**Research review on drainage pipe defect identification technology**

**Abstract**

**As urban underground drainage networks age, various internal defects gradually develop in pipelines, compromising their operational efficiency. Consequently, condition assessment of drainage systems has become essential for municipal authorities. However, manual inspection methods remain prevalent due to inefficiency and subjectivity, often leading to misjudgments. To address these challenges, researchers have integrated pipeline detection technologies with machine learning and deep learning frameworks, achieving automated and efficient defect identification. This paper systematically reviews existing methodologies and research achievements in drainage pipeline defect recognition, providing a comprehensive overview of current approaches.**

**Keyword**

**Drainage pipes; defect identification; machine learning; deep learning**

**1. Introduction**

As a vital infrastructure for urban operations, the drainage network system directly impacts economic development and plays a crucial role in maintaining modern city functions, serving as a key safeguard for environmental cleanliness[1]. With accelerated urbanization in recent years, pipeline coverage has expanded significantly. However, most drainage systems have been in service for over a decade, and with extended operation periods, defects such as leaks, deformation, and ruptures gradually emerge[2]. If these issues remain undetected and unrepaired, contaminated water containing microorganisms can pollute soil, hinder vegetation growth, and even cause blockages leading to urban flooding – posing safety risks to residents. Therefore, conducting defect detection on drainage pipelines is essential to ensure public safety and property protection[3]. The challenge of efficiently identifying pipeline defects while maintaining drainage network stability remains a critical research focus[4].

Current assessment of drainage pipeline conditions remains constrained by existing detection technologies. Delays in pipeline inspection can lead to numerous issues in network management and maintenance[5-7], making regular system health checks essential for municipal departments to formulate maintenance strategies[8]. However, the complex internal structures of pipelines present significant challenges: the built-in lighting systems of inspection equipment often cause reflections when water is present, resulting in blurry video or image quality. Traditional manual inspections suffer from low efficiency and require substantial human input. Moreover, subjective factors in pipeline reflection detection frequently lead to misjudgments during condition assessments[8]. Therefore, developing intelligent pipeline defect detection systems offers dual advantages: it significantly reduces labor costs while simultaneously enhancing detection efficiency and accuracy. By eliminating subjective errors in manual interpretation, this approach provides more reliable data support for pipeline system operation and maintenance decisions.

The technologies employed for drainage pipeline inspection primarily include Closed-Circuit Television (CCTV) detection, QV detection, laser detection, ground-penetrating radar detection, and ultrasonic detection[9]. While all these methods can assess the internal condition of drainage pipelines, each has its limitations. Among them, CCTV detection stands out as the most practical approach for defect identification across various pipeline scales, making it the primary method in drainage pipeline inspection[10]. However, since manual interpretation of image data captured by CCTV systems results in low efficiency, many researchers have integrated machine vision and deep learning techniques into pipeline inspection processes. This paper introduces and analyzes the application of computer vision and deep learning in image processing for drainage pipeline defect detection, while also presenting future prospects for the development of pipeline inspection technologies.

**2. Classification and detection technology of drainage pipe defects**

**2.1. Classification of drainage pipe defects**

Drainage pipeline defect identification not only detects the presence of defects but also determines their specific types. Defect coding forms the foundation of pipeline defect recognition, with variations observed across countries in defect definition, classification, and evaluation processes[11]. The UK categorizes drainage pipeline defects into three types: structural, functional, and construction-related. Structural defects are classified based on physical condition and severity of structural damage, comprising 13 subcategories; functional defects are categorized according to operational capacity, including 7 subtypes; while construction-related defects follow construction content principles, featuring 11 levels of classification. Compared to international standards, China's defect classification system exhibits two distinctive features: first, fewer categories with simpler classifications; second, coexistence of qualitative and quantitative assessments for individual defects. This dual approach provides annotation support for intelligent classification and grading of defect samples. According to China's current unified standard "Technical Code for Inspection and Evaluation of Urban Drainage Pipelines" (CJJ 181-2012), drainage pipeline defects are classified into two main categories: structural defects (including ruptures, misalignment, leaks, deformation, concealed branch connections, foreign object penetration, and disconnections) and functional defects (such as tree roots, obstructions, scaling, and sedimentation[12]). See Table 1.

