Automated Pipeline Integrity Assessment and Defect Detection Using Deep Learning

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Abstract- *The drainage pipeline network constitutes a critical component of municipal infrastructure. Effective inspection of drainage pipelines is crucial for maintaining urban functions. However, manual inspection methods are inefficient and prone to error. To address this, an intelligent system for detecting, tracking and managing defects in drainage pipelines using YOLO-DeepSort (YOLO-DS) is proposed for automated defect information collection. Initially, YOLOv7 is employed to train the defect detection model, achieving a mean Average Pression (mAP) of 91.1% and processing at 172 frames per second (FPS). Subsequently, the YOLO-DS detection-based tracking algorithm is utilized to track defects in the pipeline video. Moreover, within the tracking framework, an innovative fusion module combining detection and ReID features enhances cross- frame matching robustness. Under conditions of lens rotation, jitter, and blur, the system achieves confidence levels exceeding 87% for potholes, 78% for misalignments, and 80% for obstructions, respectively, demonstrating strong robustness. Lastly, the detection and tracking algorithms are integrated into the information management platform. The management platform facilitates intelligent identification and counting of pipeline defects, and includes a professional communication module for automatic generation drainage pipeline health assessment reports, thereby streamlining manual inspection processes and saving assessment time.*

Keywords- Pipeline, YOLO-DS, defect detection, defect tracking, system.

I. INTRODUCTION

Due to the aging and disrepair of drainage networks, pipeline defects such as potholes, misalignments, and obstructions are becoming more prevalent. Such defects can lead to environ- mental pollution, road collapse, and adverse consequences for society, the economy, and the ecological environment [1]. Traditional passive maintenance methods fail to promptly identify potential hazards, inconveniences inhabitants and increasing maintenance costs. Proactive inspection enables the collection of pipeline defect information and provides effective maintenance guidance [2]. Therefore, routine testing is imperative [3]. Utilizing visual inspection technologies such as CCTV robots and drones results in a substantial volume.

photos or videos. Nevertheless, manual interpretation of this visual data proves ineffective. To overcome this limitation, there is an increasing trend towards using intelligent techniques to identify pipeline defects in images. Computer vision techniques, along with machine learning and deep learning methods, have been widely applied in pipeline analysis though image processing.

These methods primarily emphasize automated detection and classification of defects, significantly enhancing defect detection efficiency [1], [3]. Nevertheless, quantifying many defect categories remains a challenge, highlighting the need for deep learning techniques in defect analysis. Developing a deep learning-based pipeline defect inspection model necessitates creation of a reliable dataset. During dataset preparation, the following challenges commonly arise: Insufficient data volume and diversity pose a challenge due to the extensive range of pipeline systems and the varied types, sizes, and locations of defects. Given these challenges, a substantial volume of data must be gathered and categorized in order to train a model that is capable of producing accurate results. It is imperative to address these disturbances in order to enhance the robustness of the model.

II. OBJECT DETECTION

Recent years have witnessed exponential advancements in computer capabilities, leading to swift evolution in deep learning technologies. Deep learning techniques have become the predominant approach for target detection and recognition. This study utilizes the Convolutional Neural Network (CNN) [5], a modified version of the multi-layer perceptron (MLP). Several researches have made significant advancements in pipeline defect detection using CNNs. Kumar et al. [6] and Hassamet al.[7] developed systems that use CNNs to classify various defects in sewage closed-circuit television (CCTV) images.

This research focuses on using CNNs to classify root intrusions, deposits, and cracks in sewage defects. However, CNNs lack subclass classification capability. In images with multiple flaws, the system classifies defects based on the highest likelihood Peng Shugang and colleagues [8] enhanced a convolutional neural network and introduced the IM-CNN technique.

III. OBJECT TRACKING

Most current research focuses on categorizing, identifying, and segmenting pipeline anomalies. While object detection is capable of precisely identifying the nature of defects, it lacks the ability to differentiate whether the defects detected in the preceding and succeeding frames are same. Hence, it is imperative to investigate the methodology for tracking pipeline defects in order to effectively monitor, pinpoint, classify, and quantify each individual problem.

