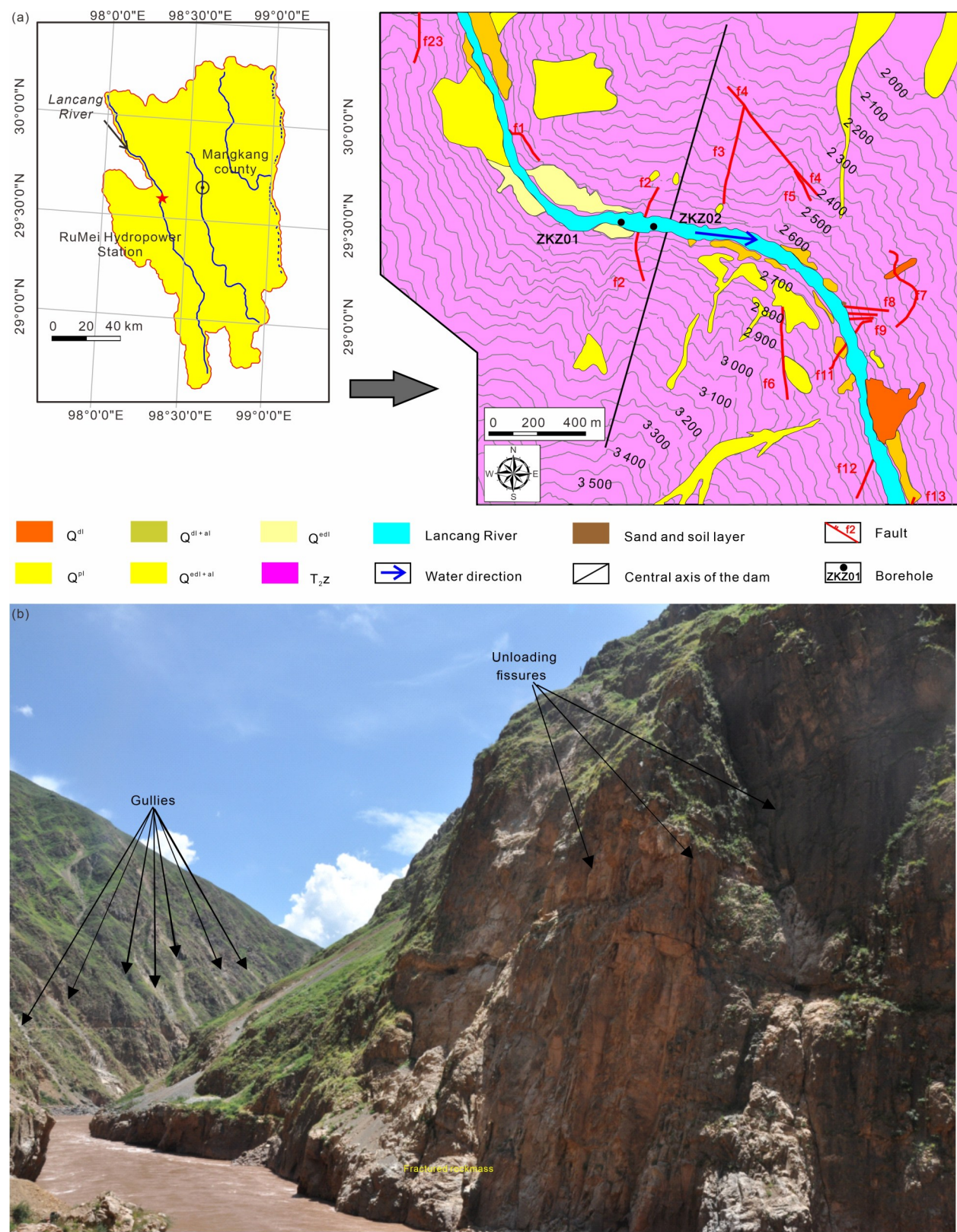


Figure 1. Location and geological map of the study area (a) and the typical outcrop in the study area (b).

Specifically, randomized horizontal flipping mirrors the image from left to right, while randomized vertical flipping mirrors the image from top to bottom.

The principle of the randomized flipped image data enhancement algorithm is based on the following obser-

vation: symmetry is a universal feature of many objects, so introducing flipping in training can improve the model’s ability to recognize objects. In addition, by randomly flipping, the model can be better adapted to images under different viewpoints and orientations, thus im-

