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Research Article

Analysis of Yolov11 Model for Real-World Pipeline Defect Detection

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Abstract:
With the rapid urbanization, the scale of underground pipeline systems continues to expand, making the detection and maintenance of pipeline defects increasingly critical. Traditional pipeline defect detection methods primarily rely on manual inspections and mechanical means, which are inefficient and prone to false positives and missed detections. To address these issues, this paper proposes an automatic pipeline defect detection method based on the YOLOv11 object detection algorithm. By constructing a diversified dataset and leveraging YOLOv11's deep convolutional neural network, the model efficiently identifies defects such as cracks, corrosion, and misalignment in pipelines. Experimental results show that YOLOv11 outperforms traditional manual methods in both detection accuracy and speed. In particular, YOLOv11 demonstrates strong detection capabilities for small objects and complex backgrounds, significantly improving detection efficiency. Compared to manual inspection, YOLOv11 reduces detection time by over 30% and exhibits a low miss detection rate. In the future, the application of YOLOv11 in pipeline detection will be further extended to real-time detection and multi-modal data fusion, enhancing its adaptability in complex environments.

Keywords: YOLOv11, pipeline defect detection, object detection, deep learning, automated detection, data augmentation

1. Introduction

The underground pipeline system in urban areas is a fundamental infrastructure for the stable operation of modern cities, covering various systems such as rainwater, sewage, potable water, and natural gas [1,2]. It plays a crucial role in supporting urban drainage capacity, water supply safety, and environmental sustainability. With the ongoing progress of urbanization, the density and length of underground pipelines continue to increase [3-5]. According to the "Urban Underground Pipeline Statistical Yearbook," the total length of underground pipelines in China has steadily grown over the past decade, with the drainage network system expanding rapidly. As a result, the pressure for maintenance has intensified [6].

The aging of pipelines, caused by prolonged usage, has led to the widespread occurrence of defects. Common defect types include structural damage (such as cracks, misalignment, and ruptures) and functional failures (such as sedimentation, corrosion, and root intrusion) [7,8]. If these defects are not detected and repaired in a timely manner, they may lead to catastrophic secondary disasters, such as pipeline collapse, road surface subsidence, and urban flooding, directly threatening urban operation safety and the safety of residents' lives and property [9,10]. In response to these potential hazards, pipeline defect detection has become a critical component of municipal maintenance systems, with its importance increasingly recognized [11]. Traditional pipeline inspection methods mainly rely on closed-circuit television (CCTV) systems, where video footage is reviewed manually to identify defects on the interior of the pipelines [12,13]. However, this method heavily depends on the operator's experience, is subjective, lacks standardization, and is prone to false positives and missed detections [14-16]. This issue is particularly problematic when dealing with high-density, large-scale pipeline systems, where the inefficiency and high labor intensity of manual detection can no longer meet the growing demands for pipeline maintenance in rapidly developing cities [10, 17]. To enhance the objectivity and efficiency of the detection process, it is necessary to introduce high-precision, more automated technologies to aid the development of intelligent urban pipeline systems.

In recent years, with the rapid advancements of deep learning in computer vision, automated image recognition technology has been gradually introduced into the maintenance of urban infrastructure. Among them, YOLO (You Only Look Once) algorithms have garnered significant attention due to their end-to-end modeling approach and excellent real-time detection capabilities. The YOLO model can perform both object localization and classification in a single forward pass, thereby improving detection efficiency while maintaining accuracy. Compared to traditional two-stage detection algorithms like R-CNN, YOLO has faster processing speeds, making it especially suitable for scenarios where response time is critical [16]. As the latest upgraded version of the series, YOLOv11 introduces multi-scale feature fusion, lightweight module optimization, and attention mechanism enhancements, significantly improving its detection performance in complex backgrounds and for small targets, striking a new balance between accuracy and speed [13]. In practical drainage pipeline detection tasks, small target defects such as cracks, slight corrosion, and misaligned joints are often more concealed, thus requiring higher precision from detection algorithms. The C3K2, SPFF, and C2PSA modules integrated in YOLOv11 effectively enhance the model's ability to perceive local features, strengthen its response to small objects, and minimize environmental interference, thereby improving overall detection accuracy and robustness [15]. Additionally, YOLOv11's end-to-end neural network structure reduces intermediate data conversions and post-processing overhead, maintaining efficient inference while ensuring optimal resource utilization. This makes it more suitable for deployment on embedded terminals or edge devices, offering strong potential for practical engineering applications.

