Intelligent Defects Recognition Method of Weld Radiographic Film Based on YOLO V5

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Abstract: With the rapid development of oil pipeline construction, the workload of pipeline weld film evaluation has increased dramatically. The traditional computer-aided evaluation model has problems such as low accuracy rate of multi-classification defect recognition, lack of quantitative analysis methods for defects, and inability to be applied to industrial films, which are difficult to meet the actual needs of engineering. In response to the above problems, this paper takes the image of weld radiographic film of oil pipelines as the research object, and conducts research on the intelligent recognition technology of multi-classification defects in weld radiographic film based on deep learning methods. Firstly, the defect image features of pipeline weld radiographic film images is studided and a dataset of original weld radiographic film images containing defects is constructed. Then, based on convolutional neural networks and migration learning methods, an intelligent defect recognition model based on YOLO V5n for weld radiographic film is established to achieve the intelligent recognition of five defect types: rounded defects, linear defects, lack of fusion defects, incomplete penetration defects, crack defects. Finally, with the weld radiographic film defect image database and the YOLO V5-based weld film defect intelligent recognition model as the core, the weld radiographic film defect intelligent recognition system is developed. The application test is also carried out on 37 industrial weld radiographic film. The intelligent evaluation process takes 43 seconds, with a defect detection rate of 83.16%, a defect type compliance rate of 84.21% and a false alarm rate of 10.37%. The intelligent identification system for weld radiographic film defects achieves qualitative and quantitative analysis of weld radiographic film while identifying defects with high accuracy and low leakage rate, covering the entire process of weld radiographic film inspection, assisting the evaluation staff to complete the evaluation work and effectively improving the evaluation efficiency, which is of great significance to achieve intelligent inspection of weld films.

Keywords: Weld Radiographic Film；YOLO V5；Defect Identification；Intelligent Detection

1 INTRODUCTION

By the end of 2021, China has built a total of 150,000 kilometers of long-distance oil and gas pipelines [1]. Welds are one of the weakest points in pipelines, and they are susceptible to failure, especially under the influence of additional loads such as soil movement. Once a pipeline fails, it can result in a significant loss of life, property, and environmental pollution. According to recent statistics on pipeline accidents, weld failure is one of the primary causes of leaks and pipeline explosions in long-distance oil and gas pipelines [2]. Non-destructive testing (NDT) can be used to effectively detect pipeline weld defects to avoid these incidents. NDT typically includes ultrasonic, eddy current, infrared, magnetic leakage, and X-ray techniques. X-ray inspection is more accurate and precise, yielding more visible results [3]. In order to avoid pipeline safety accidents, it is necessary to carry out effective NDT of welds during the pipeline construction period and operation service period. Weld radiographic films should be checked by certified inspectors to evaluate and interpret the quality of welds, which is called human interpretation. However, the radiogram quality, the welding over-thickness, the bad contrast, the noise and the weak sizes of defects make the task difficult [4]. There are some drawbacks for human interpretation. Firstly, the inspectors are generally trained and have relevant expertise and experience. However, it is still difficult for the skilled inspector to recognize the small flaws within a short time. Secondly, the human interpretation is usually short of objectivity, consistency and intelligence. The labor intensity of human interpretation is large because lots of films are produced each day due to the improvement of production efficiency in modern industry. Finally, human visual inspection is 80% effective, and this effectiveness can only be achieved if a rigidly structured set of inspection checks is implemented [5]. Thus many researchers began to build the intelligent systems based on computer. Such computer-aided systems typically take the digital images as the object to extract the welds and detect the flaws in the images by various algorithms. Thus, for the conventional films, the digitization should be necessary. Unlike the conventional films which can only be evaluated manually, the digitized radiographic images not only enable the storage, management and analysis of radiographic inspection data easier, but also make the more intelligent inspection of welds possible [6]. In this paper, we propose a YOLOv5-based intelligent recognition method of weld radiographic defects images to evaluate the radiographic films with fast detection speed, high detection accuracy and high detection efficiency.