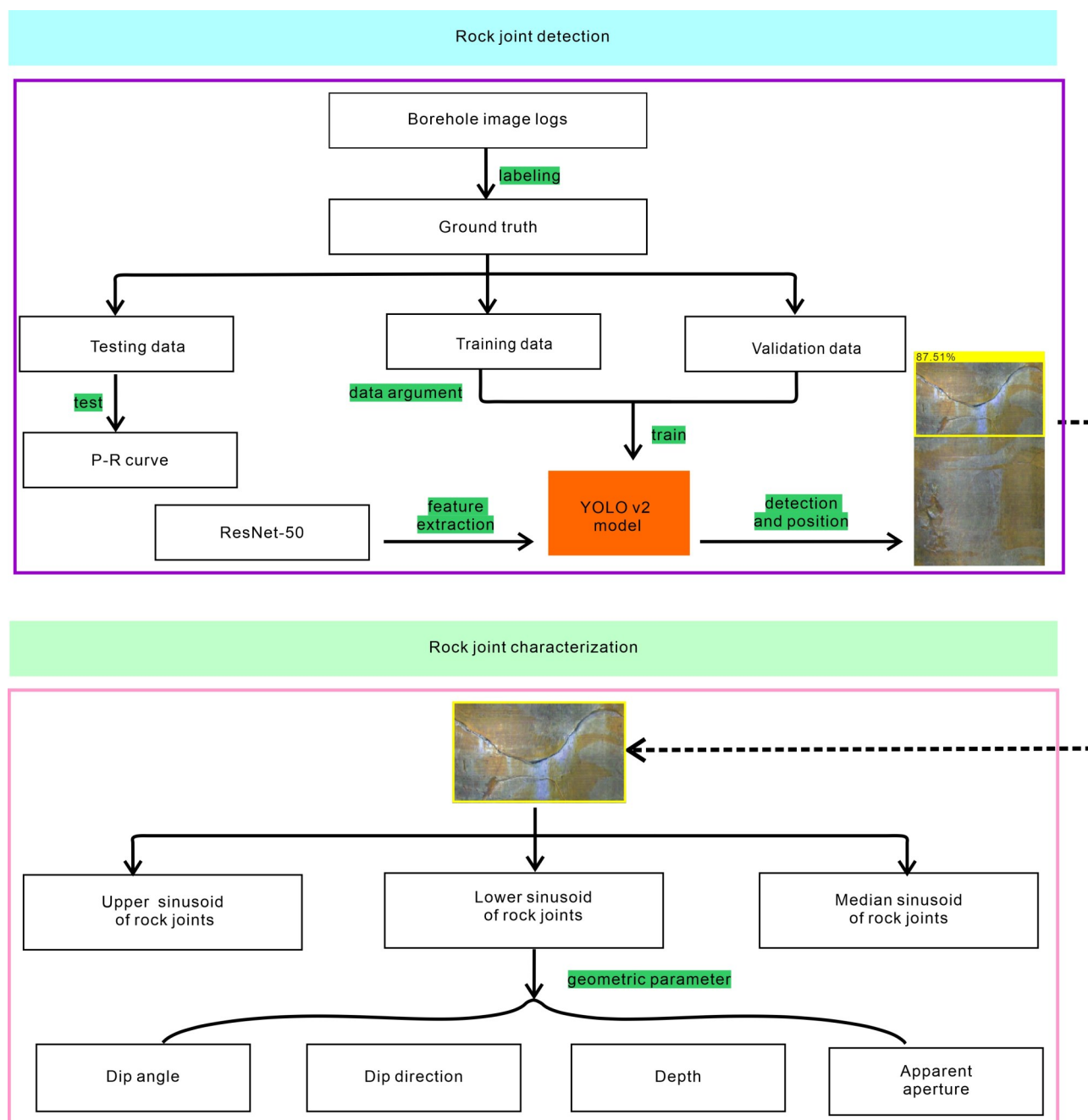


Figure 2. Workflow for rock joint detection and characterization.

proving robustness.

An image can be converted into four images through data augmentation, in this manner, we can obtain 1 800 images (four times of the original images) with rock-joint labels (Figure 4). Note that, the augmentation algorithm was applied to all training sets to increase the number of learning samples.

2.2 The Principle of Rock Joint Detection Using the YOLO Model

When detecting rock joints using the YOLO model, the input rock joint image was subdivided into $M \times M$ grid cells with equal size first, and then k anchor boxes with confidence scores were predicted for each grid cell. Each

anchor box consisted of the following attributes: box center (x, y), box width (w), and box height (h). These anchor boxes were overlaid each other on the input image and regarded as the basis for predicting the location of the rock joints in the image. Furthermore, the YOLO model extracted the features from these anchor boxes via the feature extraction layers to forecast the bounding box (the yellow outline) which contained the rock joint (Wu et al., 2020; Sang et al., 2018; Shinde et al., 2018). Meanwhile, the bounding box was also determined to represent the reliability of the location prediction (bounding box) of the rock joints from the input image (Figure 5).

When using multiple anchor boxes to detect the rock joint in the image, a threshold was specified to remove

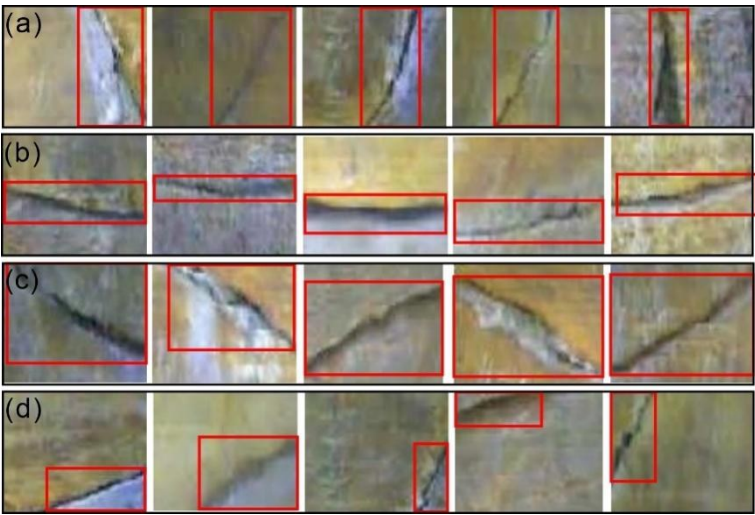


Figure 3. Examples of ground truth (regions within red bounding boxes contained rock joints). (a) the parts of rock joints located vertically in the images; (b) the parts of rock joints located horizontally in the images; (c) the parts of rock joints titled across the images, (d) rock joints in the corners of the images, and (e) rock joints with white fillings.

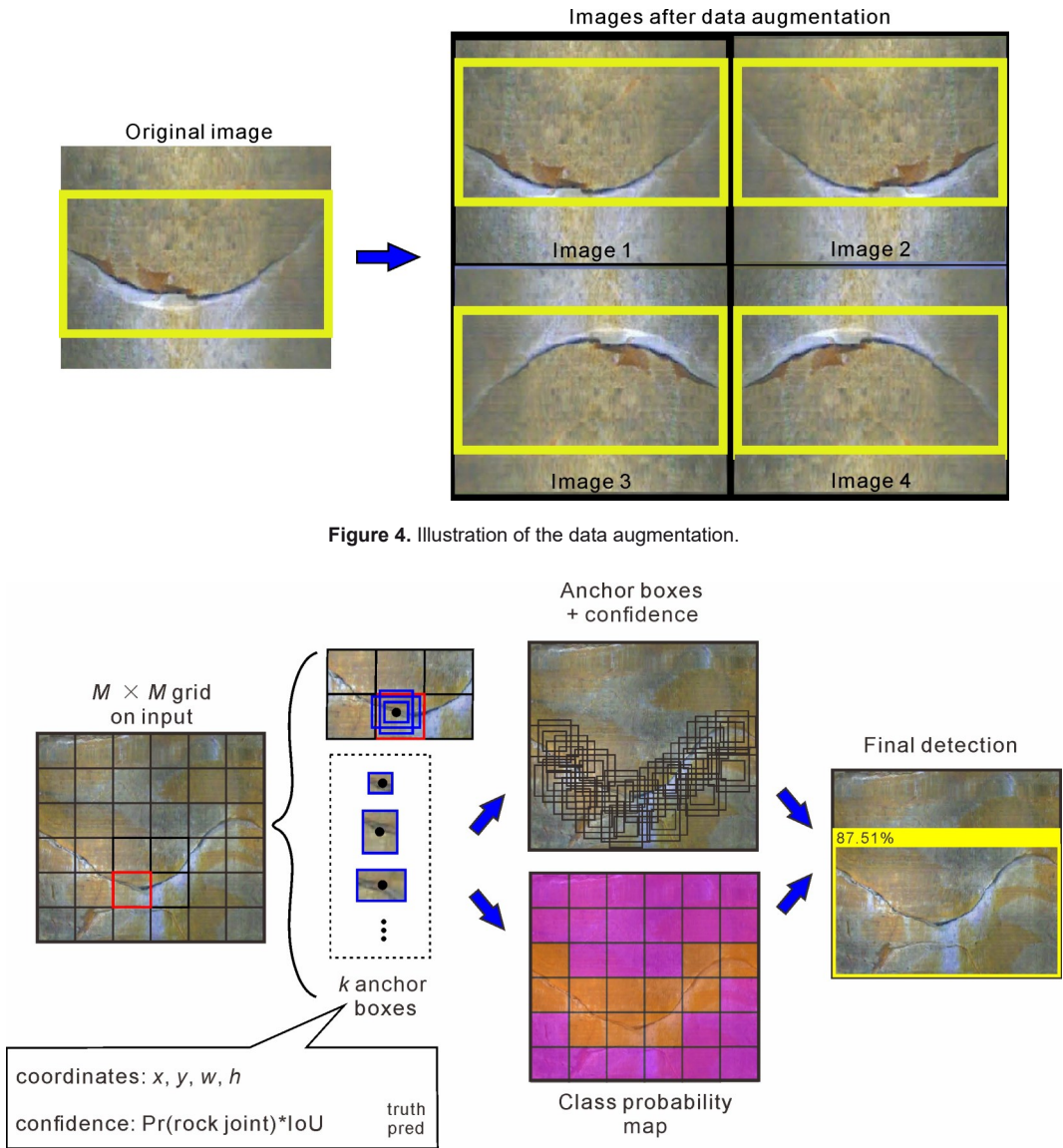


Figure 5. YOLO detection principle.