This paper investigates the application of the YOLOv11 model in urban drainage pipeline defect detection. By constructing a high-quality defect image dataset, conducting systematic training and hyperparameter tuning, and analyzing its detection performance across different defect scenarios, the study compares YOLOv11 with traditional manual inspection methods to assess its practicality and superiority in real-world projects. The research aims to explore the feasibility of implementing intelligent detection methods based on YOLOv11 in pipeline maintenance, promoting the transition of urban pipeline management from "reactive response" to "proactive early warning," and providing data support and decision-making basis for the healthy management of urban infrastructure.

2. Experiment Design and Dataset

2.1 Data Collection and Image Annotation

The dataset used in this study is derived from a real-world urban pipeline inspection project, encompassing a variety of pipeline defect types, including cracks, corrosion, misalignment, and root intrusion. These defects exhibit different shapes, sizes, and environmental backgrounds. To ensure the representativeness and diversity of the dataset, CCTV technology was employed to capture pipeline video footage, from which multiple representative image frames were extracted. These images not only clearly showcase the defects within the pipeline but also minimize redundant data, improving analysis efficiency. Each image was annotated using the LabelImg tool to ensure the accuracy and consistency of the annotations. The type and location of each defect within the image were meticulously labeled, using the YOLO format, ensuring data consistency and high quality for subsequent training. This process provided the high-quality input required for the model, enabling YOLOv11 to accurately learn and recognize pipeline defects. Figure 1 illustrates the distribution of different defect types within the dataset, reflecting the proportional distribution of each defect type. The figure clearly shows the proportion of each defect type, ensuring that the dataset covers a wide range of pipeline defects, offering a balanced dataset for the subsequent training process.

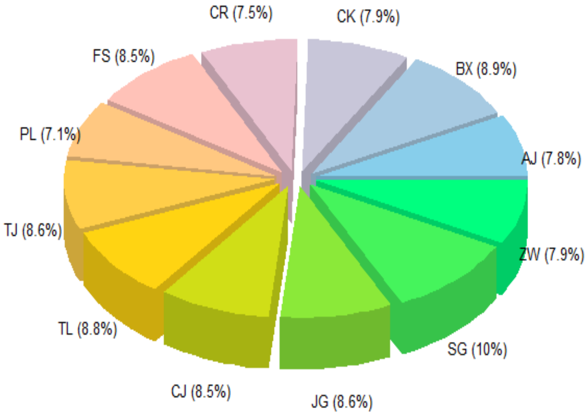

Figure1 Distribution of pipeline defect data

Table 1 lists the changes in the sample sizes of the pipeline defect dataset before and after data augmentation, illustrating the balance adjustments made in the augmented dataset. The table clearly shows the initial count of each defect type, the sample size after augmentation, and the final number of samples, ensuring that each defect type is adequately represented in the dataset for training. This approach avoids the issue of underrepresentation of certain defect types, thereby improving the accuracy of the training process and enhancing the model's generalization ability.