Image recognition technology is developing rapidly, and many models for weld radiographic film assisted defect detection using computers have been proposed, and these models are divided into two main categories:
(1) One is the classification model for image recognition of weld radiographic film based on defect features. The image recognition and classification technique based on defect features often includes the work of image preprocessing, segmentation of the image core region, effective description of the defect features, and the design of classifiers[7]. The Weld defects commonly exist in the weld region or the edge region of the weld in the weld radiographic film, and the accuracy of defect recognition depends on whether the weld edge is accurately extracted. For defects located at the weld edge region, the detection accuracy is often low. Different types of defects have obvious differences in gray value, shape, texture, etc. By effectively describing these differences, the defects are detected by combining support vector machine and self-designed shallow artificial neural network.
(2) The other is deep learning-based image recognition classification model for weld radiographic film. Deep learning-based image recognition and classification techniques are often combined with various types of big data. The more defective sample images used for training, the better the resulting model results in the case of effectively reducing model overfitting.

In recent years, many scholars have done a lot of research on intelligent detection of weld defect based on deep learning. Yang proposed a model based on CNN to classify the X-ray weld images by improving the convolution kernel and the activation function[10]. Based on the principle of visual perception, Li constructed a deep learning network with 10 layers to directly determine the type of suspected defect[11]. Hou developed a model based on a deep convolutional neural network (DCNN) to extract the deep features directly from the X-ray images without any preprocessing operation[12]. Mirapeix proposed a new method for automatic welding defect detection and classification based on the combination of principal component analysis and artificial neural network.[13] Malarvel established a new method based on multi-class support vector machine (MSVM), which can recognize weld defects such as porosity, longitudinal cracks, incomplete penetration of welding, slag inclusion etc. [14]. Zeng et al. in order to improve the efficiency and automation of the welding system, the optimal SVM model for the identification of weld defect types was established by using the slope distribution of the laser curve and the interval of the characteristic points of the welded joints as the feature vectors[15].

2 INTELLIGENT DEFECTS RECOGNITION MODEL

2.1 Transfer Learning Methods

Transfer learning is to apply the knowledge learned on one task to another but usually related task. This method can significantly improve learning efficiency and performance, especially when there are relatively few data and samples for new tasks. In transfer learning, there are usually two main tasks : source task and target task. The source task is a trained task, we extract knowledge from this task. The target task is a new task that we want to improve performance.

In the field of intelligent recognition of defects in pipeline weld radiographic film, there are problems such as the difficulty of obtaining on-site engineering radiographic film and the scarcity of weld image containing various types of defective features, which makes it difficult to rebuild a convolutional neural network applicable to the intelligent recognition of weld radiographic film. By transforming the convolutional neural network trained with a large amount of data using the transfer learning method, the number of training data, computational power, and engineering talents required to build a deep learning model for weld radiographic film defect recognition is further reduced, and the convolutional neural network-based weld radiographic film defect recognition model is easier to be developed and has better performance.

2.2 Convolutional Neural Network Model Selection

In the field of image analysis and recognition, convolutional neural network models can be classified into two main categories, one is the image recognition classification model and the other is the target detection model. By analyzing the image characteristics of the weld radiographic film, it is characterized by multiple defect types, different sizes of different types of defects, inconspicuous defect features, and large image size. In the application field of intelligent recognition of defects in weld radiographic film, although the image recognition classification model based on convolutional neural network can accurately predict the defect types, when there are multiple defect types in a radiographic film, the performance of the model depends largely on reasonable image segmentation algorithms, and when the image of the weld radiographic film is unreasonably segmented, it only outputs the defect type with the highest confidence in the block image, and it cannot accurately identify multiple defects in the radiographic film. At the same time, the overall size of the weld radiographic film is large, and the amount of computation required for detecting defect types is relatively large. If the second-order algorithm model for target detection based on convolutional neural networks is used, it may cause problems such as low detection efficiency and high hardware requirements. Compared with other models, the first-order algorithm YOLO series model has the characteristics of multi-scale feature detection, high flexibility and fast detection speed, which is suitable for the intelligent recognition of defects in weld radiographic film image application scenarios, so this paper selects the YOLO series model to carry out the research. Meanwhile, referring to domestic and international literature[16]It can be seen that YOLO V5 outperforms other target detection models, and the intelligent recognition model based on YOLO V5 has higher detection accuracy and shorter recognition time than those based on Faster RCNN and YOLO V4.

