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Research on the Method and Application of Bolt Detection Based on Improved YOLOv5

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ABSTRACT
To address the issue of low recognition accuracy for bolts in coal mine environments due to complex backgrounds, variable lighting, and visual interference, this paper proposes an improved YOLOv5-based bolt detection method. The approach involves capturing images of underground bolts using cameras, performing real-time analysis and processing on an underground AI controller, and transmitting the results to a surface software platform for display.In terms of model architecture, a TRANS module is introduced into the YOLOv5 backbone network to enhance feature extraction and global context modeling. Additionally, the neck network incorporates GhostBottleneck and depthwise separable convolutions to achieve model lightweighting. Through image enhancement and multi-scale feature fusion strategies, the model's ability to recognize bolts in complex backgrounds is significantly improved. Experimental results demonstrate that the improved YOLOv5 model achieves higher detection accuracy and faster inference speed in bolt detection tasks. The mean average precision (mAP) is significantly improved, and the inference time per image is only 12.5 ms. In practical applications, the developed intelligent bolt recognition platform enables real-time dynamic bolt detection and anomaly warning underground, with a stable recognition accuracy of over 99%. This effectively enhances the intelligence level of coal mine support operations.

KEYWORDS
Anchor bolt identification Improve YOLOv5; Deep learning Image processing Real-time detection

1 Introduction

The precise identification and positioning of anchor rods are important prerequisites for evaluating the quality of coal mine roadway support [1]. Limited by the complex underground environment, changes in lighting and visual interference, traditional recognition methods often perform poorly in practical applications. For this reason, the academic community has successively proposed various improvement schemes: Wang Hongwei et al [2]. integrated visual images and light point cloud information to construct an intelligent recognition and positioning process for anchor protection hole positions; Hao X et al. developed a positioning and measurement method for anchor bolt robots based on monocular vision, achieving real-time and high-precision acquisition of underground positions [3]. Zhang Dongbao systematically summarized the current research status of domestic anchor hole identification and positioning technology, and focused on analyzing the accuracy influencing factors in steel strip hole identification and drilling anchor positioning [4]. Song Guodong proposed applying 3D vision technology to support robots to achieve automatic identification of drilling positions [5].

Although the relevant methods are constantly evolving, there is still room for improvement in terms of detection accuracy and system real-time performance when dealing with complex coal mine backgrounds. Therefore, it is of great practical significance to study an efficient and accurate anchor bolt identification technology. Based on the improved YOLOv5 anchor bolt recognition model, combined with image enhancement and multi-scale feature fusion strategies, an anchor bolt recognition method in the complex environment of coal mines is proposed, and its effectiveness is verified in practical applications.

2 Overall architecture design

The images of the anchor rods underground are collected by a camera [6]. The collected images are directly analyzed and processed in real time by the AI controller underground. The processing results are displayed through the CAN bus sensor robot controller, showing the recognized and unrecognized anchor rods. The recognition accuracy is improved through real-time processing underground. The identification results of the anchor rods are transmitted through the underground ring network sensing ground, and a software platform is built on the ground to display the identification results in real time.