Currently, there exists a dearth of scholarly investigations pertaining to object defect tracking inside the domain of engineering. Shao et al. [21] introduced a proficient adaptive approach for the automatic detection of weld defects. This method relies on real-time ray picture sequences and employs a low-threshold defect segmentation technique. Once the algorithm has successfully segmented the potential weld defects in each image of the sequence, the enhanced Hough Transform method is employed to trace the center of gravity of these potential defects in the image sequence. Subsequently, any prospective defects that cannot be accurately tracked are eliminated as false defects. Wang et al. [22] improved the Kernel Correlation Filter (KCF) tracking algorithm by incorporating the median flow algorithm and introduced a novel approach for detecting surface flaws on particleboard, utilizing the tracking of moving objects. This modification aimed to enhance the system's ability to capture moving objects with surface defects. Ma et al. [23] employed the conventional Median flow algorithm for the purpose of tracking pavement cracks, resulting in precise crack counting. Then Wang et al. [2] introduced a framework that utilizes defect detection and metric learning of the Fast RCNN algorithm to track defects in drainage pipelines. Yu et al. [24] proposed an improved YOLOX- DeepSORT algorithm for port automatic RTG multi-target detection and tracking. This framework enables the tracking of many defects in order to facilitate statistical examination of distinct defects observed in videos.

IV. METHODLOGY

Given the current stage of study in the field of deep learning for pipeline failure tracking, there remains a lack of sufficient research on this subject. Considering the scarcity of datasets, the intricacy of the environment, and the limitations imposed by the construction site, it is reasonable to explore alternative methods for monitoring pipeline defects and develop a platform system that simplifies the handling of defect information.

This study primarily consists of three parts, namely pipeline defect detection, pipeline defect tracking, and defect information management. The defect detection module encompasses the generation of defect detection datasets by the utilization of labeling software, namely labelImg, as depicted in Figure 1. Additionally, it involves the partitioning of these datasets into training sets, validation sets, and test sets. The YOLO network is employed for training, aiming to achieve optimal training outcomes. Subsequently, a comparative analysis is performed to assess the detection results obtained from different models. The initial step in the defect tracking module is dataset preparation. Subsequently, the YOLO-DS network is integrated to track defects in video footage of pipeline defects. This is followed by evaluating and analyzing the tracking findings using indexing techniques

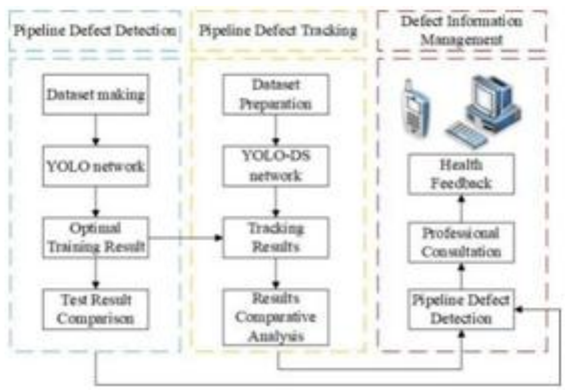

FIGURE 1. Architecture diagram of this paper.

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This convergence speed was insufficient. In our work, we implemented a warm-up strategy combined with the Cosine Annealing learning rate decay method. This approach gradually increases the learning rate from a small value to the set initial rate, followed by a cosine decay, resulting in improved convergence performance. Consequently, the system successfully accomplishes precise, real- time, and consistent detection and tracking of multiple objects. We developed a comprehensive pipeline defect information management platform, comprising three key components: pipeline defect detection, professional service provision, and health information feedback.

V. YOLO DS ARCHITECTURE

The primary approach employed in this paper is a detection- based tracking system. The initial step involves utilizing the detection algorithm to identify defects within the pipeline image or video. Subsequently, the detection outcomes are collected.

Following this, the Kalman filter, Hungarian algorithm, and feature extraction techniques are employed to get further information. The provided statement emphasizes the importance of tracking defect information and emphasizes the need to track defects in each frame. The procedure of implementing the particular algorithm is illustrated in Figure 3.

A. DETECTION ALGORITHM

The YOLOv7 model is employed as the object detection method in this study.

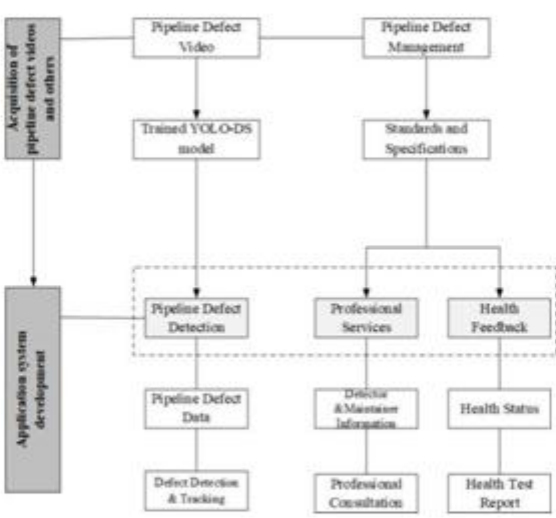

FIGURE 2. Development method and functional composition.