2.3 YOLO V5 Network Model

In comparison with the existing major convolutional neural network models, YOLO V5 is chosen as the basic framework of the model in this paper. YOLO V5 is one of the convolutional neural network models, which is capable of realizing multi-scale target detection, and has the characteristics of high flexibility and fast detection speed. In the YOLO v5 model, there are three main components: Backbone, Neck, and Head. The Backbone is responsible for extracting features from the input data. The Neck is responsible for enhancing the features extracted by the Backbone. The Head is responsible for outputting the category and location information of the target[19].

The network structure of YOLO V5 is shown in the figure below and consists of 5 basic modules.

The CBS module consists of a convolutional layer, a BN layer, and an activation function. The BN layer is a normalization layer added after the convolutional layer to normalize the distribution of feature values in the neural network, which helps to speed up training, improve the generalization ability of the model, and alleviate the model's dependence on initialization. The activation function is a nonlinear function that enriches the expression of defective features.

The SPPF module is a pooling module that implements the transformation of feature maps of different sizes into feature vectors of the same size through three scales of pooling operations, which are transmitted to the fully connected layer to achieve spatial invariance and positional invariance of the input data and further improve the recognition ability of convolutional neural networks.

The C3 module is an important component of the YOLO V5 network, consisting of three convolutional layers and a CSP structure, which enhances feature extraction by increasing the depth and sensory range of the convolutional neural network.

Concat module mainly implements the tensor splicing function, which expands the dimensions of two tensors. Upsample module forms large-size feature maps by performing various interpolation algorithms on small-size feature maps.

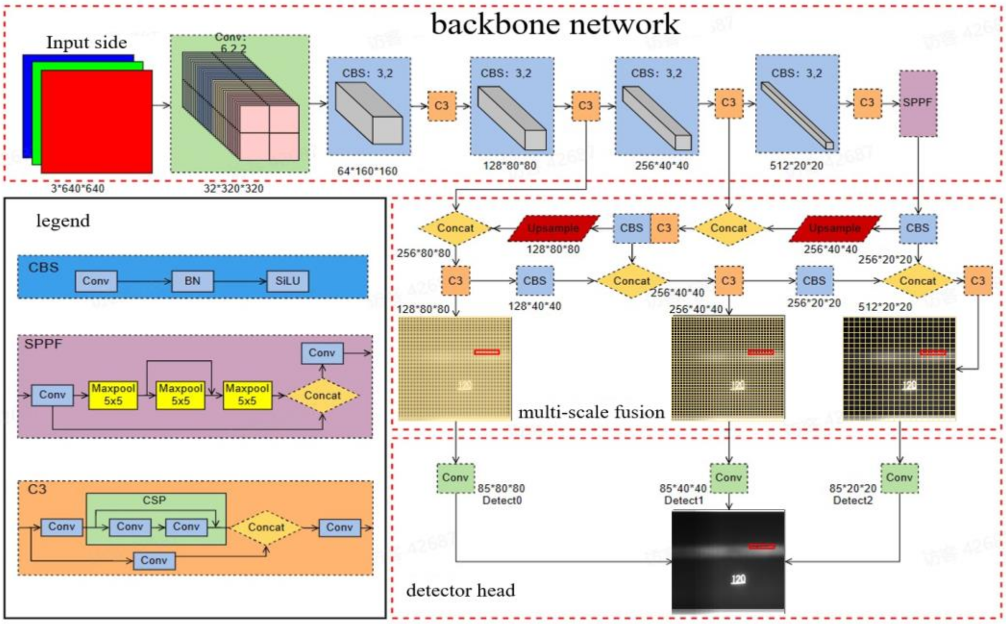


Fig. 1 YOLO V5 network structure

3 YOLO V5 MODEL TRAINING

To carry out supervised learning, YOLO V5 needs to pre-label all kinds of defect features, specify the types of defect features and their coordinates in the defect image. The models of YOLO V5 is trained by defect images with known defect information, and an intelligent recognition model based on YOLO V5 is established to realize the intelligent recognition of multi-classified defects in the weld radiographic film images.