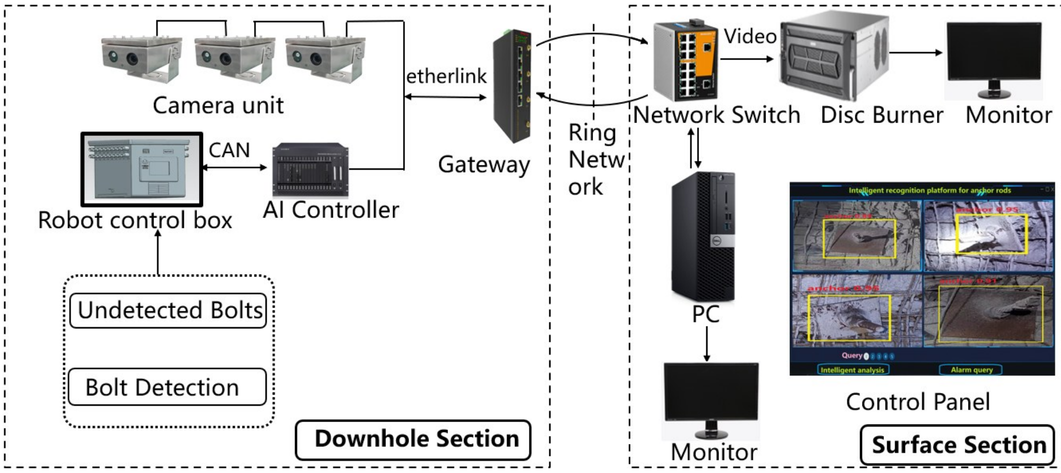


Figure 1 Overall architecture design

3 Anchor bolt recognition method based on YOLOv5

3.1 Image preprocessing

To improve the model's generalization capability, the following preprocessing pipeline was applied to the images before training: data augmentation techniques including random rotation, flipping, cropping, and color adjustment were implemented to enhance the model's adaptability to lighting and perspective variations; all input images were uniformly resized to 640×640 pixels to comply with the YOLOv5 network's [7] input specifications; pixel values were normalized to the [0,1] range and further standardized to accelerate convergence during the training process. Representative examples of the preprocessed images are demonstrated in Figure 2.

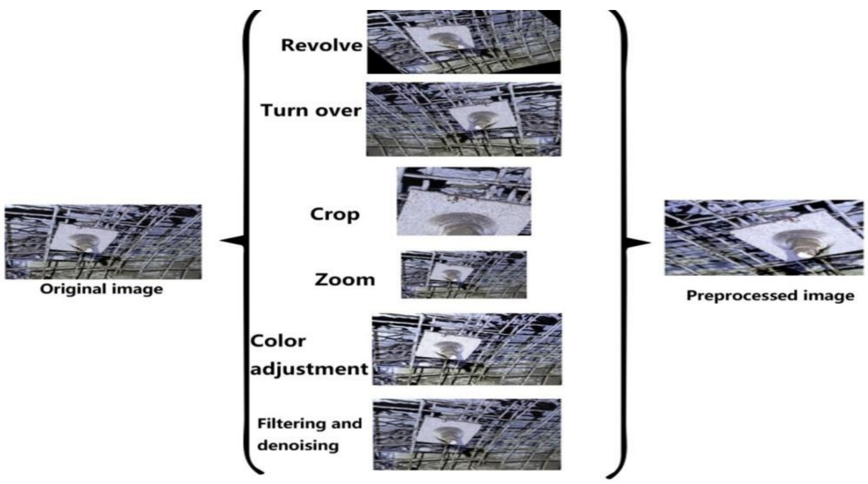


Figure 2 Image preprocessing

3.2 Image annotation and format conversion

A set of image datasets for standardized drilling by drilling RIGS was constructed for the drilling videos of underground coal mines. Firstly, intrinsically safe mining cameras were used to collect drilling images of the drilling rig under different working conditions in multiple mine working faces, including image samples under different lighting conditions. The dataset contains a total of 4,000 images with a resolution of 640×640, marking the drilling of different types of drilling RIGS under various backgrounds. Among them, there are 3,200 training sets, 400 validation sets and test sets. All data files are named using a 6-digit coding rule to ensure a one-to-one correspondence between image files and annotation files. Use the LabelImg tool [8] to label the anchor bolt images, generate an XML file in VOC format, and convert it to the TXT format required by YOLOv5. The annotation example is shown in Figure 4.

All the input anchor bolt images were uniformly scaled to the same size. The following figure shows a batch containing 16 input images. Each image is a data augmentation image. During training, the label id was used instead of the original label. Images from multiple different scenes were randomly stitched together, and the blank Spaces were filled with gray. The marked image is shown in Figure 5.