Table 1 Distribution of pipeline defect data

Defect type	**Original quantity**	**After Initial screening**	**Data processing method**	**Final quantit**
AJ (Branch pipe dark connection)	**748**	**620**	**Data augmentation**	**1550**
BX (Deformation)	**1021**	**890**	**Data augmentation**	**1780**
CK (Misalignment)	**4469**	**3154**	**Removal**	**1577**
CK (Misalignment)	**610**	**600**	**Data augmentation**	**1500**
FS (Corrosion)	**2234**	**1694**	**—**	**1694**
FS (Corrosion)	**3301**	**2824**	**Removal**	**1412**
TJ (Disconnection)	**2318**	**1714**	**—**	**1714**
TL (Interface material detachment)	**795**	**702**	**Data augmentation**	**1755**
CJ (Sedimentation)	**4102**	**3416**	**Removal**	**1708**
JG (Scale)	**1602**	**1150**	**Data augmentation**	**1725**
SG (Tree Roots)	**2306**	**2006**	**—**	**2006**
ZW (Obstruction)	**3696**	**1572**	**—**	**1572**
QF (Undulations)	**325**	**325**	**Discard**	**0**
SL (Leakage)	**483**	**483**	**Discard**	**0**
FZ (Floating slag)	**71**	**71**	**Discard**	**0**
CQ (Residual wall, Dam base)	**78**	**78**	**Discard**	**0**
Total				**19993**

2.2 Data Augmentation Methods

Due to the relatively small number of pipeline defect image samples and the significant variation in the manifestation of different defect types, a single dataset cannot encompass all the possible scenarios encountered in pipeline detection. To enhance the robustness and generalization ability of the model, this study employs a variety of data augmentation techniques, including rotation, translation, scaling, flipping, brightness adjustment, color jittering, and noise perturbation. These methods effectively increase the diversity of the dataset, helping the model adapt to various detection conditions.

Through rotation, translation, and scaling operations, the model is enabled to accommodate defects displayed at different capture angles and scales. Brightness adjustment and color jittering enhance the model's adaptability to images under varying lighting conditions. Additionally, noise perturbation simulates the image noise encountered during pipeline inspections, thereby improving the model's ability to handle complex environments. These augmentation techniques significantly increase the diversity of the dataset, particularly with respect to varying lighting conditions, viewing angles, and image noise. As shown in Table 1, the data augmentation process effectively expands the sample size of each defect type, ensuring a balanced distribution of defect samples during training and further optimizing the model's performance.

2.3 Data Processing and Preprocessing

After image data collection and augmentation, data preprocessing is a critical step to ensure smooth model training. Raw video data often contains noise and redundant information that may negatively affect subsequent model performance. Therefore, in the preprocessing phase, denoising is the first step to eliminate background noise and enhance the clarity of defect features, allowing the model to focus more effectively on the core areas of pipeline defects.

Data normalization is another crucial step in the preprocessing process. The pixel values of each image are normalized to a range between 0 and 1, ensuring consistency and numerical stability across the image data. Additionally, to meet the input requirements of the YOLOv11 model, all images are resized to a uniform dimension, typically 416x416 or 608x608 pixels. These preprocessing steps ensure that the model can be trained in a standardized and efficient manner, thus improving training speed and promoting model convergence. Through these preprocessing steps, a dataset that meets the YOLOv11 training requirements was created, providing stable and efficient training data for subsequent pipeline defect detection. This process not only enhances the quality of the dataset but also ensures that the model can effectively learn the critical features of pipeline defects.

3. YOLOv11 Model Application

3.1 Model Architecture and Training Strategy

YOLOv11 is the latest version in the YOLO series, incorporating several significant optimizations over its predecessors, particularly in terms of handling small objects and complex backgrounds. The core innovations of the model include the C3K2, SPFF, and C2PSA modules, which effectively enhance YOLOv11's detection accuracy for small objects and improve its ability to recognize pipeline defects in complex environments. Common small objects in pipeline defect detection, such as cracks and corrosion points, often occupy relatively small regions within the image, making precise identification of these objects critical. By optimizing convolutional layers and feature extraction networks, YOLOv11 significantly improves the detection accuracy of such small objects, providing strong support for accurate recognition in pipeline defect detection tasks [15].

