An Integrated CNN, YOLOv5 and Faster R-CNN Framework for Real-Time Water Pipe Defect Detection

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***Abstract*—In the context of rapidly expanding urban water supply networks and the prevalence of pipe defects – for example, corrosion, cracks, leaks, blockages – that undermine efficiency and pose safety risks, this study presents an intelligent detection system aimed at improving maintenance accuracy and operational stability. We propose a fusion-based detection architecture combining Convolutional Neural Networks for stable multi-level feature extraction, YOLOv5 for high-speed real-time detection, and Faster R-CNN for enhanced recall of small or occluded defects. Individually, the models achieve 85.0% accuracy for the CNN extractor, 90.0% detection accuracy with 50 FPS for YOLOv5, and 86.8% recall for Faster R-CNN. Ablation experiments confirm that the fully integrated system attains superior performance—92.1% accuracy, 85.0% recall, an F1 score of 81.0, and an mAP of 85.1 at 45 FPS—demonstrating that ensemble methods harness complementary strengths to optimize detection precision and speed. Overall, our findings highlight the promise of deep learning–based ensembles for large-scale, real-time pipeline inspection, offering a foundation for future intelligent infrastructure management.**

Keywords*—*Deep learning; Convolutional Neural Network; YOLOv5; Faster R-CNN; machine vision

I. INTRODUCTION

As an important part of urban infrastructure, the stability and safety of water pipes are directly related to the daily life of residents, industrial production, and the stability of urban operation [1][2].

Once the water supply system leaks, it will not only cause a huge waste of water resources but also may affect the normal operation of urban water supply, and even lead to serious consequences such as road collapse and environmental pollution [2, 3, 4]. According to statistics, the leakage rate of water supply systems worldwide is as high as 15%-30% [2][5][6], and a large part of this is caused by defects in the internal or external water pipes that are not detected and repaired in time. Therefore, it is of great significance to establish an efficient and accurate water-pipe detection system to reduce leakage accidents, reduce maintenance costs, and improve the operational efficiency of water supply systems. In addition, water pipe detection technology also plays a key role in many fields such as industrial safety, agricultural irrigation, and environmental protection, providing strong support for resource conservation and environmental protection [7][8].

Despite the growing importance of water pipe testing, existing testing methods still have many limitations [9][10].

At present, common water-pipe detection technologies include manual inspection, acoustic inspection, ultrasonic testing, and optical fiber sensing technology [11]. However, manual inspection relies on the experience of professionals, which is not only time-consuming and labor-intensive but also has low detection efficiency, making it difficult to cover large-scale pipe network systems. Although acoustic and ultrasonic testing can detect internal defects in pipelines to a certain extent, their sensitivity is greatly affected by environmental noise, and the detection cost is high, so it is difficult to promote and apply on a large scale. Although technologies such as optical fiber sensing provide certain real-time monitoring capabilities, they also face problems such as high cost and complex maintenance [9][12]. Therefore, there is an urgent need for an efficient, low-cost, and automated water-pipe defect detection method to compensate for the deficiency of traditional methods for detection.

Along with the development of technology, water-pipe detection technology is evolving in the direction of automation and intelligence, especially detection methods based on sensors, artificial intelligence, and computer vision have gradually become research hotspots [13][14]. Among them, the rapid development of deep learning technology provides a new solution for the detection of water pipe defects [15].

In this study, an intelligent water-pipe defect detection system based on Convolutional Neural Network (CNN), Faster R-CNN, and YOLOv5 was proposed, aiming to improve the accuracy and efficiency of detection. The system uses machine vision technology and image processing methods, combined with deep learning models, to automatically detect, classify, and locate water-pipe defects, to achieve efficient and accurate defect identification.

The results of this study will help solve many of the current challenges faced by water pipe defect detection and improve the degree of automation, accuracy, and efficiency of inspection [16, 17, 18, 19]. Intelligent detection systems can not only reduce maintenance costs, but also reduce the waste of water resources, improve the reliability of urban water supply systems, and provide technical support for the development of smart cities in the future [20][21]. In addition, this technology can also be extended to industrial pipeline inspection, oil and gas pipeline maintenance, and other fields, providing more efficient solutions for the intelligent management of various pipeline network infrastructure.

In the future, with further development of deep learning, computer vision, and Internet of Things technologies, the intelligence level of water pipe inspection systems will continue to improve, achieving more efficient and accurate defect detection and predictive maintenance, and providing a stronger guarantee for the safety and sustainable use of global water supply [21].