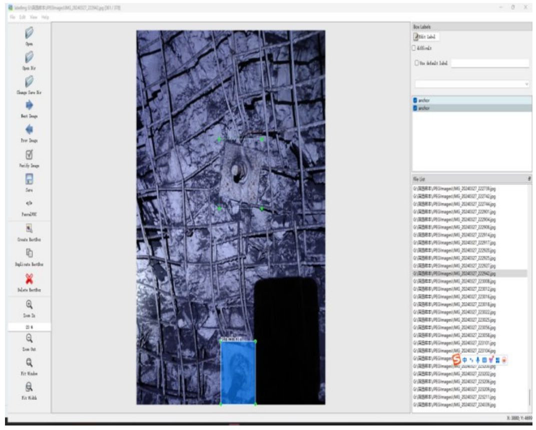


Figure 4 Is a sample annotation diagram

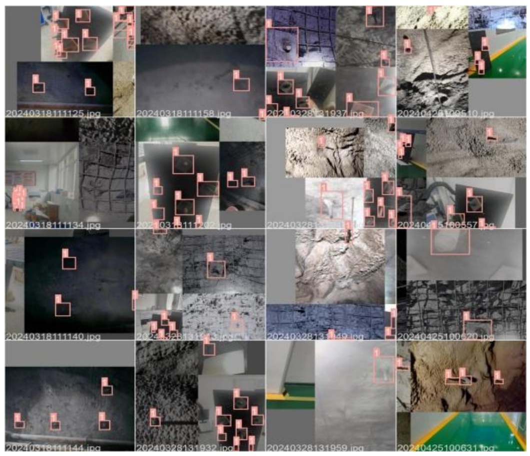


Figure 5 Labeled bolt dataset

3.3 Improved YOLOv5 network model

To address the shortcomings of the original YOLOv5 model in bolt recognition tasks within underground coal mines, we have optimized its backbone network. The core improvement involves introducing a TRANS (Transformer) module [9], which significantly enhances the model's feature representation capability by strengthening feature extraction and fusion mechanisms. This optimization aims to precisely reduce both the false detection rate and missed detection rate in practical applications. The improved YOLOv5 model is illustrated in Figure 6.

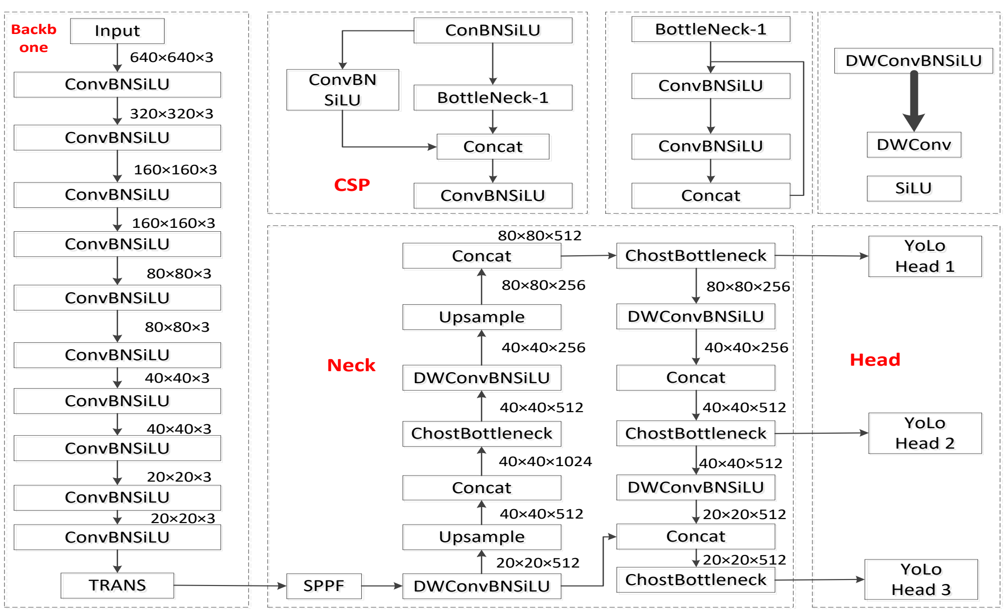


Figure 6 shows the improved network structure diagram of YOLOv5

A lightweight TRANS module is introduced at the end of the backbone network, whose core consists of a multi-head attention mechanism and a feedforward network. This design aims to overcome the locality limitation of convolution and enhance global context modeling by capturing long-range dependencies in the feature map. This move significantly enhanced the model's representational ability, thereby suppressing false detections and missed detections. The multi-head attention mechanism can be expressed as:

$$\mathrm{MultiHead}(Q,K,V)=\mathrm{Concat}(\mathrm{head}_1,\cdots,\mathrm{head}_h)W^O \tag{2}$$