This study utilizes YOLOv11's end-to-end deep convolutional neural network (CNN) for automatic pipeline defect detection. During the training process, the standard YOLO loss function is employed, including classification loss, localization loss, and confidence loss, ensuring that the model can balance the optimization of various objectives in multi-task learning. Additionally, based on the characteristics of the pipeline defect dataset, hyperparameters such as input size, learning rate, and batch size were adjusted to ensure optimal model performance during training. These optimization measures help improve the model's accuracy and ensure its efficiency and effectiveness in complex pipeline defect detection tasks [10].

3.2 Model Training Performance Evaluation

During the model training process, YOLOv11's performance was assessed using common evaluation metrics such as Precision, Recall, and F1 score. Analysis of the training results revealed that the model exhibited outstanding performance across various evaluation metrics, particularly in the detection of small objects such as cracks and corrosion points, where it demonstrated a significant advantage. This advantage can be attributed to its innovative modules and optimized architecture, which effectively enhance its ability to recognize small objects, leading to strong performance in pipeline defect detection tasks.

Throughout the training, the YOLOv11 F1 curve, shown in Figure 2, provides a clear visualization of the model's F1 score variations at different confidence thresholds. The figure illustrates the performance of various defect types during the training process, with the blue curve representing the overall F1 score for all defect categories. This curve highlights the model's stability and performance in detecting different types of defects. As confidence increases, the F1 score gradually improves, indicating that the model's recognition ability for various defects is significantly enhanced at higher confidence levels [11].