the anchor boxes whose confidence score was lower than the threshold. Because a lower confidence score suggested that the anchor box was insufficient for identifying the rock joints. However, sometimes a threshold alone was not enough to accurately filter out all the anchor boxes with low confidence scores. Hereon, the non-max suppression (NMS) algorithm was used to determine the final anchor box from the multiple anchor boxes for the rock joints according to the following steps: (1) The best anchor box was selected based on the confidence score, which was calculated by the intersection over union (IoU) function; (2) all the other anchor boxes with high overlap with the best one were removed (Wang et al., 2021). More details about the IoU function are provided in the next subsection.

2.2.1 IoU

As mentioned above, each anchor box consists of five parameters: x , y , w , h , and a confidence score (Figure 5). Confidence is used to judge the accuracy of boundary frames of rock joints, and high confidence scores indicate high accuracy of the rock joint detection using the trained deep learning model. The confidence score includes two aspects—IoU and Pr (rock joint). If there is no rock joint within the anchor box, Pr (rock joint) equals '0'; if there is a rock joint in the anchor box, Pr (rock joint) is '1'. IoU quantifies the accuracy of the anchor box position about the rock joint and can be determined by comparing the relative location of the anchor box and the ground truth box (Eq. (1)). The product of the IoU and Pr (rock joint) is the confidence score as shown in Eq. (2).

$$\text{IoU} = \frac{\text{Area}(\text{anchor box}) \cap \text{Area}(\text{ground truth})}{\text{Area}(\text{anchor box}) \cup \text{Area}(\text{ground truth})} \quad (1)$$

where, $\cup$ is the overlap area between the anchor box and ground truth, and $\cap$ denotes the combined area between the anchor box and ground truth (Figure 6).

$$\text{Confidence score} = \text{IoU} \times \text{Pr}(\text{rock joint}) \quad (2)$$

2.2.2 K-means

To determine an anchor box with a proper size (height and width) for the rock joint detection, the K -means clustering was performed for the 1080 training image samples. The function of K -means clustering is

shown in Eq. (3).

$$\min \sum_{i=1}^K \sum_{j=1}^N (1 - \text{IoU}(\text{anchor box}[i], \text{ground truth}[j])) \quad (3)$$

Where K is the number of cluster centers, and we selected K to be 3 in this paper, which meant three anchor boxes of different sizes would be applied for positioning; N is the number of ground truth boxes; anchor box $[i]$ represents the i -th cluster center box; ground truth $[j]$ represents the j -th ground truth box; $\text{IoU}(\text{anchor box}[i], \text{ground truth}[j])$ is intersection over the union of cluster center box and ground truth box. The smaller the objective function, the larger the IoU, which indicates that the cluster center is closer to the width and height of the real target frame. In addition to accounting for the resizing of the rock joint images before training, we resized the training data into $112 \times 112 \times 3$ for estimating anchor boxes.

2.2.3 Loss function

The loss function in the YOLO model can be written as Eqs. (4)–(7) (Redmon and Farhadi, 2017). Among this, localization loss is used to calculate the errors between the ground truth box and predicted bounding box; Confidence loss calculates the confidence score for the above-mentioned errors (Loey et al., 2021).

$$\text{YOLO loss} = \text{Localization loss} + \text{Confidence loss} + \text{Classification loss} \quad (4)$$

Localization loss =

$$q_1 \sum_{a=0}^{g^2} \sum_{b=0}^v 1_{ij}^{obj} \left[(x_i - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2 \right] + q_1 \sum_{a=0}^{g^2} \sum_{b=0}^v 1_{ij}^{obj} \left[\left(\sqrt{w_i} - \sqrt{\hat{w}_i} \right)^2 + \left(\sqrt{h_i} - \sqrt{\hat{h}_i} \right)^2 \right] \quad (5)$$

$$\text{Confidence loss} = q_2 \sum_{a=0}^{g^2} \sum_{b=0}^v 1_{ij}^{obj} (cs_i - \hat{cs}_i)^2 +$$

$$q_3 \sum_{a=0}^{g^2} \sum_{b=0}^v 1_{ij}^{obj} (cs_i - \hat{cs}_i)^2 \quad (6)$$

$$\text{Classification loss} = q_4 \sum_{a=0}^{g^2} 1_{ij}^{obj} \sum_{z \in \text{classes}} (p_i(z) - \hat{p}_i(z))^2 \quad (7)$$

where, g is the number of the grid that an input rock joint image is divided into in the YOLO model; v is the number

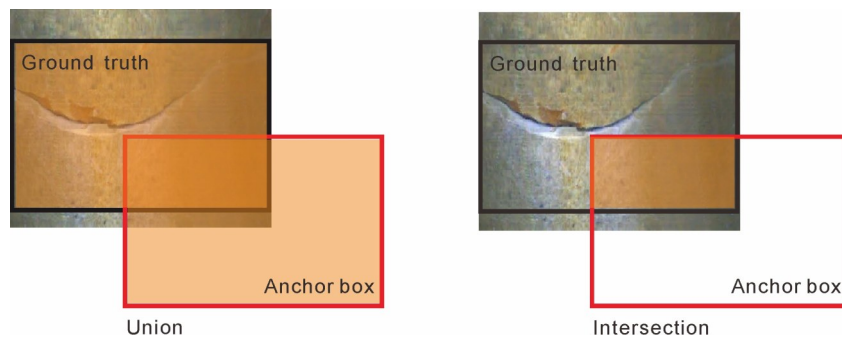


Figure 6. Schematic diagram of the IoU calculation.

of the bounding boxes contained in each grid; (x_i, y_i) is the centroid of the i -th bounding box with a width of w_i and a height of h_i ; cs_i is the confidence score of the i -th bounding box; $p_i(z)$ is the class probability of the i -th bounding box; $\hat{x}_i, \hat{y}_i, \hat{w}_i, \hat{h}_i, \hat{cs}_i$, and $\hat{p}_i(z)$ are the corresponding ground truth of x_i, y_i, w_i, h_i, cs_i , and $p_i(z)$. 1_{ij}^{obj} is equal to 1 when there is a rock joint (object) in the i -th grid and the confidence of the j -th bounding box is the highest among all bounding boxes in the i -th grid; 1_{ij}^{noobj} is the opposite of 1_{ij}^{obj} ; 1_{ij}^{obj} is 1 when there is a rock joint in the i -th grid and 0 otherwise; q_1, q_2, q_3 , and q_4 are the weights in the three loss functions.

