Journal of Electronic Research and Application, 2025, Volume 9, Issue 3
http://ojs.bbwpublisher.com/index.php/JERA
ISSN Online: 2208-3510
ISSN Print: 2208-3502

Drone Digital Twin Is Used for Water Plant Inspection

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Abstract: Inspection is a fundamental task for water plants, yet traditional methods are often labor-intensive, time-consuming, and costly. The rapid advancement of drone technology has significantly transformed environmental inspections, particularly in water plant assessments. Digital twins enhance modeling and simulation capabilities by integrating real-time data and feedback. This paper presents an intelligent water plant detection system based on YOLOv10 and drone technology. The system aims to monitor environmental conditions around water facilities and automatically identify anomalies in real time. The design utilizes dataset images of construction vehicles, maintenance hole covers, and pipe leaks collected from publicly accessible websites. The system integrates real-time drone inspection data into a digital twin platform for dynamic monitoring.

Keywords: Drone inspection; Digital twin; YOLO v10; Water plant

Online publication: 5 June, 2025

1. Introduction

1.1. Research background

Water treatment plants, serving as essential components of urban water supply networks, are crucial for maintaining consistent residential water usage and supporting industrial activities. By the close of 2023, the total number of urban water plants in China surpassed 8,000, with a planned daily water processing capacity reaching 170 million cubic meters. Despite their significance, traditional inspection techniques continue to depend heavily on manual labor, which is often inefficient, expensive, and limited in scope. Additionally, these methods are prone to oversight or incorrect assessments due to differences in individual expertise. As urbanization progresses and water plant sizes expand, conventional management strategies are becoming increasingly inadequate to address the need for more precise operational standards.

In recent years, the rapid development of drone technology and digital twin technology has provided innovative solutions for water plant inspections [1,2]. Drones leverage their mobility to efficiently cover complex areas of water facilities, collecting real-time data through high-definition cameras and infrared sensors. Meanwhile, digital twin technology enables real-time monitoring and predictive maintenance by creating virtual replicas of physical infrastructure. This paper proposes a smart inspection system for water plants that integrates drone technology with digital twins, incorporating the YOLOv10 algorithm to achieve real-time detection and intelligent analysis of environmental anomalies around water facilities. The system has been validated through practical applications, demonstrating significant improvements in inspection efficiency and accuracy, thereby offering technical support for the digital transformation of the water industry.

1.2. Research purpose and significance

This study focuses on developing an intelligent inspection system for water plants by combining drone technology with digital twin solutions. This system facilitates continuous surveillance of the plant's external environment and automates the process of detecting anomalies. Its primary objectives are to improve inspection efficiency and precision, cut down operational expenses, and ensure reliable protection for the secure and consistent operation of water infrastructure. The research carries substantial practical significance in terms of accelerating the digital evolution of the water sector and reinforcing urban water supply safety. From a broader industry standpoint, it encourages the fusion of cutting-edge technologies such as digital twins and AI into water management practices, thereby fostering advancements in smart water systems. On a societal scale, the system enhances the dependability of water delivery, lessens the negative consequences of supply interruptions on daily living and industrial activities, and guarantees the uninterrupted performance of essential urban services.

1.3. Research status at home and abroad

Global studies on digital twin technology and its applications in smart water plants have progressed earlier and achieved relatively advanced technological implementation. Several developed nations have effectively incorporated digital twin systems into the planning, building, and operational oversight of water infrastructure. Through the creation of highly accurate digital representations, these systems facilitate continuous surveillance of equipment conditions, early fault detection, and enhanced optimization of water plant operations [3–6].

Digital twin technology establishes dynamic cyber-physical systems by merging information from physical objects, sensor inputs, and simulation frameworks [7–9]. In the context of smart water plant construction, this method integrates BIM models, oblique photography measurements, and additional resources to produce simplified 3D virtual representations while improving operational decisions through live data synchronization [10,11]. As an example, Singapore's PUB Water Authority achieved a 30% reduction in equipment failure reaction times by leveraging digital twin technologies [12].

The growing adoption of drone technology in water plant operations is driven by its efficiency and cost-effectiveness, gradually replacing traditional manual inspection techniques. Researchers both domestically and internationally have extensively explored the use of drones equipped with multisensory payloads for detailed assessments of infrastructure and pipeline systems. By following preprogrammed flight routes, drones can perform multi-perspective inspections of essential assets such as structures, pipelines, manholes, and more, while simultaneously gathering environmental data like temperature, humidity, and pressure levels. A prominent case is seen in Dali City, located in Yunnan Province, where intelligent drone-based inspections now monitor 80 square kilometers each day, resulting in an efficiency enhancement 16 times greater than conventional manual approaches [13].