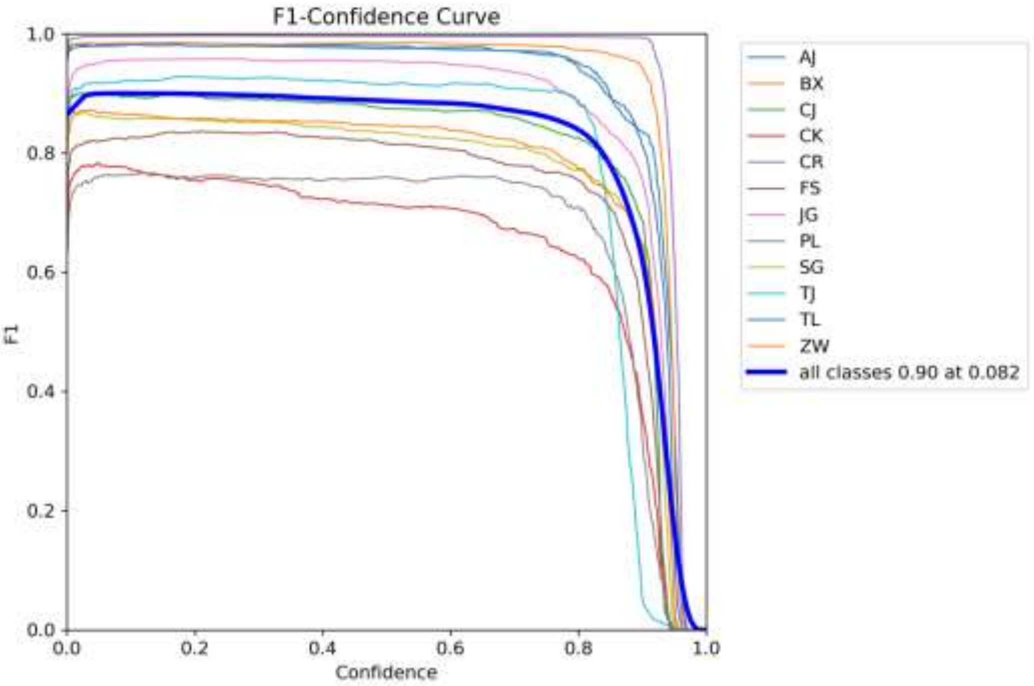

Figure 2 YOLOv11 F1 curve

Additionally, Figure 3, the YOLOv11 Recall curve, illustrates the model's recall performance at different confidence thresholds. The figure demonstrates that as the confidence threshold increases, the recall rate gradually decreases. However, at lower confidence thresholds, YOLOv11 maintains a relatively high recall rate, which is critical for detecting smaller defects, such as minute cracks and tiny corrosion points. Overall, YOLOv11 exhibits excellent recall performance across various defect types, especially in handling complex backgrounds and dynamic detection scenarios, where the model's robustness is thoroughly validated. These performance evaluations indicate that YOLOv11 not only improves precision in pipeline defect detection but also maintains a high recall rate, ensuring accurate recognition of different pipeline defects in complex environments. The analysis of training loss and evaluation curves further confirms the model's superiority in the pipeline detection domain [9].

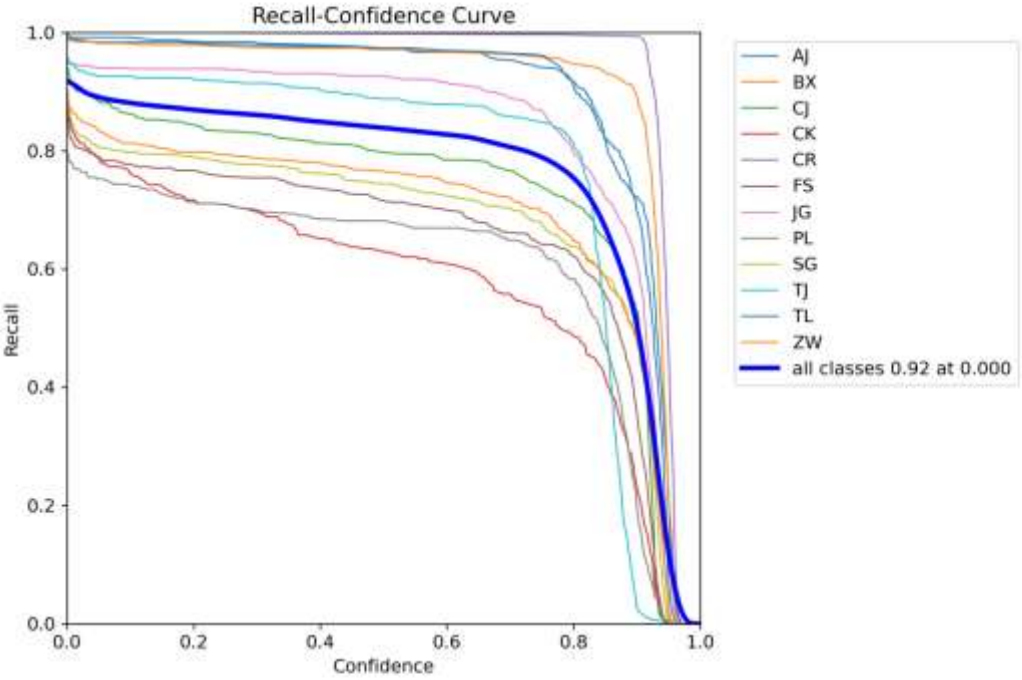

Figure 3 YOLOv11 Recall (R) curve

4. Model Comparison and Practical Application Analysis

4.1 Comparison of YOLOv11 and Manual Detection

To comprehensively evaluate the practical application of YOLOv11 in pipeline defect detection, this study conducted a comparative analysis between YOLOv11 and traditional manual detection methods. The experimental results clearly show that YOLOv11 significantly outperforms manual detection across multiple key metrics, particularly in terms of accuracy and detection time. In the detection of small objects, YOLOv11 demonstrated high recognition capability for minor defects such as cracks and corrosion, which is crucial for pipeline defect detection [9].

Figure 4 presents a comparison of YOLOv11 and manual detection in pipeline defect detection. YOLOv11 excels in both defect identification and accuracy, with a significantly lower miss detection rate compared to manual methods. The data in the figure indicates that YOLOv11 completes the same detection tasks in a much shorter time, which is especially important for pipeline inspection projects that require efficient processing of large volumes of data.