In the formula, $\mathrm{head}_i=\mathrm{Attention}(QW_i^Q,KW_i^K,VW_i^V)$, $\mathrm{Attention}(Q,K,V)=\mathrm{softmax}(\frac{QK^T}{\sqrt{d_k}})V$。 Among them, Q, $K$and$V$represent the query, key, and value matrices, respectively, W_i^Q, W_i^K, $W_i^V$are the corresponding transformation weights, and$d_k$denotes the dimension of the key vectors. The feed-forward fully connected network can be expressed as:

$$\mathrm{FFN}(x)=\max(0,xW_1+b_1)W_2+b_2 \tag{3}$$

This module is embedded into the backbone output layer and fused with the original feature map F_{input}:

$$F_{trans}=\mathrm{Concat}(F_{input},\mathrm{FFN}(\mathrm{MultiHead}(Q,K,V))) \tag{4}$$

4.4 Neck network improvements

To achieve the objective of lightweight design, the neck network was optimized by introducing GhostBottleneck modules and comprehensively adopting depthwise separable convolutions. This scheme significantly reduces both the number of model parameters and computational cost without significantly compromising detection accuracy, while achieving a notable increase in inference speed.

4 Cross-Validation and Performance Evaluation

To validate the model's generalization capability, cross-validation was conducted on both simulated and field-collected datasets. An experimental platform was built based on the PyTorch deep learning framework, utilizing an NVIDIA RTX 5080 GPU for parallel accelerated computing and leveraging the AVX-512 instruction set of an Intel i9-13900K processor to optimize the data preprocessing pipeline. At an input resolution of 640×640 pixels, a multi-phase training strategy was designed to balance model convergence speed and overfitting risk.

To evaluate the detection accuracy of the improved YOLOv5 algorithm, a comparative experiment was carried out under the same sample set, involving four network architectures: YOLOv3, YOLOv4, YOLOv5, and YOLOv8n, with the number of iterations set to 250. By comparing the loss value trends during training, it was observed that the improved YOLOv5 network achieved the most rapid decrease in loss values during the initial training phase. This result demonstrates that the improved YOLOv5 significantly enhances learning efficiency and exhibits superior convergence performance during training. Detailed data and curves are shown in Figure 7.