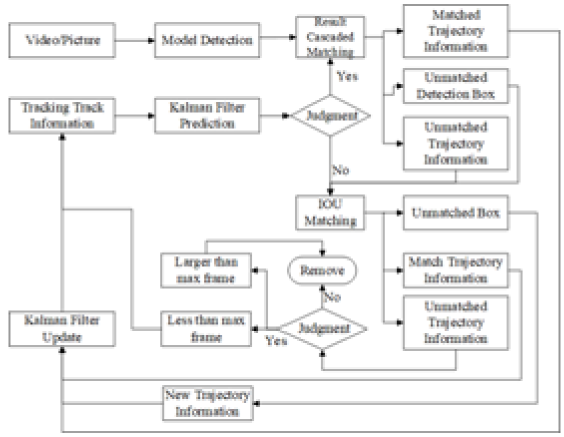

FIGURE 3. Overall algorithm flowchart.

network structure, detailing the distinct constituents of each individual network component. The YOLOv7 model introduces a novel network architecture that incorporates an additional head during the training phase.

B. LOSS FUNCTION

The loss function comprises three components, namely positioning loss, target confidence loss, and classification loss. The calculation of the positioning loss is performed by employing the loss function. The Intersection over Union (IoU) is a metric that quantifies the ratio between the area of overlap between the target box and the prediction box, and the combined area of both boxes. It is sometimes referred to as the cross and compare method.

C. KALMAN FILTER FOR TRACKING ALGORITHM

It is assumed that the scene for tracking defects in the pipeline is described in an 8- dimensional state space $\dot{u}$, $\dot{v}$, γ ,˙ $\dot{h}$, $\dot{x}$. This state space includes the coordinates (u, v) of the box center, the aspect ratio γ , the height h, and their related velocities in the image coordinate system. Let (u, v, γ , h) represent the direct observation of the state of the object.

In the context of target tracking, it is necessary to estimate two key parameters of the target: the mean and the covariance. Both the prediction phase and update phase of the Kalman filter involve the calculation of the estimated mean x_k and covariance P_k of the filter. The mean value $\hat{x}_{k-1}$ of the preceding instant $k - 1$ is estimated using the posterior distribution.

D. HUNGARIAN MATCH FOR TRACKING ALGORITHM

The Mahalanobis distance is alternatively referred to as the covariance distance. In order to incorporate the object's motion information, the Mahalanobis distance between the predicted state and the measured state is employed. The formula can be expressed as follows:

$$d^{(1)}(i, j) = (d_i - y_i)^T Si{-}1(d_j - y_j)$$

One of the distances used in this context is the Mahalanobis distance, denoted as d (1)(i, j). The variables d and y represent the measurement distribution and the prediction distribution, respectively. Additionally, S refers to the covariance matrix that describes the relationship between these two distributions. The utilization of the Mahalanobis distance can yield effective tracking outcomes

VI. DEFECT INFORMATION MANAGEMENT PLATFORM

A pipeline defect detection information management platform was developed, utilizing deep learning techniques, in order to achieve efficient detection and management of pipeline defects. The platform primarily utilizes a B/S architecture, which consists of three components: the data layer, service layer, and terminal. The front-end and backend deployment is based on Python and React Flask. The data layer employs the MySQL database, which encompasses pipeline defect data, employee records, and evaluation reports. The service layer primarily functions as a network model for pipeline defect detecting and tracking.

VII. CONCLUSION

This study introduces a technique for detecting and tracking defects in drainage pipelines using YOLO-DS model. It successfully accomplishes automated identification and counting of three different types of defects. First, the YOLOv7 algorithm significantly enhanced defect identification and monitoring effectiveness. Second, the DeepSort multi-object tracking algorithm successfully tracks and counts defects by utilizing outcomes from the YOLOv7 detection algorithm. This has effectively resolved the issue of redundant counting in conventional detection methods. Third, an information management platform for detecting defects in drainage pipelines has been developed. The platform utilizes intelligent detection and tracking techniques to analyze defects according to professional evaluation criteria. It generates health assessment reports for different sections of the pipelines, facilitating the development of maintenance plans.

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