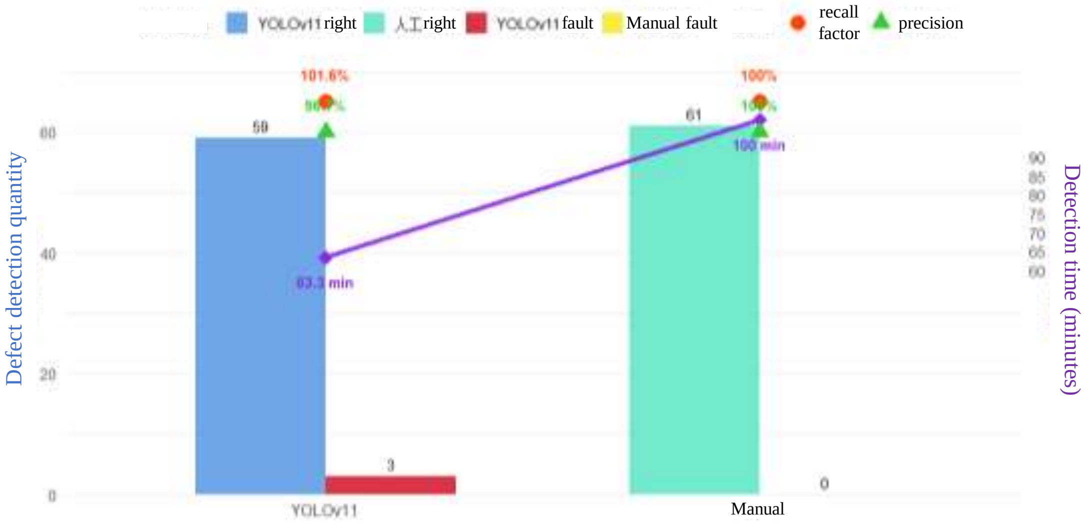

Figure 4 Pipeline detection results comparison

Table 2 further presents a detailed comparison between YOLOv11 and manual detection in terms of detection accuracy, miss detection rate, and detection time. From the table, it is evident that YOLOv11 not only achieves accuracy levels comparable to, or even surpassing, manual detection but also significantly reduces detection time, demonstrating its potential for large-scale pipeline inspection tasks. Compared to manual detection, YOLOv11's efficiency provides a clear advantage in industrial applications, particularly in scenarios where time constraints are stringent [15].

Table 2 Pipeline detection data results

Detection data Pipeline	**Defect count (Units)**		**Judgment time (Minutes)**	
	YOLOv11	**Manual**	**YOLOv11**	**Manual**
Pipeline 1	**21**	**20**	**20**	**30**
Pipeline 2	**24**	**24**	**18.95**	**32**
Pipeline 3	**17**	**17**	**24.35**	**38**
Total	**62**	**61**	**63.3**	**100**

4.2 Real-World Performance in Engineering Projects

In real-world pipeline inspection projects, YOLOv11 has demonstrated exceptional adaptability and stability. Particularly under challenging environmental conditions, such as low light, bright light, and tilted angles, YOLOv11 has maintained a high level of detection accuracy.

Figure 5 presents the actual detection results of YOLOv11 across different pipeline scenarios. It is evident that even in complex shooting environments, YOLOv11 can still accurately identify various defects within the pipeline, including cracks, corrosion, and misalignments. Through automated defect detection, the model significantly enhances both the efficiency and accuracy of pipeline inspections [6].