2.3 YOLO Network Architecture

The YOLO deep learning network was adapted for detecting rock joints in this study, based on the YOLO model's success in image classification (Redmon et al., 2016). The YOLO architecture consists of a feature extraction network and a detection network. The feature extraction network utilizes a portion of ResNet-50 to extract feature maps from the anchor box; the detection network was responsible for conversion and output to improve the accuracy of object localization.

2.3.1 Overall network architecture

After completing the improvement above, the structure of the YOLO model is finalized, and the overall model structure diagram is shown in Figure 7. The feature ex-

traction network consists of a single convolutional layer (represented by the yellow cuboid) and 13 residual blocks, connected by additional layers. The residual blocks can be categorized based on their composition. The first category includes three convolutional layers, two 1×1 convolutional layers, and one 3×3 convolution in parallel; The second category has four convolutional layers, with the former first category plus one additional 1×1 convolution in parallel. The residual blocks are color-coded according to these categories in Figure 7; the first blue, the first orange, and the first purple residual blocks belong to the second category, while the others belong to the first category. Based on the number of parameters, there are three categories: blue, orange, and purple, as shown in Figure 7. The residual blocks of the same color have the same parameters but produce different outputs, Table S1 provides a detailed overview of the specific parameters for each residual block in Figure 7. For example, residual blocks 1–3 correspond to the blue residual block in Figure 7, residual block 1 consists of a 1×1 convolution kernel with 64 filters, a 3×3 convolution kernel with 64 filters, and two 1×1 convolution kernel with 256 filters. Residual blocks 2 and 3 share the same parameters but have one less 1×1 convolution kernel with 256 filters than Residual blocks 1. In contrast, the orange residual block has 128 or 512 filters, while the purple block has 256 or 1 024 filters.

In addition, integrating batch normalization into all

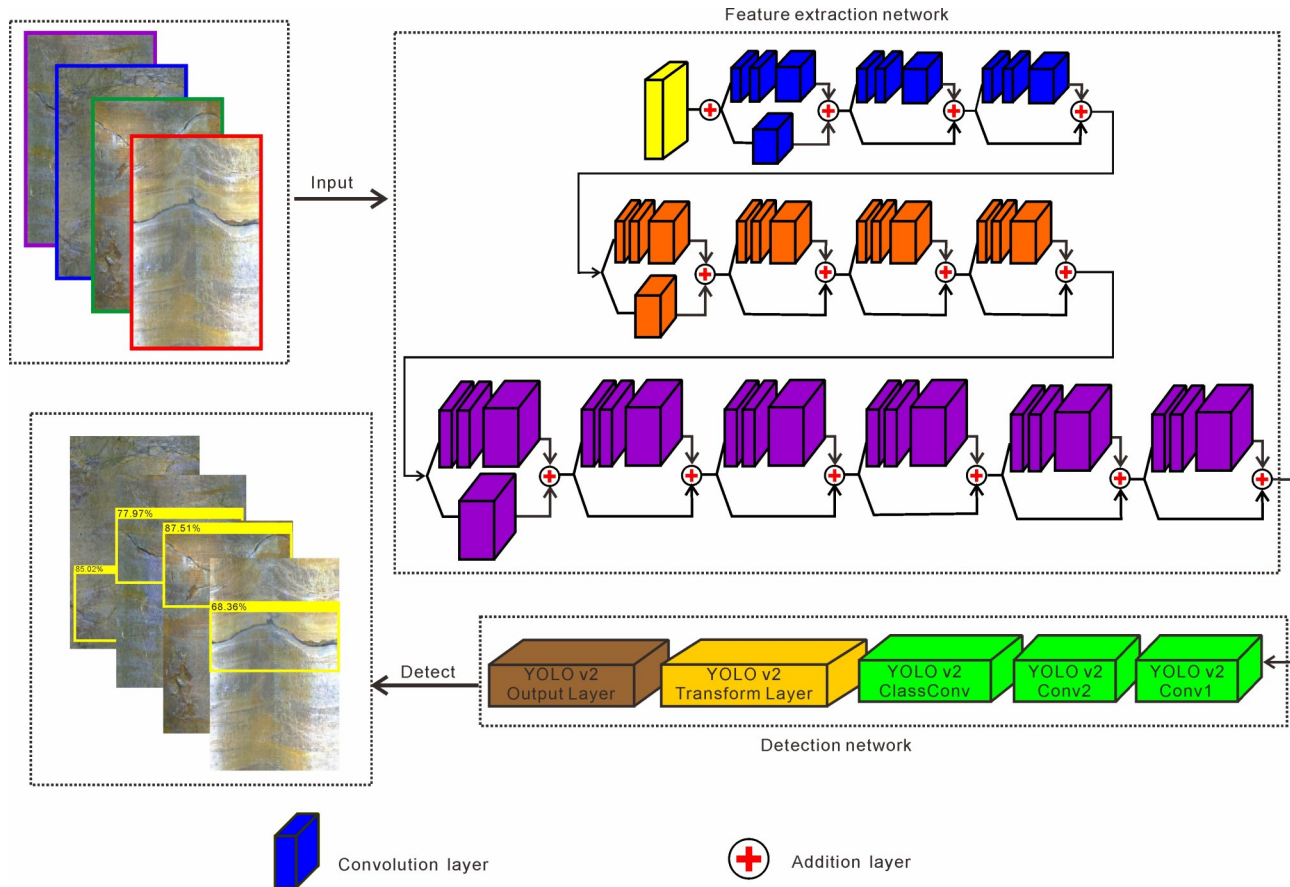


Figure 7. The overall network architecture of YOLO.

convolutional layers of the YOLO feature extraction network can effectively improve post-training convergence, as shown in recent research by Dais et al. (2021). The detection network of YOLO is relatively simple, consisting of only three convolutional layers, one transform layer, and one output layer. The transform layer serves to convert the anchor box forecast to the outline of the target box as well as extract the activations of the convolutional layer to enhance model stability. The output layer produces the locations of the pure anchor box for rock joint detection.

2.3.2 Feature extraction network—ResNet-50

The residual network (ResNet-50) was a deep learning network that used multiple convolution layers to learn residual connections between inputs and outputs. This allows them to extract rich feature maps and pass them to the following network, ultimately solving complicated tasks and increasing detection accuracy while maintaining good generalization on validation samples (Wen et al., 2020; Zagoruyko and Komodakis, 2016).

Structurally, ResNet-50 has a network depth of 50 layers and begins with a convolution layer followed by 16 residual blocks, a fully connected layer, a softmax layer, and finally ends with an output layer. In this experiment, the YOLO model designed the 'activation_40_relu' layer as the feature extraction layer, replacing the layers after 'activation_40_relu' with the detection network. Therefore, layers such as 3 residual blocks, 1 fully connected layer, and 1 softmax layer were all deleted, while the layers before 'activation_40_relu' were retained to form the feature extraction layer.