2. Intelligent inspection model based on deep learning

The mainstream deep learning object detection algorithms can be categorized into two primary structures: two-stage detection algorithms and single-stage detection algorithms. While the two-stage approach generally offers slightly higher detection accuracy, it is associated with a relatively slower detection speed. This type of algorithm incurs significant computational costs when identifying candidate regions and often experiences some degree of overlap or crossover in the methods used to acquire these regions. In contrast, the single-stage detection algorithm addresses these issues by rasterizing the input image. Consequently, this study employs the single-stage object detection algorithm YOLOv10 for inspection anomaly recognition. This choice not only decreases computational expenses but also enhances detection efficiency.

2.1. YOLOv10 network

The YOLO (You Only Look Once) series currently represents one of the most prominent end-to-end object detection algorithms. Initially introduced by Redmon *et al*., it has evolved and led to the release of several versions [14]. The YOLO series has remained a leader in this field due to its ability to balance effectiveness with computational efficiency. Nevertheless, its dependence on non-maximum suppression (NMS) and certain architectural limitations hinders it from reaching peak performance. Through the implementation of a unified dual allocation strategy that eliminates the need for NMS during training, YOLOv10 achieves further improvements in both efficiency and precision compared to earlier models like YOLOv7 [15].

YOLOv10 focuses on enhancing both the efficiency and accuracy of the model during its design phase. It introduces a training strategy that eliminates the need for non-maximum suppression (NMS), utilizing dual label assignment and a consistent matching metric, which results in high efficiency and competitive performance. Building upon C2f, YOLOv10 incorporates a compact inversion module and leverages depth-wise separable convolutions for feature extraction, thereby reducing computational demands while preserving feature representation capabilities. The C2fCIB module initially extracts and fuses multi-path features via the C2f module, followed by expanding and compressing these features through the CIB module, which significantly boosts the overall feature expression capacity.

Self-attention mechanisms have gained popularity in numerous visual tasks due to their exceptional ability to model global relationships. Nevertheless, these mechanisms often come with high computational demands and significant memory usage. To address this issue, YOLOv10 introduces an efficient partial self-attention module. More specifically, the feature maps are split into two equal portions using a 1×1 convolution. One of these portions is subsequently passed through an NPSA block, which integrates a multi-head self-attention component and a feedforward network. Following this, the two feature subsets are concatenated and merged via another 1×1 convolution operation. This approach enables the incorporation of global representation learning into the YOLO framework with minimal computational overhead, thereby strengthening the model's capacity and boosting its overall performance.

2.2. YOLOv10 model configuration and training

This study utilizes network open datasets and manually gathered UAV inspection images as samples. The focus of this research is on three types of anomalies: missing manhole covers, unauthorized construction, and pipeline leaks. Considering the current challenges in water plant pipeline inspections, such as extensive coverage areas, significant lengths, and delayed awareness of on-site conditions, an intelligent inspection approach has been developed for the following three scenarios, as illustrated in **Table 1**.

Table 1. Describes the inspection scenarios

ID	Scenes	Scene statement
1	Missing manhole cover	Identify water plant manhole covers that are missing or broken through inspection pictures
2	Illegal construction	Through inspection of pictures to identify whether there is illegal construction around the water plant
3	Pipeline leakage	Through inspection pictures to identify the water plant around the pipeline whether there is bare leakage or pipe leakage

Choose various datasets based on specific inspection scenarios and utilize the YOLOv10 network to combine and train these multiple datasets. The scale of the datasets, along with the number of labels associated with each scenario, can be found in **Table 2**.

Table 2. Data set introduction

Scenes	Data set size (number of pictures)	Number of annotations	Type of label
Missing manhole cover	3748	4337	10
Illegal construction	4981	7798	10
Bare leakage of line	3586	3586	2

To align closely with engineering application scenarios, the images were neither resized nor cropped, and no adjustments were made to their brightness or contrast. The Labelme tool was utilized for segmenting and marking anomalies within the images. These annotated images were subsequently divided into a training set, validation set, and test set at a ratio of 7:2:1, respectively, for purposes of model training, performance validation, and testing.

During the model's training phase in this study, the original YOLOv10n model served as the baseline. All experiments incorporated the pre-trained weights supplied officially. To maintain consistency and comparability in experimental outcomes, an SGD optimizer was chosen, with each round of experiments set to run for 100 epochs. Throughout the training process, a cosine annealing strategy was employed to adjust the learning rate, ensuring effective learning by the model. Details of the experimental environment are presented in **Table 3**, while the parameters utilized by the model are outlined in **Table 4**.

Table 3. Experimental configuration

Name	Parameters
Operating system	Ubuntu
GPU	NVIDIA GeForce RTX 4080*2
CUDA	12.4
Deep learning Framework	Pytorch
Language	Python

Table 4. Parameter settings

Name	Argument
Training batch size (batch-size)	16
Picture size (img-size)	640 x 640
Number of training iteration rounds (epochs)	200

2.3. Training results and test analysis

Assessing the YOLO model is a crucial step in analyzing its performance following the training phase. This process aids in pinpointing the model's advantages and disadvantages while informing the refinement of future training approaches. The evaluation employs a range of metrics to measure the model's effectiveness in object detection tasks, such as precision, recall, F1 score, and mean average precision (mAP), among others.