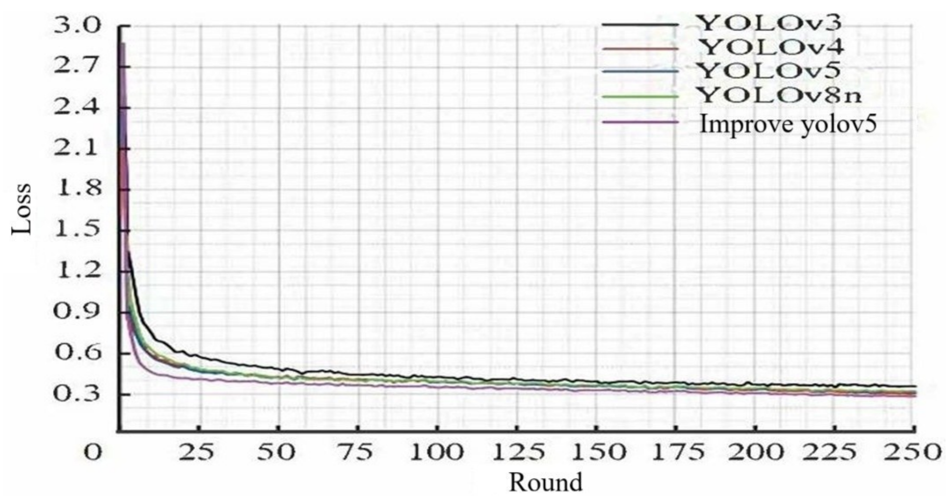


Figure 7 Comparison of loss curves of different models on the training set

To verify the rationality of the improved Yolov5 algorithm design, four network structures, namely Yolov3, Yolov4, the original Yolov5 and Yolov8n, were selected as the comparison objects in the study. During the training process, the metrics of Precision (Precision), mean Average Precision (mAP), Recall (Recall), and Inference Time for a single image of each model were monitored and recorded. The detailed data of the relevant experiments have been sorted out and are shown in Table 1.

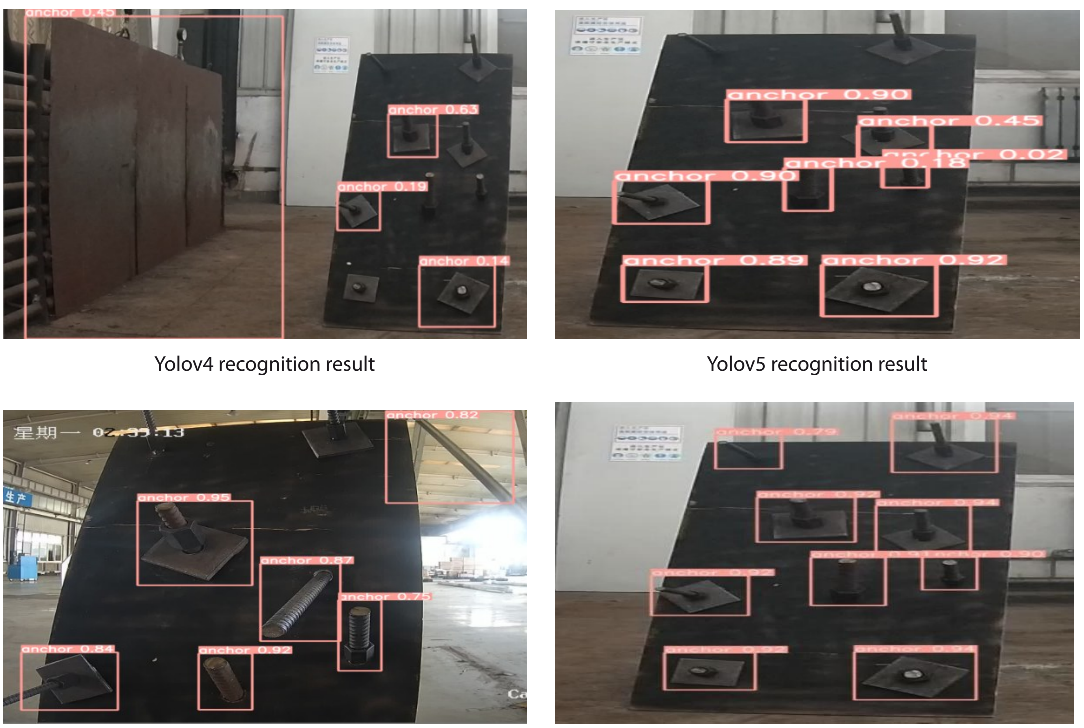
Table 1 Comparison of recognition based on the improved Yolov5 algorithm

Network model	Accuracy /%	Recall rate /%	Inference time /ms
YOLOv3	97.65	97.18	14.6
YOLOv4	98.03	97.78	15.1
YOLOv5	98.56	98.56	16.8
YOLOv8n	99.07	98.67	14.7
Improve YOLOv5	99.12	98.71	12.5

To verify the recognition performance of different network structures for anchor bolt supports, in the laboratory environment, the fabricated anchor bolt supports were taken as the research objects, and recognition verification experiments of four models, namely Yolov4, the original Yolov5, Yolov8n and the improved Yolov5, were carried out, with a focus on analyzing the accuracy and efficiency of the models in the detection of anchor bolt supports.