2.3.3 Training and test model

This experiment was performed on the HP Pavilion computer. The detailed computer specifications are

Table 1 The hardware environment

Hardware	Environment
Windows edition	Windows 10 Professional
Processor	Intel® Core (TM) i5-8300H 2.30 GHz dual-core
GPU	NVIDIA GeForce GTX 1050Ti GPU
Installed memory	8 G of RAM
System type	64-bite operation system
Purchasing data	Dec., 2018

Table 2 The training and validation loss under different max epochs

Max epoch	Time elapsed	Training loss	Validation loss
10	0:15:03	0.917 8	0.881 8
20	0:30:18	0.736 1	0.748 4
40	0:45:11	0.482 9	0.524 0
60	1:00:12	0.210 8	0.256 7
80	1:14:58	0.095 1	0.108 3
100	1:29:41	0.126 6	0.170 8

shown in Table 1. The goal of the YOLO model training was to obtain the optimal training parameters to increase the accuracy of the detection of rock joints. The Adam optimizer was utilized for the iteration process which could add the nonlinear factors to improve the expressiveness of the model (Yang et al., 2018), only need to modify learning rate, the max epoch, the batch size three parameters. In the experiment in this article, the initial learning rate was 0.001, the batch size was set to 8. The main parameter is selected as the max epoch.

Epoch refers to the number of times the network processes the entire training dataset during the training process. It is a crucial parameter that determines the convergence and accuracy of the model. Its value is proportional to the time and computational resources needed for training, making it a vital parameter in determining both model accuracy and convergence. A higher epoch value may lead to over-fitting, while a lower epoch value may result in under-fitting. Table 2 illustrates the performance of YOLO v2 on the rock joint detection under different max epochs during the phase of the training and validation.

From Table 2, it can be seen that as the number of the max epoch increases, the training loss and the validation loss in the model keep decreasing, when the max epoch = 80, the training loss and verification loss are below 10%. However, when the max epoch = 100, the training loss and the validation loss start to diverge, compared with the stable convergence when the max epoch is from 10 to 80. The reason is that there is a rise in loss due to over-fitting. By comparing the iteration ending loss in Table 2, the experiment was conducted with the max epoch as 80.

To assess the accuracy of identifying rock joints of the YOLO v2 model, we use the average precision (AP) as the evaluation index in this experiment. AP is a measure of the precision and recall of rock joints in the test data (Russakovsky et al., 2015; Everingham et al., 2010). The precision refers to the percentage of the correctly detected rock joints in the total test image area, calculated as shown in Eq. (8); The recall refers to the percentage of rock joints that are correctly detected in the total rock joints, it is calculated as shown below.

$$\text{Precision} = \frac{TP}{TP + FP} = \frac{TP}{n} \quad (8)$$

$$\text{Recall} = \frac{TP}{TP + FN} \quad (9)$$

where, the false negative (FN) represents that the model predicts that there is no rock joint in the image, but the image does contain one (Chang et al., 2019). The true positive (TP) represents that both the predicted result and the fact contain a rock joint. The false positive (FP) represents that the model detects a rock joint in an image where there is none. The TP and FP value is calculated based on the computing of the IoU between anchor boxes and ground truth, when IoU greater than 50% results in TP, while a value less than the threshold results in FP. N represents the total number of test data sets.

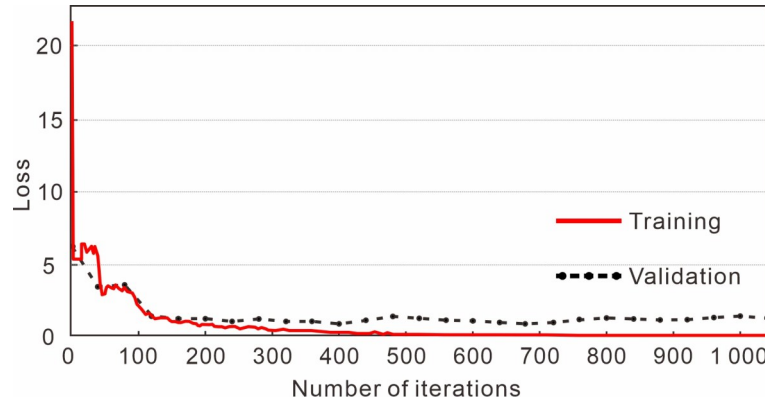


Figure 8. Training and validation loss.

Average precision is the most straightforward way to measure the model performance it is a ratio of correctly predicted observations to the total number of test datasets. In the analysis of test results, the accuracy rate and recall rate is the vertical and horizontal axis, respectively. The area of the P-R curve represents the average precision value, and the calculation equation is as follow.

$$\text{Average precision} = \frac{\sum \text{Precision}}{\text{Recall}} \quad (10)$$

2.4 Determination of Geometric Parameter of Rock Joints

The standard and nonstandard rock joints were identified by the cylindrical borehole reference plane, which intersects the cylindrical surface and generates a three-dimensional ellipse. Expanding this three-dimensional ellipse in the borehole image, a standard sine curve spreading horizontally can be obtained. The nonstandard rock joint is an approximate sinusoidal curve on the borehole image. Therefore, by fitting the sinusoidal curve of the rock joint in the borehole image, the geometric parameters can be calculated by the coefficient of the sinusoidal curve. The greater the amplitude of the sinusoidal curve, the greater the dip angle of the rock joint, and the greater the dip direction, the greater the minimum point of the sinusoidal curve.

In Section 3.3, the YOLO model detected and positioned the rock joints. The upper, middle, and lower edges of the rock joint respectively correspond to obtain three sinusoidal curve functions, as shown in Eq. (11). Four geometric parameters: dip direction, dip angle, depth, and apparent aperture of the rock joints are directly calculated according to the coefficients of the sinusoidal curve functions. Among these, the dip direction, dip angle, and depth are calculated by the parameters of the middle sine curve function as Eqs. (12)–(14); and the apparent aperture is calculated by the upper and lower sine curve function as shown in Eq. (15) (Wang et al., 2017b).

$$j = P_1 - P_2 \sin\left(i \frac{2\pi}{N} + P_3\right) \quad (11)$$

dip direction

$$\alpha = \begin{cases} P_3 + 270^\circ (0^\circ \leq P_3 \leq 90^\circ) \\ P_3 - 90^\circ (90^\circ \leq P_3 \leq 360^\circ) \end{cases} \quad (12)$$

dip angle

$$\beta = \arctan \frac{2KP_2}{D} \quad (13)$$

depth

$$d = \frac{1}{N} \sum_{i=1}^N j_{mi} \quad (14)$$

apparent aperture

$$A_a = \frac{1}{N} \sum_{i=1}^N (j_{ui} - j_{li}) \quad (15)$$

where i is the coordinate of a pixel in the row direction; j is the coordinate of a pixel in the column direction. Each row has N pixels. P_1 , P_2 , and P_3 are the desired parameters that can be estimated through fitting analysis. In this experiment, K is 3 mm, which is defined as the real dimension between two adjacent pixels in the depth direction. D is 91 mm, which is the diameter of the borehole. j_{mi} is the coordinate in the depth direction of the i th pixel in the median sinusoid. j_{ui} is the coordinates of the pixel in the column direction in the upper sinusoid; j_{li} is the coordinates of the pixel in the column direction in the lower sinusoid.