The data labels of YOLO V5 are mainly labeled by labelImg software, which is an image labeling software commonly used in target detection models to generate defect label files for specific data sets. The defect labeling process is shown in the figure below, and the resulting label file contains five factors, namely, the defect type code, the horizontal and vertical coordinate values of the center point of the label box, and the length and width of the label box.

A total of 16248 defect labels were formed by labeling 7613 defective image datasets of weld radiographic film. The number of labels for the defects is 5,763 labels for rounded defects 4,947 labels for linear defects, and 4,947 labels for lack of fusion defects 2415 labels, 1558 labels for incomplete penetration defects, and 1565 labels for crack defects.

Table 1 Defective weld film images and number of labels

Defect type	**Number of images**	**Number of labels**
Rounded defects	1540	5763
Linear defects	1503	4947
Lack of fusion defects	1548	2415
Incomplete penetration defects	1498	1558
Crack defects	1524	1565

Although the number of images of the five types of defects is basically the same, but due to the different size of defects, for small-sized defects (such as rounded defects, linear defects, etc.) there may be more than one defect in the same defective image, so it results in a large difference in the number of labels of various types of defects.

Usually, the training of a supervised learning neural network model divides the dataset into a training set and a validation set, generally in accordance with the 8:2 ratio. The training set is used to train the convolutional neural network model and determine the parameters in the network; the validation set is used to validate the accuracy of the model in each iteration during the training process, and to measure the performance and classification ability of the model. The reasonable division of the two sets of the original data is helpful to obtain the convolutional neural network model with the best accuracy and the best generalization ability. Considering the number of labels of various types of defects and the complexity of defect features, and because small-size defects have more diverse forms of expression on the weld images, the number of training and validation sets is increased appropriately for the two types of defects, and the two datasets formed by the division are shown in the table below.

Table 2 The number of defective samples in the training and validation sets

Defect type	**Training set**		**Validation set**	
	Number of images	**Number of labels**	**Number of images**	**Number of labels**
Rounded defects	711	2650	186	656
Linear defects	824	2632	206	652
Lack of fusion defects	826	1302	203	312
Incomplete penetration defects	1198	1252	300	306
Crack defects	1220	1237	304	328
Grand total	4779	9073	1199	2254

The model training is performed by PyTorch, and the same defective image dataset is used to train five different versions of YOLO V5 network, and the model training parameters are set as shown in the Table 3. By setting the number of early stopping rounds, the training is stopped if the model performance is not improved after 100 rounds, which further ensures the training effect and avoids model overfitting. At the same time, due to the limitation of GPU performance, different training batches are set according to the complexity of the network, with lower training batches for relatively complex networks and higher training batches for networks with fewer layers.

Table 3 Training parameters

Parameter name	**Value**
Initial learning rate	0.01
Cyclical learning rates	0.01
Learning rate momentum	0.937

Parameter name	Value
Weight attenuation coefficient	0.0005
Threshold for IoU training	0.2
Number of iterations	500
Training batches	32/16/8
Optimizer	SGD
Number of early stopping rounds	100
Pre-trained model	YOLO V5n