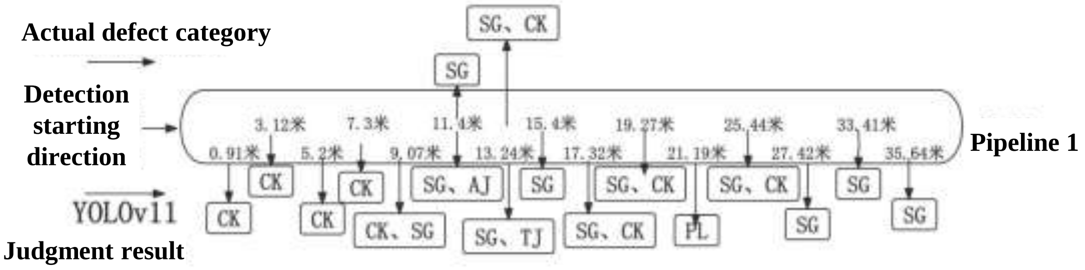

Figure 5 Pipeline 1 detection results comparison

The deployment of YOLOv11 has not only enhanced the level of automation in detection but also effectively reduced detection time. Table 3 presents the differences in cost and time between YOLOv11 and traditional manual inspection methods. From the table, it is evident that the deployment of YOLOv11 significantly reduces the time and cost required for manual inspections, especially in large-scale inspection tasks. For instance, in the inspection of Pipeline 1, YOLOv11 completed the detection in 63.3 minutes, while manual inspection required 100 minutes, with nearly equivalent accuracy. This comparison highlights YOLOv11's advantage in its efficient and accurate detection capabilities, which significantly alleviate the workload and reduce the error rate of manual inspections [9]. The application of YOLOv11 in pipeline defect detection has proven to be highly effective, not only improving the accuracy and efficiency of inspections but also reducing labor costs and time overhead. Its stable performance in complex environments, along with its high recognition capability for small objects, makes it an ideal choice for the pipeline inspection field and suggests a wide range of industrial applications in the future [15].

Table 3 Defect detection project cost analysis

Detection mode	Project	Pipeline length (km)	Workdays (8 hours/day)	Number of people (units)	Unit cost (person/¥/workday)	Total (Workdays × People × Unit cost)
Fully manual detection	Ezhou project	275.1	60	6	400	144000
	Huanggang project	254	55	6	400	132000
	Jiangxia project	65	14	6	400	33600
	Total					309600
Algorithm pre-processing + Manual review	Ezhou project	275.1	10	1	400	4000
	Huanggang project	254	10	1	400	4000
	Jiangxia project	65	3	1	400	1200
	Total					9200

5. Conclusion

This study proposes an efficient and precise pipeline defect detection method based on the YOLOv11 model and experimentally verifies its superiority in pipeline defect detection. The key conclusions are as follows:

(1) High Accuracy and Improved Detection Speed: YOLOv11 demonstrates high accuracy in pipeline defect detection, particularly in detecting small objects (such as cracks and corrosion points) and recognizing defects in complex backgrounds. Compared to manual detection, YOLOv11 achieves accuracy close to that of manual inspection, while significantly improving detection speed. For instance, in the inspection of Pipeline 1, YOLOv11 completed the detection in 63.3 minutes, whereas manual inspection took 100 minutes, showcasing YOLOv11's efficiency in large-scale pipeline inspection tasks.

(2) Significant Progress in Small Object Detection: YOLOv11, through its innovative modules (such as C3K2, SPFF, and C2PSA), has made significant advances in detecting small objects. In comparative experiments with YOLOv5 and YOLOv10, YOLOv11 excelled in multiple metrics, achieving an mAP of 91.9%, higher than YOLOv5 (91.5%) and YOLOv10 (90.6%). This indicates that YOLOv11 is more precise in identifying small defects within pipelines.

(3) Enhanced Detection Efficiency and Automation: YOLOv11 not only improves detection accuracy but also significantly enhances detection efficiency. In the inspection of Pipeline 1, YOLOv11 successfully identified 21 defects, while manual inspection could only detect 20 defects. This improvement in defect identification demonstrates YOLOv11’s ability to significantly increase the level of automation in detection, providing an intelligent and automated solution for pipeline defect inspection.

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