3 RESULTS

3.1 Rock Joint Detection Using the YOLO Model

After training the YOLO model with the optimal parameters, a plot of the training and validation loss values for the iterative process is shown in Figure 8. When iterations reached nearly 300, the model converged; when iterations reached 1 040, the training stopped. The iterative process was successful, with the model converging at around 300 iterations and training stopping at 1 040 iterations. During the first few iterations, the training loss value decreased rapidly and approached 0 at around 300 iterations.

After the model training was complete, the 135 testing data borehole images were inputted into the trained YOLO model for test verification. The model performed with high accuracy, as shown in Figure 9 which displays

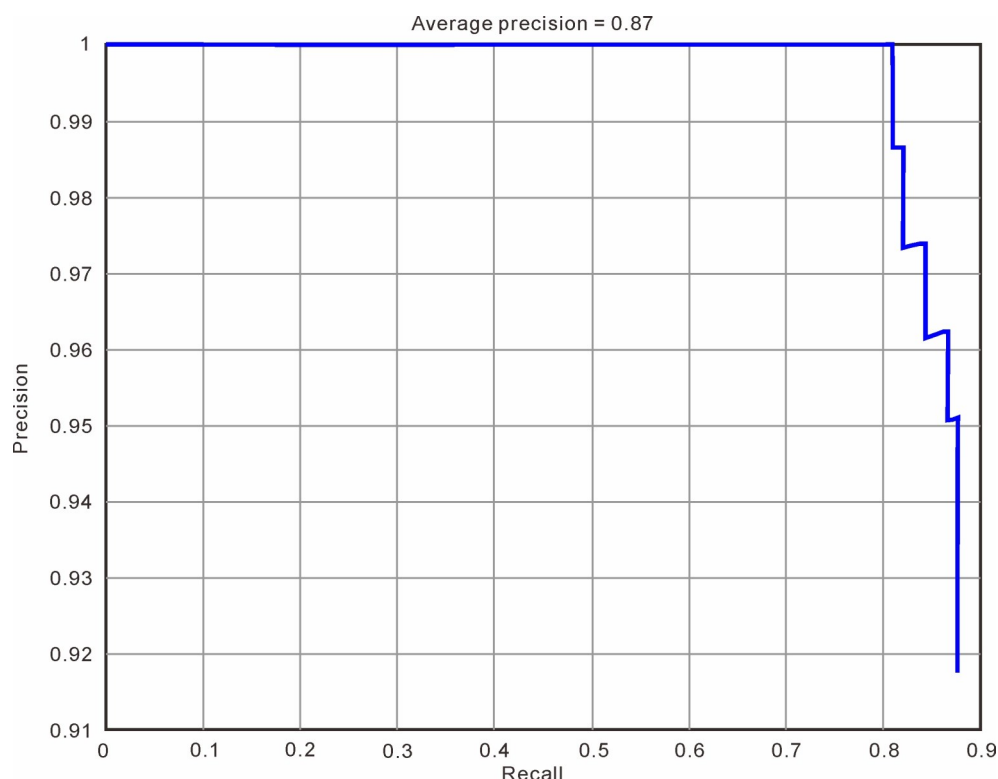


Figure 9. P-R curve of the testing set.

the P-R curve and the average precision. The P-R curve had a top value of 1 and maintained high precision until surpassing a recall of 0.8. And the average precision reached 0.87 which was remarkable for the YOLO model, meaning that almost every rock joint was detected with minimal errors.

The ZKZ02 images and part of the testing set of ZKZ01 were inputted into the YOLO model to automatically detect and locate rock joints. The model successfully identified most rock joints, as shown in Figure 10. The yellow rectangle denotes the position of the rock joint, and the percentage value represents the model's confidence in the detection accuracy. From the perspective of visual contrast, most rock joints were detected and located well. Among these, rock joint images in Figures 10a–10d were part of the testing set from drill hole ZKZ01, and images in Figures 10e–10l were selected from drill hole ZKZ02.

The rock joints are generally black or dark brown (filled with argillaceous cement), with only a few appearing white due to calcareous cementation, which is obvious from the non-rock joint. therefore, the YOLO model detects and positions rock joints based on the color difference between the joint and the surrounding rock. However, the yellowish-brown clay fillings on the surface of ZKZ02 borehole image logs, some of which have a similar shape to sinusoidal curves as shown in Figure 10i, may interfere with rock joint detection, resulting in detection frames that are slightly larger than the actual joint size, such as for rock joints in Figures 10i and 10c. In addition, some small cracks with approximately sinusoidal

shapes are very close to the rock joint, which will also lead to slightly larger yellow rectangular boxes and increase detection error, such as Figure 10j. Finally, the left and right width of detected results for rock joints in Figures 10e, 10f, and 10g are slightly smaller than the actual rock joint width, but this has little effect on the subsequent calculation of rock joint's geometric parameters.

3.2 Geometric Parameters Calculation of the Detected Rock Joints

Taking rock joints in Figures 10b, 10c, and 10g as examples, the results of the sinusoidal curve fitting and parameter measurement are shown in Figure 11. To identify the edges of rock joints, the Canny detector algorithm was used on the rock joint regions detected in the previous subsection, and the upper, median, and lower sinusoidal curves were then fitted on the selected edges, as shown by the green and blue curves in Figures 11a, 11c, and 11e (Ge et al., 2022b). The yellow diagonal area represents the aperture of each rock joint. It can be analyzed that the boundary fitting results of the upper and lower rock joints are relatively consistent, and the upper and lower boundaries of the three rock joints are located within the sinusoidal curve.

In Figures 11b, 11d, and 11f, the depth position of the rock joint is shown by the green line, while the blue curve represents the fitting edge sinusoidal curve. It can be observed that the sinusoidal curve can cover the rock joint which indicates the middle edge sinusoidal curve fits the rock joints well.