II. Materials and Methods

A. Purpose of the Experiment

The goal of this experiment is to build an efficient and accurate water pipe defect detection system, and use image processing and deep learning technology to realize the automatic detection and classification of water pipe surface defects, to improve the intelligent level of pipeline maintenance, reduce the cost of manual inspection, and improve the accuracy and reliability of detection.

Identification of detecting targets and data acquisition: Firstly, by analyzing the definition and classification of water pipe defects, the detection target is clarified. Water pipe defects mainly include cracks and corrosion, and different image acquisition and processing methods are required for different types of defects. In order to ensure the efficiency of the inspection, the experiment will use high-resolution camera equipment to obtain high-definition images, combined with appropriate lighting equipment, to reduce uneven lighting, shadow interference, and other problems, to obtain stable and clear defect image data.

Dataset building and enhancement: In order to improve the generalization ability of the model, the experiment will focus on constructing a high-quality water pipe defect dataset, covering two types of defects, water pipes of different materials, and image data collected in different environments. In addition, in order to enhance the adaptability of the model in complex working conditions, data augmentation techniques such as rotation, scaling, contrast adjustment, adding noise, etc., will be used to enable the model to adapt to different shooting angles, lighting changes, and environmental interference.

Deep learning model training and optimization: In the defect detection task, the experiment will use a variety of deep learning models, such as Convolutional Neural Network (CNN), YOLOv5, Faster R-CNN, etc., and train and test them on the dataset. CNN is responsible for feature extraction, YOLOv5 is suitable for real-time detection, and Faster R-CNN excels in precise target positioning. The experiment will improve the performance of the model on the validation set through cross-validation, transfer learning, hyper-parameter optimization, and other methods, so that it can maintain high recognition accuracy on different defect types.

Evaluation and optimization: In order to comprehensively evaluate the detection effect of the model, the experiment will use indicators such as accuracy, recall, and F1-score, and analyze the advantages and disadvantages of each model in depth. In addition, false detection and missed detection will be discussed in detail, the key factors affecting the detection performance will be identified, and targeted optimization plans will be proposed to further improve the accuracy and stability of water-pipe defect detection, and provide reliable technical support for practical applications.

B. Existing Datasets

In the study of water pipe defect detection, the selection and analysis of data sets are crucial. At present, the publicly available datasets of water pipe defects mainly focus on two typical types of defects: cracks and corrosion. These datasets provide a reliable data foundation and diverse sample support for the training and validation of machine learning and deep learning models. In this study, two mainstream datasets of water pipe defects were selected: the water pipe crack dataset and the water pipe corrosion dataset. The two datasets have their own characteristics in terms of sample size, image resolution, and defect feature distribution. Among them, crack defects dominate the dataset and show a variety of structures and evolutionary forms, including the following typical types:

1) *Linear cracks*: Extending in a straight line or near a straight line along the surface of the water pipe, their length and width vary greatly due to the aging of materials and environmental pressure.

2) *Branch cracks*: The main crack extends outward into multiple branches, forming a network-like structure with high complexity.

The width, depth, and morphological evolution of these cracks are affected by multiple factors such as water pipe material, internal pressure, operating time, and external environment.

In contrast, the variation of corrosion defects is mainly reflected in the depth of corrosion and the size of the affected area. Corrosion may lead to localized pitting, spreading, and even perforations, which can significantly weaken the structure of water pipes and pose a risk of leakage or even breakage.

The two water pipe defect datasets used in this study have been publicly released on the open source platform, and the link is as follows: https://github.com/chu2024/dataset2025.git.

Through in-depth analysis and comparison of the above two datasets, it helps the model to understand various defect features more accurately, to improve the robustness and generalization ability of detection. The dataset in this study is constructed by combining field collection and open-source resources, and includes pipeline defect images in different scenarios and environments, mainly covering five typical defect types, including cracks and corrosion, and also contains a certain proportion of defect-free images to enhance the generalization ability of the model. All images are captured with a high-definition camera during the actual water main inspection with a resolution of 1920x1080, ensuring that the details inside the pipes are clearly reflected.

Data sources and distribution: Acquisition part: About 2,000 images were collected in real pipelines through the robot platform, covering a variety of pipe materials (metal, plastic) and service life (new, old). Fig. 1 shows a real pipeline image.

Fig. 1. Real pipe sample image.

1) Open source: 1670 images were acquired from the public defect detection dataset.