(1) Precision: The proportion of samples predicted as positive that truly belong to the positive class. A greater value suggests fewer mistakes in the positive class of samples identified by the model;

(2) Recall: The ratio of actual positive samples correctly identified as positive. A higher value indicates that the model is capable of identifying a greater number of true positive instances.

(3) F1 score: A balanced metric that combines precision and recall through a weighted harmonic mean, utilized to assess the model's overall performance on both positive and negative samples;

(4) Mean average precision (mAP): A combined metric utilized to assess an object detection model. It computes the average precision (AP) for each category and subsequently calculates the mean of these AP values across all categories. By considering the model's effectiveness across various classes, mAP offers a comprehensive evaluation of the model's overall performance.

Recall focuses on the predicted positive and negative cases about the actual positive cases. A higher recall indicates fewer false negatives (FN), meaning fewer positive cases are incorrectly classified as negative. This can be interpreted as selecting a greater number of positive cases. Higher recall corresponds to fewer overlooked instances. The precision-recall (P-R) curve is constructed using precision and recall as the respective coordinates. The closer the P-R curve approaches the upper-right corner of the coordinate system, the better the model's performance. As shown in **Figure 1**, the model's average precision value is 0.835.

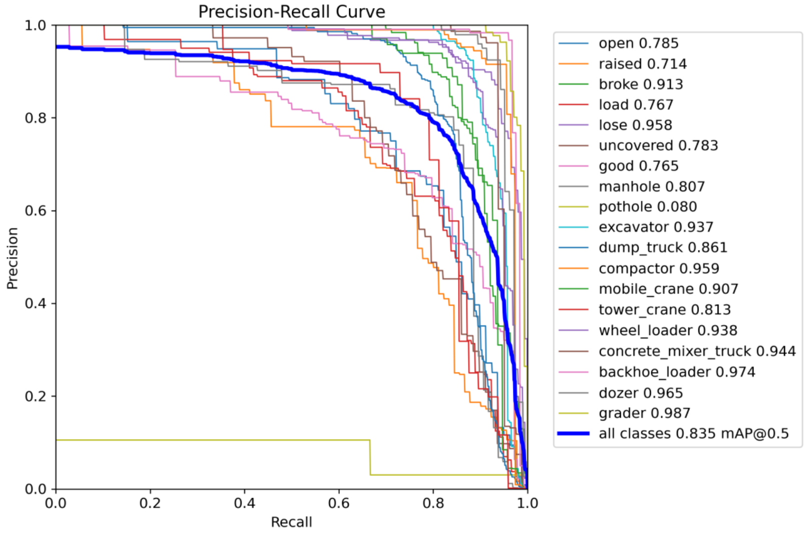

Figure 1. P-R graph

3. Drone inspection based on digital twin platforms

A digital twin platform is a unified system that utilizes digital tools to fully simulate, oversee, and manage water supply infrastructure.

The platform integrates visualization techniques with video fusion and Building Information Modeling (BIM). It establishes a digital twin data framework by choosing source plants as research objects, leveraging geographic information, images, oblique photogrammetry models, BIM designs, surveillance footage, and videos captured by drones.

By leveraging this data infrastructure, the platform incorporates cutting-edge technologies like machine learning and artificial intelligence to create image recognition-driven smart inspection functionalities. Furthermore, it integrates models for analyzing reservoir capacity in water resource management, facilitating early alerts and predictive simulations of water supply conditions.

The inspection system, equipped with image recognition capabilities, utilizes drones to reach challenging areas, perform real-time surveillance, and gather information, greatly improving both the efficiency and safety of inspections. While in operation, these drones can quickly evaluate the status of pipelines and provide instant notifications regarding significant problems, such as pipeline damage caused by construction activities.

The implementation of digital twin technology in intelligent water supply plants forms an integrated system that enables complete simulation and oversight of the infrastructure. The smart inspection model utilizes sophisticated algorithms, such as object detection and image recognition, to automate the process of detecting abnormalities.

Drones, fitted with high-resolution cameras and advanced sensors, carry out detailed inspections of peripheral facilities, collecting a wealth of image and data information. Real-time processing of this data is achieved through deep learning-powered anomaly detection algorithms. Built around the Digital Twin platform, the system incorporates an intelligent inspection module, where drones send live video streams to cloud servers using 5G technology. Seamless interaction with the digital twin platform is enabled through RESTful API interfaces, creating a comprehensive operational framework.

4. Conclusion

This research effectively established an intelligent inspection system for water plants by combining drone technology with digital twin concepts. The system integrates anomaly detection via drones using the YOLOv10 algorithm, the creation and visualization of digital twin models, and advanced inspection capabilities. Real-world application examples indicate that this system substantially improves inspection efficiency and precision, cuts down on operational expenses, and ensures reliable support for the secure and stable functioning of water infrastructure. Additionally, the novel fusion and practical implementation of these technologies during the study provide meaningful insights for promoting the use of digital twins within the water sector.

Disclosure statement

The authors declare no conflict of interest.

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