Then, we sequentially fitted 12 rock joints, numbered

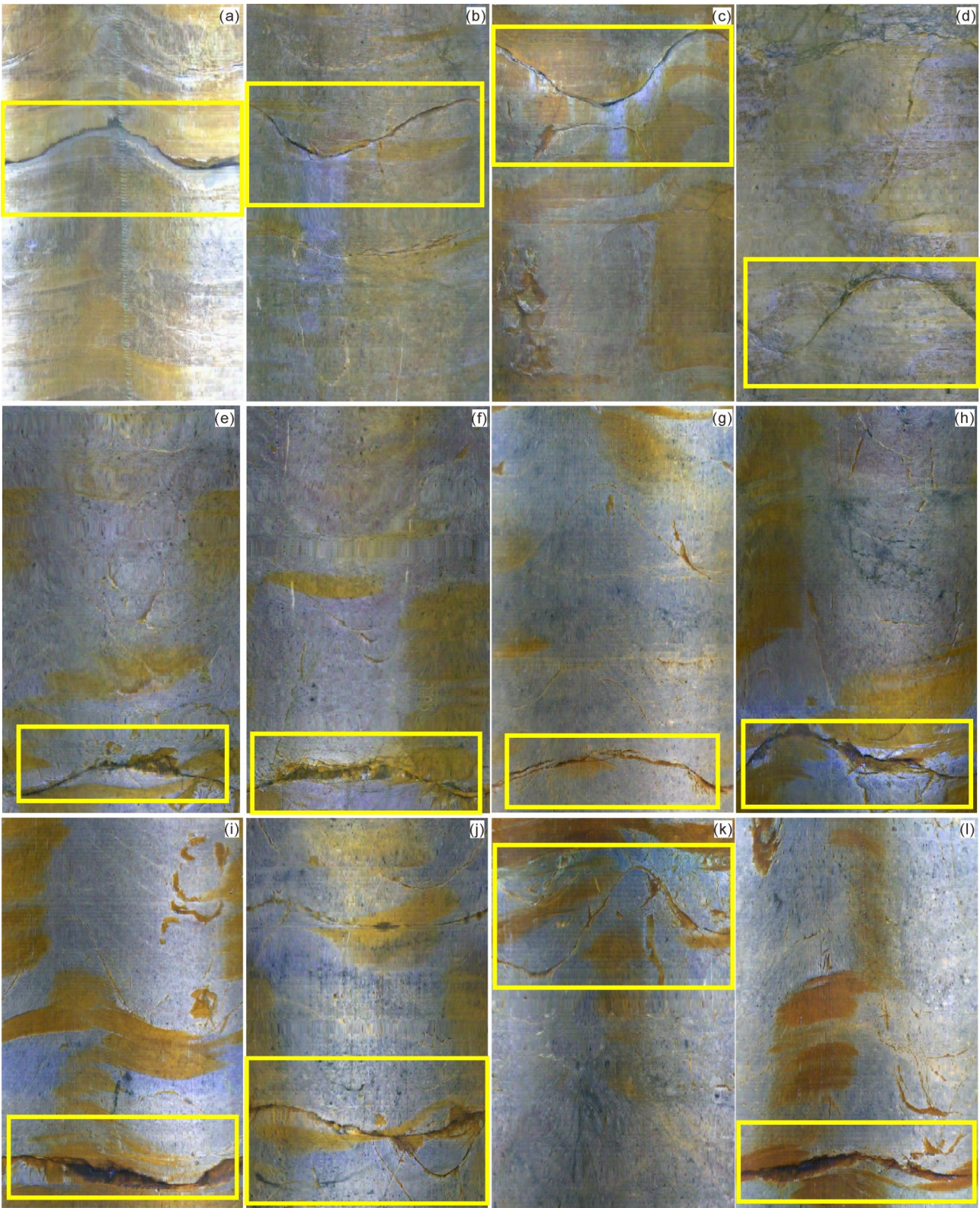


Figure 10. Automatic detection and position results of rock joint by YOLO model.

10- (a) – 10- (l), by applying sinusoidal parameters Eqs. (11)–(15) to calculate four geometric parameters (depth, dip direction, dip angle, apparent aperture). The final results were shown in Table 3 (4 decimal places were reserved for the results).

4 DISCUSSION

The YOLO model presented an acceptable accuracy in detecting the rock joints from borehole images in this paper, specifically ZKZ01 and ZKZ02. However, it may not be suitable for detecting rock joints with complex shapes in non-standard, highly-weathered rock forma-

tions or other research areas. For instance, in Figure 12a, the rockmass is severely broken and in Figure 12b, two rock joints are too close to each other, resulting in imprecise rectangular frames. Thus, further research may be required to evaluate the model's effectiveness in these scenarios.

This is due to the following four reasons: (1) ZKZ01 and ZKZ02 are located in the same research area, with the same basic geological conditions, which results in the same bedrock (the background of the borehole image is the same), and similar filling materials on the rock joints

in both boreholes. So accurate detection of the rock joints was feasible. (2) Detection of broken and complex rock joints has been a longstanding challenge for even the most experienced researchers. (3) The relatively poor quality of training samples in this study has limited the model's ability to recognize. (4) During the labeling process, the experts marked rock joints with a rectangular area larger than the rock joint itself, including non-rock joint areas in the ground truth, further impacting the accuracy of the model.

In this study, the ZKZ01 borehole image data were

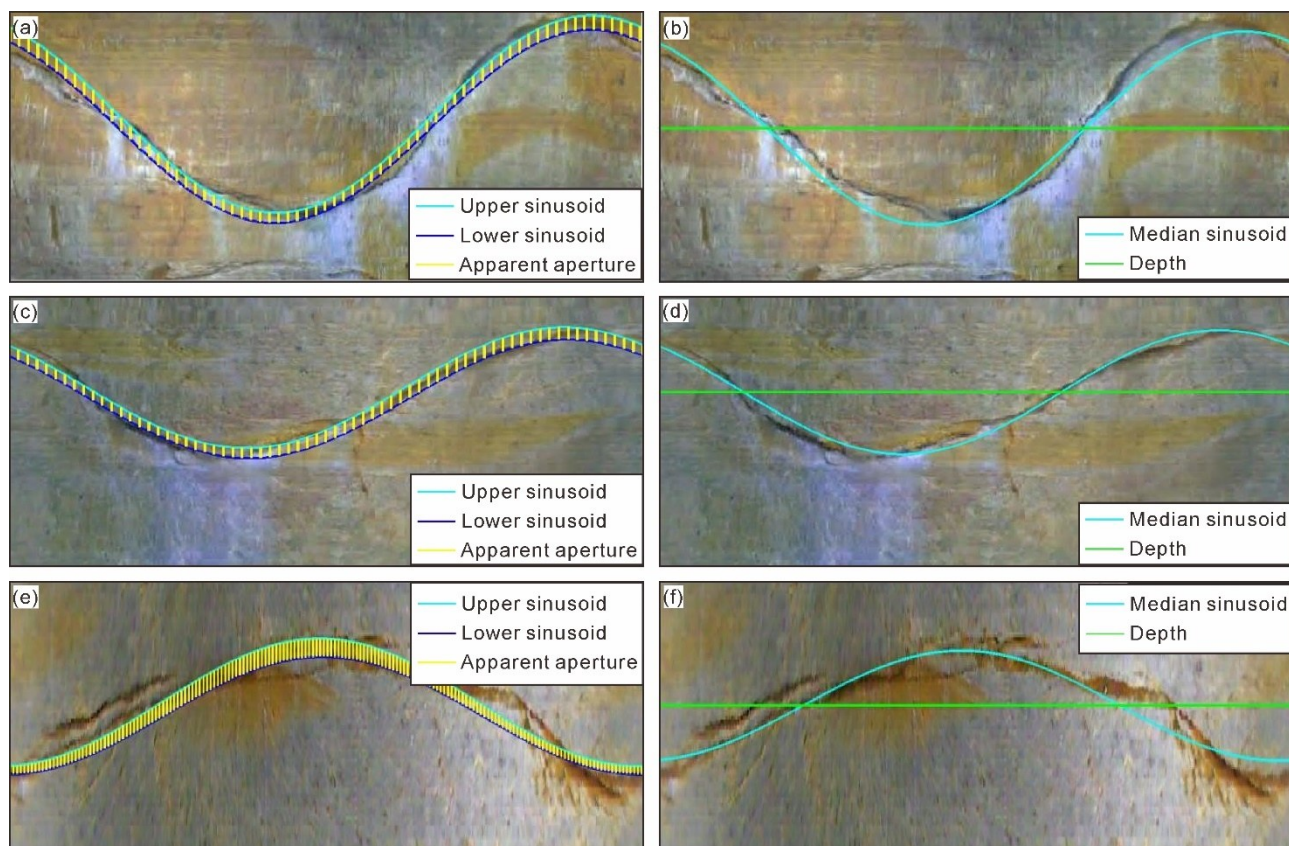


Figure 11. Rock joints fitting sinusoid curve result. (a) and (b) are parameter calculations for the rock joint in Figure 10c; (c) and (d) are parameter calculations for the rock joint in Figure 10c; (e) and (f) are parameter calculations for the rock joint in Figure 10g.