Before the experiment, a sample set was constructed: processed anchor bolt brackets with surface conditions (no rust, slightly rusted) were selected. By adjusting the placement Angle (0° -90°) and adding local obstructions (simulating foreign object obstructions in actual installation scenarios), the experimental results showed that: The improved Yolov5 has the best comprehensive performance in the recognition of anchor bolt brackets, with a single-piece inference time of 12.5ms. Although it is slightly higher than the lightweight Yolov8n (14.7ms), it is much faster than Yolov4 (15.1ms) and the original Yolov5 (16.8ms). Error analysis reveals that Yolov8n is prone to misjudging the rust texture on the surface of the bracket as impurities, and the positioning accuracy of the original Yolov5 fluctuates greatly in occluded scenarios. It is specifically shown in Figure 8.

In conclusion, the improved Yolov5 has achieved a balance between accuracy and efficiency in the identification task of anchor bolt brackets in the laboratory, making it more suitable for the detection requirements of processing anchor bolt brackets. If you need to supplement the detailed identification data of anchor bolt supports of different specifications or optimize the test plan in combination with the actual installation scenario, please let me know at any time for further improvement.



Yolov4 recognition result

Yolov5 recognition result

Yolov8n recognition result

Improve the recognition results of Yolov5

Figure 8 Shows anchor bolt identification in the laboratory

5 Field application

To adapt to the complex working environment in underground coal mines, an intelligent recognition platform for underground coal mine anchor rods is constructed to achieve full-process functional coverage including anchor rod detection, abnormal early warning, system linkage and data support. The core functions of the platform revolve around the identification of anchor rods, with a focus on the improved target detection model. It can perform real-time dynamic identification of anchor rods underground, not only accurately counting the number of anchor rods but also ensuring a stable identification accuracy rate of over 99%. Even in scenarios where there is dust interference underground, dim light, or the anchor rods are partially blocked by coal gangue, it can still maintain efficient recognition performance, effectively avoiding the problems of missed counts and incorrect counts that are prone to occur in manual counting. It is specifically shown in Figure 9.

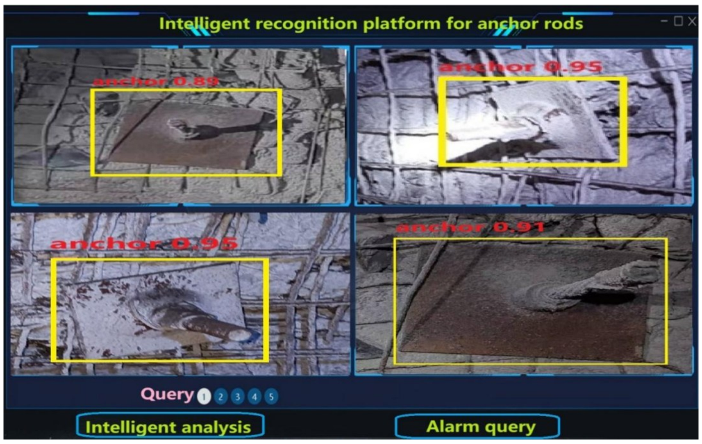


Figure 9 Intelligent recognition platform for anchor rods

6 Conclusion

The proposed anchor rod recognition method based on the improved YOLOv5 significantly enhances the feature representation ability and reasoning speed of the model in complex coal mine environments by introducing the TRANS module and the GhostBottleneck module. The experimental results show that the improved model achieves a balance between accuracy and efficiency in the anchor bolt recognition task, with a stable recognition accuracy rate of over 99%. Moreover, it can maintain high recognition performance in scenarios with dust interference, dim light, or partial occlusion of anchor bolts.

In addition, the AI intelligent recognition platform for underground coal mine anchor bolt identification has achieved full-process functional coverage including anchor bolt detection, abnormal early warning, system linkage and data support, providing strong support for the intelligent management of underground coal mine support operations.

About the Author

Wanhao Cui, is a male engineer with a Master's degree. He is engaged in research on artificial intelligence technologies for coal mining applications.

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