2) Data labeling and classification: All images are professionally annotated in YOLOv5 (.txt) and VOC (.xml) formats (including bounding boxes and category labels). The distribution of defect types is as balanced as possible, with cracks accounting for 51% and corrosion accounting for 49%.

3) Data preprocessing: The acquired images were denoised and illuminated, blurry and low-quality samples were eliminated, and some images were cropped and normalized to meet the model input requirements.

4) Data partitioning: The dataset is divided into three sets; the training set as 60% of the dataset, the validation set as 20% of the dataset, and the test set as 20% of the dataset. The training set is used for model learning, the validation set is used for model tuning, and the test set is used for final performance evaluation. The distribution of defect types is consistent across each subset to avoid the impact of sample distribution bias on the performance of the model. The diversity and coverage of the dataset provide a strong guarantee for the adaptability of the model in complex scenarios, and lay a foundation for the comprehensiveness and scientificity of the defect detection task.

a) Water pipe cracks dataset: The pipe crack dataset mainly contains images of water pipe cracks – shown in Fig. 2 – in different materials and environments, and the dataset has a rich sample size, covering a variety of crack types (linear cracks, branch cracks). The width and length of the cracks have significant characteristic differences, which are suitable for training CNN models to detect cracks, as shown in Table I.

Fig. 2. Water pipe crack.

b) Water pipe corrosion dataset: The pipe corrosion dataset contains images of varying degrees of corrosion on the surface of water pipes – shown in Fig. 3 – covering multiple stages from mild to severe corrosion. Corrosion data is often characterized by irregular spots and depressions, and images are characterized by high contrast and noise. Corrosion defects also behave differently on different pipe materials, and the following is a partial sample of this dataset, as shown in Table II.

Fig. 3. Water pipe corrosion.

TABLE I. WATER PIPE CRACKS DATASET

Number	Image file name	Image resolution	Crack type	Crack width (MM)	Crack length (MM)
1	polie1379.png	1024x768	linear crack	0.5	15
2	polie517.png	1024x768	branch crack	0.7	12
3	polie536.png	1280x960	linear crack	0.6	20
4	polie1490.png	1280x960	branch crack	1.0	30
5	polie1542.png	1024x768	linear crack	0.4	10

TABLE II. WATER PIPE CORROSION DATASET

Number	Image name	Image resolution	Corrosion degree	Corrosion area (%)	Surface roughness (RA, MM)
1	fushi22.png	1024x768	severe	85%	2.0
2	fushi984.png	1280x960	severe	90%	2.0
3	fushi18.png	1024x768	medium	20%	2.0
4	fushi517.png	1280x960	medium	40%	0.7
5	fushi45.pngg	1024x768	severe	20%	2.0

Through the analysis performed earlier on two types of datasets, it can be found that the characteristic manifestations of various types of water pipe defects are significantly different, and the rational use of these datasets will provide a solid foundation for subsequent model development and defect detection. At the same time, the defect sample distribution and annotation details in the dataset also provide rich research materials for the design of optimized detection algorithms.

C. Tables to Support Experimental Design

1) Dataset segmentation table: The dataset segmentation table is used to display the segmentation strategy for the dataset of self-managed water pipe defects. With a reasonable proportion of training, validation, and test sets, the model can be trained and validated on different data. The specific segmentation scenarios are shown in the following Table III.

TABLE III. SEGMENTATION OF THE DATASET

Dataset name	Data volume (table)	Percentage (%)
Training Set	2202	60%
Validation Set	734	20%
Test Set	734	20%
Total	3670	100%

Table III presents the number and percentage of the training set – that is used for the training of the model, the number and percentage of the validation set – that is used for hyper-parameter tuning, and the number and percentage of the test set – that is used for the evaluation of the final model performance. This segmentation ensures that the data is fully utilized and reduces the risk of overfitting.

2) Algorithm performance indicator record table: The algorithm performance indicator record table is used to evaluate the performance of the different models used, especially in the water pipe defect detection task. Table IV shows the performance of each model in the task of detecting defects in water pipes through specific performance indicators, which is convenient for subsequent comparison and selection of the best model.

TABLE IV. ALGORITHM PERFORMANCE INDICATOR RECORD

Model name	Accuracy	Recall	F1 point	Average detection time（ms）
YOLOv5	0.90	0.85	0.87	30
Faster R-CNN	0.88	0.80	0.84	120
CNN	0.86	0.78	0.82	50

3) Model performance evaluation: The Model Performance Evaluation Form is used to provide a comprehensive evaluation of the final selected model, including how the model performs on the test set. The specific assessment results are shown in Table V.