Table 3 Geometric parameters of 12 rock joints

Rock joint ID	Depth, d (m)	Dip direction, α ($^{\circ}$)	Dip angle, β ($^{\circ}$)	Apparent aperture, Aa (mm)
10-(a)	91.405 0	309.810 7	47.912 9	34.876 3
10-(b)	152.623 2	144.028 6	64.153 6	17.372 8
10-(c)	138.130 3	182.071 6	73.758 6	15.581 7
10-(d)	171.890 3	59.037 8	70.598 4	10.177 9
10-(e)	193.611 3	13.705 0	22.681 8	4.929 6
10-(f)	190.867 7	278.269 1	19.367 8	6.146 6
10-(g)	116.559 7	315.162 2	17.625 3	3.482 2
10-(h)	140.946 7	285.241 7	50.268 3	17.950 0
10-(i)	136.472 5	289.644 8	18.550 3	8.697 5
10-(j)	159.701 2	174.486 8	22.186 2	4.686 0
10-(k)	102.607 6	49.883 8	67.558 7	12.872 7
10-(l)	96.567 8	82.244 9	9.568 2	10.780 0

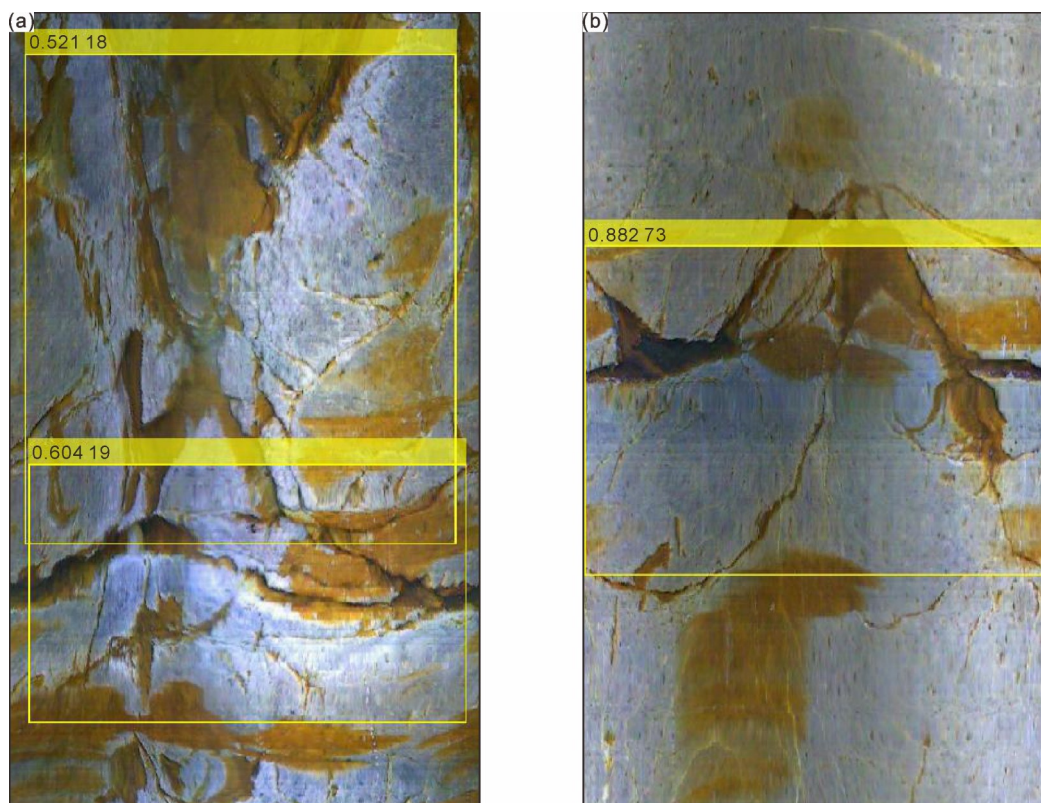


Figure 12. Rock joint detection results. (a) Broken rockmass; (b) two overlapped rock joints.

used for model training, then the model was applied to the identification of the rock joints in a new borehole ZKZ02 and achieved good identification results that proved the practicability of this research method. A long-term goal going forward is to collect borehole images with different lithology and boreholes and build a more comprehensive ground truth dataset to enhance the robustness of the YOLO model. With enlarged samples, theoretically, the YOLO detector obtained from this training can be applied to all borehole recognition (assuming a sufficiently large sample size).

Like any deep learning algorithm, the performance of our model is highly dependent on the quality and diversity of the training data. While our model demonstrates promising results within the scope of our study, we acknowledge that its generalization capabilities to different geological settings and rock types remain to be tested. We highlight the need for further validation across diverse datasets to ensure reliable performance in new environments.

5 CONCLUSIONS

This research used the YOLO model—a deep learning algorithm—to detect and locate the rock joints, followed by the calculation of four geometric parameters associated with these joints.

The 450 borehole images from ZKZ01 of the Rumei Hydropower Station were selected as the dataset, from which ground truth was constructed. The dataset was subsequently partitioned into a training set (60%) a vali-

dation set (10%), and a test set (30%). In building the YOLO model, a part of the ResNet-50 network was utilized for feature extraction. The model was trained using the training data and validation data. The P-R curve using the test data was utilized to test the model detection performance. Finally, the model performed well, with an average precision of 0.87.

The upper, median, and lower three sine curve functions were utilized to fit the rock joints, and four geometric parameters (dip direction, dip angle, depth, and apparent aperture) of the rock joints were calculated.

The borehole image from ZKZ02 and part of the testing data of ZKZ01 were inputted into the trained model, resulting in the identification and location of rock joints. These results were subsequently used to fit 12 rock joints with three sine curve functions, from which four tables of geometric parameters were obtained.

The potential for combining our deep learning model with other technologies is an exciting avenue for future research. To reach the goal, that will be good attempts to integrate additional geological features into the training set, to employ transfer learning techniques, and to explore newer versions of the YOLO architecture to enhance precision and efficiency of the rock joint detection using the convolutional neural networks model.

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Conflict of Interest

The authors declare that they have no conflict of interest.

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