4 ANALYSIS OF INTELLIGENT DEFECTS RECOGNITION RESULTS

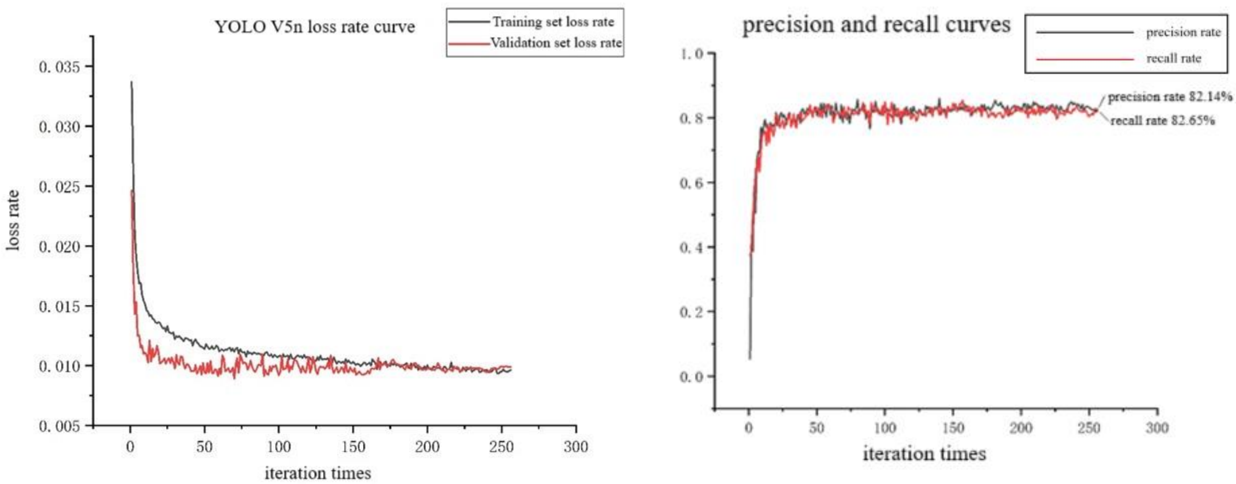
In this paper, the loss rate curve, Precision, Recall, F1-score, Accuracy, Missed detection rate, mean Average Precision (mAP) are used to comprehensively evaluate the strengths and weaknesses of the model[20].

The F1-score is a measure of the target classification problem and is often used to evaluate the performance of the model. The value is taken as the best output of the model is obtained at 1 and the worst output of the model is obtained at a value of 0.

$$F1-score = 2\times\frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

AP is the average precision of the model for calculating a single category. For the target detection model, each category has a corresponding Precision and Recall, and the corresponding P-R curve can be obtained, and the area under the curve is the AP value of the category. The larger the value of mAP and AP, the better the model performance.

Training was carried out using YOLO V5n as the base network and stopped after a total of 256 rounds of training. It contains a total of 214 network layers and 1770682 weight coefficients.



(a) (b)

Fig. 2 YOLO V5 training curve:(a) loss rate curve (b) accuracy and recall transformation curve

As can be seen by the loss rate curve change graph, as the iteration proceeds, the loss rate curve trend is consistent with a rapid decline followed by gradual stabilization, and the two datasets have similar loss rate values and the model converges.

Through the precision rate and recall curve change graph can be seen, with the iteration, the precision rate and recall the first rapid increase in the first stabilized, the fluctuation amplitude is the smallest compared to the other models, and the precision rate and recall rate values are similar to get the model of the final precision rate of 82.14%, the recall rate of 82.65%.

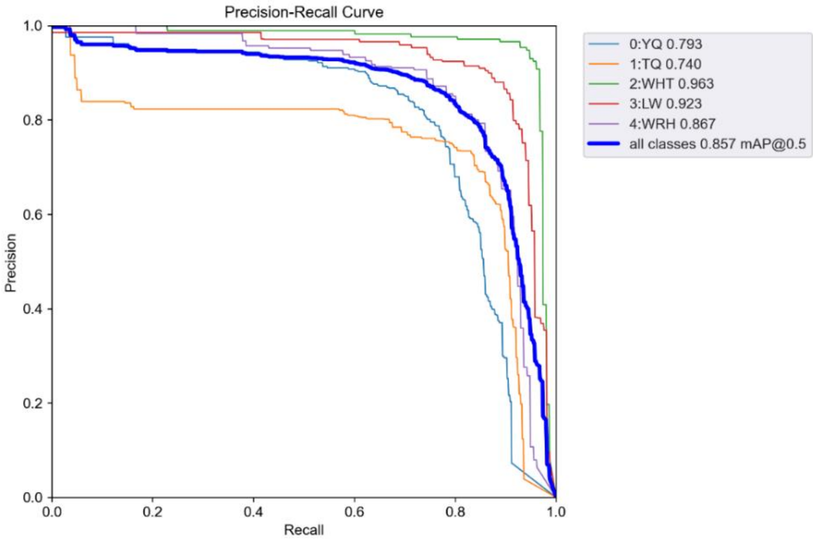


Fig. 3 YOLO V5n PR curve

The best PR curve of the model shows that the best mAP@0.5 value of the model is 0.857, the AP values of all types of defects are larger, and the overall performance of the model is good.