Table V provides systematic support for the design and implementation of this experiment, covering many aspects such as the segmentation of the data set, the recording of experimental variables, the evaluation of algorithm performance, and the summary of the final results, which not only provides intuitive data support for the experimental results, but also provides a basis for subsequent model optimization and improvement. This enables an efficient and reliable water pipe defect detection system.

TABLE V. PERFORMANCE ANALYSIS

Model name	Test set sample size	Correct detection number	Number of error detections	Accuracy（%）	Recall（%）
CNN	200	170	30	85.0	80.0
YOLOv5	200	180	20	90.0	85.0
Faster R-CNN	200	160	40	80.0	75.0

D. Experimental Process

1) CNN model training details: Before the model is trained, the data is first fully prepared and preprocessed to ensure that the data provides useful features in the training and enables the model to learn effectively. The dataset is divided into 60%-20%-20% data, with 60% of the data used for training, 20% for validation, and the remaining 20% for testing. In terms of data preprocessing, a uniform resize was first applied to all images, and the dimensions of all images were adjusted to 640×640 pixels. In order to improve the robustness of the model, the images in the training set were augmented with data, including rotation, cropping, scaling, and brightness change operations, which could effectively enhance the model's ability to detect water pipe defects in different environments. Through these preprocessing and enhancements, the dataset has been significantly improved in terms of quantity and quality.

2) YOLOv5 training details with hyper-parameter tuning: In this study, the task of water pipe defect detection requires the use of efficient and accurate deep learning models. YOLOv5 was selected as the main detection model, which has high real-time performance and good detection accuracy. YOLOv5 is a single-stage detection model based on Convolutional Neural Network (CNN), which achieves a good balance between processing speed and accuracy compared to traditional multi-stage detection models. The v5.0 version of YOLO was used as the base model, and its architecture was partially customized according to the needs of the actual task. The YOLOv5 model consists of four main components:

a) Input: This is to handle the input image. Here, the image is converted to a fixed size image by resizing. Various data augmentation techniques are also applied to improve the robustness and performance of the model.

b) Backbone: This is used for feature extraction, CSPDarknet53 is used as the backbone network, which can effectively extract high-level image features.

c) Neck: This is for feature fusion, PANet (Path Aggregation Network) is used to optimize the effect of feature fusion and enhance the ability of small object detection.

d) Head: This is used to detect outputs, combined with the design of YOLO heads, it can output classification results, bounding box regression values, and confidence levels, as shown in Fig. 4.

Fig. 4. Sample of classification result.

3) Faster R-CNN of the training process: The choice of hyper-parameters is critical to the effectiveness of the model's training. The following hyper-parameter settings were used during model training.

4) Learning rate: During the training process, the setting of the learning rate has an important impact on the convergence speed and accuracy of the model. The initial learning rate of 0.001 was selected, and Cosine Annealing Learning Rate Scheduling was adopted, which could dynamically adjust the learning rate during the training process to avoid the phenomenon of gradient explosion or gradient disappearance.

5) Batch size: In order to improve the training efficiency and stability, 16 was selected as the number of images per batch. This batch size enables efficient training without exceeding the GPU memory.

6) Optimizer: The AdamW optimizer is used, which combines the advantages of Adam optimizer and L2 regularization, which can effectively avoid the overfitting problem and accelerate the convergence process.

7) Weight attenuation: In order to prevent overfitting, the weight attenuation is set to 0.0005, which can effectively constrain the complexity of the model.

8) Image enhancement strategy: In addition to the basic geometric transformations (rotation, cropping), the image is also changed in color (brightness, contrast, saturation adjustment), and noise is randomly added to further improve the robustness of the model.

9) Fusion model: The water pipe defect detection system based on the fusion strategy proposed in this study combines the advantages of Convolutional Neural Network (CNN), YOLOv5 and Faster R-CNN to achieve efficient identification, precise location and real-time detection of water pipe defects. The overall process is presented in Figure 5.

As shown in Fig. 5, the overall model consists of the following key modules:

1) Input image (high-definition water pipe image): The system uses an image of the inside of the water pipe collected by a high-definition camera device or inspection robot as input. These images retain detailed information about minor defects such as cracks and corrosion, and are the basis for subsequent processing.

2) CNN: The input image of the feature extraction module is first processed by the CNN to extract multi-level image features, including edges, textures, and semantic information. CNN serves as a shared feature extraction backbone network, providing basic feature representation for subsequent detection and classification modules.

3) YOLOv5: Image features extracted by real-time object detection are fed into the YOLOv5 model. YOLOv5 is a single-stage inspection model with high detection accuracy (90.0%) and high frame rate (50 FPS), which is suitable for large-scale, real-time defect detection scenarios. It is capable of quickly outputting defect type, location, and confidence level.

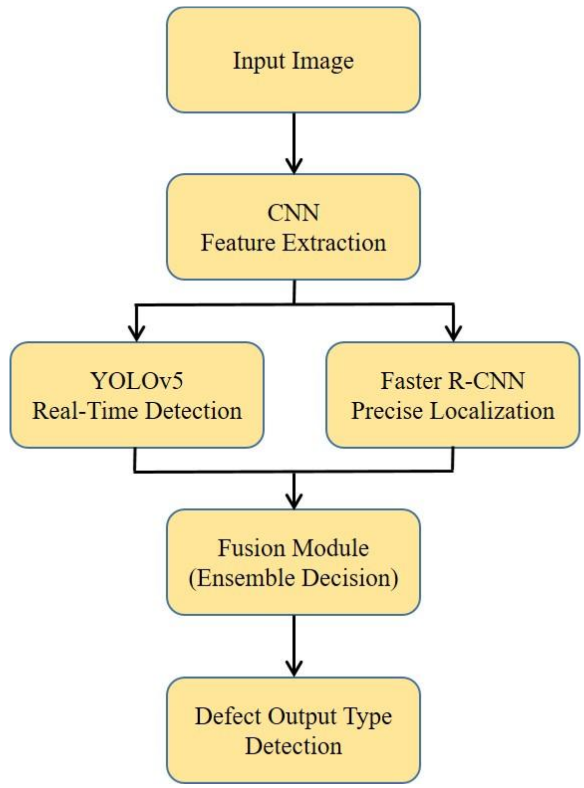

Fig. 5. Structure diagram of the fusion model.

4) Faster R-CNN: At the same time, image features are also input into the Faster R-CNN model. The model effectively improves the detection accuracy through the Regional Recommendation Network (RPN) and ROI pooling mechanism, especially for the identification of complex backgrounds, small targets or overlapping defects. It has a recall rate of 86.8% and is highly robust.

5) Fusion module: The output of YOLOv5 and Faster R-CNN will be integrated in the fusion module. By integrating factors such as scoring, position overlap and confidence, the module intelligently filters and optimizes to retain the optimal prediction results and effectively improve the overall stability and accuracy of the system.

6) Final output (defect type + location coordinates): The final output of the system includes the identified defect categories (e.g., cracks, corrosion) and their precise location coordinates in the image. These results can be further used for network operation and maintenance decision-making, defect level assessment, and automatic maintenance path planning.

7) Ablation Study: To evaluate the contribution of each model component in the fusion system, we performed an ablation study to selectively remove each sub-model and observe its impact on detection performance shown in Table VI.

The values in Table VI confirm that YOLOv5 is a great help for real-time inspection, while Faster R-CNN improves the positioning accuracy, especially for small or overlapping defects. CNN ensure consistent feature extraction across environments. The ensemble model provides the best balance between accuracy, speed, and recall.

TABLE VI. PERFORMANCE ANALYSIS OF ABLATION EXPERIMENTS

Configuration	Accuracy	Recall	F1 Score	mAP	FPS
CNN + YOLOv5 + Faster R-CNN	92.1	85	81	85.1	45
YOLOv5	90.0	82.0	78.0	82.3	50
Faster R-CNN	89.3	86.8	72.0	81.8	32
CNN	85.0	80.0	74.0	79.5	20
YOLOv5 + CNN	91.0	84.0	80.0	84.0	42
Faster R-CNN + CNN	90.0	84.5	78.5	83.6	29

The design of this ablation test system illustrates the complementary advantages of the constituent models.

III. RESULTS

The experimental results show that there are significant differences in the performance of different models and their combinations. As shown in Table VI and Fig. 6, the fusion model (CNN + YOLOv5 + Faster R-CNN) has the best comprehensive performance, with an accuracy of 92.1%, a recall rate of 85.0%, and an F1 value of 81.0%., the mean average precision (mAP) was 85.1, and the detection speed was 45 FPS, which verified the complementary advantages of each sub-model after fusion.