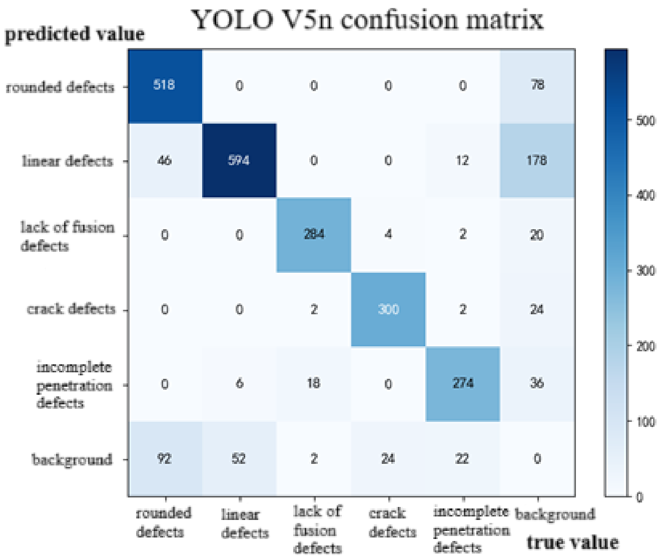


Fig. 4 YOLO V5n confusion matrix

The model accuracy rate of 87.4%, the leakage rate of 8.52%, and the recall rate and precision rate of each type of defects are obtained through the calculation of the confusion matrix, as shown in the table below.

Table 4 YOLO V5n Performance indicators by defect type

Defect type	Precision rate	Recall rate	Miss rate
Rounded defects	86.91%	79.45%	14.02%
Linear defects	71.57%	91.10%	7.98%
Lack of fusion defects	82.03%	87.82%	7.05%
Incomplete penetration defects	91.61%	92.81%	0.65%
Crack defects	91.46%	91.46%	7.32%

By comparing the recognition effects of the five YOLO models for the five types of weld defects, it can be seen that the linear defects tend to have the lowest recognition accuracy and recall rate, as well as the worst prediction performance. The main reason for this phenomenon is that the characteristics of linear defects are more varied and similar to lack of fusion defects, which makes it more difficult to recognize them.

5 CONCLUSION

This chapter firstly introduces the principle of convolutional neural network, and proposes to use migration learning method to establish an intelligent recognition model of defects in weld radiographic film image for the problem of low data of weld radiographic film image. The existing convolutional neural network models are compared and analyzed, and the YOLO V5 network model is selected to be used in the field of intelligent recognition of defects in weld radiographic film images by combining the defective features of weld radiographic film images. Secondly, the process of building the intelligent recognition model is introduced, which mainly includes the production of defect image data labels, the setting of training parameters and the training of the model. The labelImg software was used to create 16248 defect labels, and the model training set and validation set were divided according to the ratio of 8:2. Five different network models of YOLO V5 were trained by PyTorch, and the training results of the five network models were compared and analyzed to analyze the loss rate curve, precision rate, recall rate, accuracy rate, miss rate, F1-score, and mAP of each model, and to select the model with the best performance by combining with the requirements of the weld radiographic film defect detection application scenarios. However, the YOLOv5 algorithm is somewhat data-dependent; weld defect detection requires a large amount of well-labelled data, which may be difficult to obtain in practical applications. Also it requires long training time and high computational resources, especially when dealing with high resolution images. In future research synthetic data can be generated by data augmentation and Generative Adversarial Networks (GAN), which not only expands and enhances the training dataset, but also improves the generalisation ability of the model.

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