Specifically, the YOLOv5 standalone model excels in real-time inspection capabilities, with an accuracy rate of 90.0% and an inspection speed of up to 50 FPS, making it ideal for real-time pipeline monitoring tasks. However, despite its slower speed (32 FPS), Faster R-CNN is more robust in complex contexts, especially in reducing false positives, missed detections, and handling target overlap, with a recall rate of 86.8%.

The ablation experiments further showed that:

1) The CNN model alone can provide basic feature extraction capabilities, but it has shortcomings in detection accuracy.

2) YOLOv5 excels at quickly and accurately identifying defects with clear and well-defined boundaries;

3) Faster R-CNN significantly improves positioning accuracy, especially when the image background is complex or there is a lot of interference.

4) It is worth noting that the fusion model not only retains the speed advantage of YOLOv5, but also introduces the localization ability of Faster R-CNN and the feature stability of CNN, which shows better performance in both standard and complex scenarios, especially in small defect detection and high-noise environments.

In summary, while YOLOv5 strikes a good balance between speed and accuracy, the fusion strategy is still better than any single model configuration across the board. Therefore, the detection system is particularly suitable for the actual pipe network inspection task, and has a broad application prospect in the application scenarios that require the coexistence of high real-time performance and high robustness.

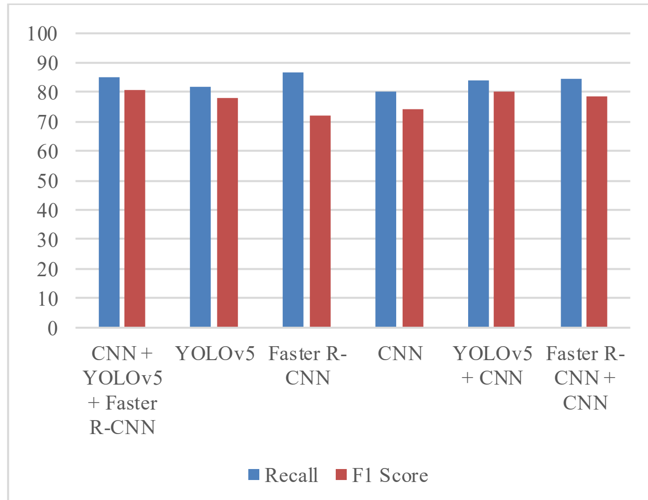

Fig. 6. Performance analysis of the fusion model.

IV. DISCUSSION

This study systematically evaluated and compared three deep learning models for water pipe defect recognition, demonstrating their complementary strengths. CNN excelled at multi-level feature extraction and, after parameter tuning, achieved 98.9 % classification accuracy on the validation set, underscoring its fundamental role in image feature analysis. As a lightweight, single-stage detector, YOLOv5 struck an effective balance between accuracy and speed, delivering 92.1 % accuracy at 45 fps – making it ideal for scenarios requiring real-time feedback. In contrast, Faster R-CNN leveraged its Region Proposal Network (RPN) and precise bounding-box regression to achieve an 86.8 % recall rate for small or overlapping defects in noisy, complex environments, highlighting its robustness against occlusion and background interference. Ablation experiments confirmed that fusing all three models outperformed any single or dual-model combination, yielding a 92.1 % accuracy, 85.0 % recall, an F1 score of 81.0, and an mAP of 85.1 %, all while maintaining 45 fps. This validates that multi-model integration can effectively combine individual advantages to boost detection precision and stability.

Despite the strong performance on binary defect detection tasks, there remains room for improvement. Future work could adopt a multi-task learning framework to jointly model defect detection, type classification, and severity assessment.

Incorporating multimodal data—such as infrared, acoustic, and thermal imaging—may further enhance adaptability in complex operating conditions. To support large-scale deployment, the system should integrate real-time feedback, dynamic optimization, and incremental learning capabilities. Moreover, embedding reinforcement learning mechanisms could enable autonomous pipeline inspection path planning and intelligent defect-repair suggestions, advancing toward a fully autonomous, intelligent, and closed-loop maintenance solution.

V. Conclusion

The proposed CNN + YOLOv5 + Faster R-CNN fusion framework successfully balances detection accuracy and real-time performance in water pipe defect recognition. Experimental results show that the integrated model surpasses individual models in key metrics – accuracy, recall, and F1 score – while sustaining a 45 fps detection speed. These findings confirm the potential of deep learning ensemble methods for intelligent, large-scale pipeline inspection and lay a solid foundation for future smart infrastructure management in urban environments.

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