Table 1 Drainage pipe defect classification system [13]

|  |  |  |  |
| --- | --- | --- | --- |
|  name  |  definition  | Defect coding | Name of defect |
|  structural limitation  | The structural condition of the pipeline is impaired and it is no longer capable, at present or in the foreseeable future, of meeting the required level of service compared with its intended condition. | PL |  break  |
| CK |  staggered joint  |
| SL |  percolation  |
| BX |  be out of shape  |
| AJ | Bypass the branch pipe |
| CR | Foreign body penetration |
| TJ |  ungear  |
|  functional defect  | The operation state of the drainage pipe is affected, and the water passing capacity is reduced and blockage occurs | SG |  tree stump  |
| ZW |  obstacle  |
| JG |  deposit  |
| CJ |  deposit  |

**2.2 Drainage pipe defect detection technology**

CCTV inspection technology, the most widely used method for drainage pipeline detection, originated abroad and was introduced to China in the 1990s[14]. This technology utilizes closed-circuit television (CCTV) systems to visually inspect pipe interiors. During inspections, a crawler equipped with high-definition cameras and lighting enters the pipeline at controlled speed, capturing real-time footage of internal defects like cracks, blockages, and corrosion. The video signals are transmitted via cables to monitors while synchronized position data is recorded using encoders or positioning systems. Post-inspection analysis software identifies defects and generates detailed reports. With its efficient operation and intuitive interface, this technology proves particularly suitable for drainage pipelines and industrial piping systems.

Laser detection technology, a non-destructive testing method for drainage pipelines that emerged in recent years, utilizes the high directionality and monochromaticity of lasers to achieve precise measurements. During operation, the laser transmitter emits a beam onto the target surface. By receiving reflected light signals and combining them with optical sensors and algorithms to calculate changes in the light spot's position or phase, this technology acquires information about the measured object's dimensions, morphology, displacement, or defects. Common laser detection methods include triangulation (for contour scanning), laser interferometry (for measuring minute displacements), and laser diffraction (for detecting surface defects).

Quick View (QV) inspection, also known as periscope inspection, is a portable detection technology for rapid drainage pipeline investigation. The core equipment consists of a telescopic high-definition camera and a powerful lighting system. During operation, technicians insert the camera into inspection wells or pipe openings, adjusting the telescopic length and lens angle (typically 360° rotatable) to capture real-time images of the pipe walls transmitted to handheld terminals. Equipped with wide-angle lenses and zoom capabilities, the cameras can clearly identify defects such as cracks, sediment buildup, and tree root intrusion. Advanced models integrate laser rangefinding and GPS positioning functions to precisely locate defect locations. Compared to CCTV inspections, QV inspection eliminates the need for pipe entry, making it suitable for large-diameter pipelines, shallow burial scenarios, or temporary rapid screenings. It offers advantages like user-friendly operation, cost-effectiveness, and high efficiency. However, its detection range is limited by telescopic length (generally not exceeding 10 meters), rendering it unsuitable for long-distance or complex pipeline networks. This technology is commonly used for routine drainage pipeline inspections or preliminary assessments, providing reference data for subsequent detailed investigations.

Ultrasonic testing technology evaluates drainage pipeline conditions by utilizing the propagation characteristics of high-frequency sound waves in media. During detection, ultrasonic probes emit pulse waves toward pipe walls. When encountering defects (such as cracks or thickness variations) or sediment deposits within the pipeline, these waves undergo reflection, scattering, or attenuation. By analyzing echo signals, the probe detects propagation time, amplitude changes, and frequency characteristics to accurately determine defect locations, sizes, and remaining wall thickness. This technique is applicable to both metallic and non-metallic pipelines, demonstrating particular effectiveness in detecting hidden internal defects like cavities and delamination.

Ground Penetrating Radar (GPR) technology employs high-frequency electromagnetic waves for non-destructive detection of underground drainage pipelines. During operation, the radar antenna emits electromagnetic pulses toward the surface. When these waves encounter pipelines (demonstrating significantly different dielectric constants compared to surrounding soil) or structural defects, part of the energy is reflected back to the ground and captured by the receiving antenna. By analyzing the reflection wave's delay, amplitude, and waveform characteristics, the system can determine the pipeline's burial depth, direction, diameter, as well as detect anomalies such as voids and leakage zones in the surrounding soil. This technology offers advantages including trenchless inspection and real-time imaging (capable of generating 2D cross-sections or 3D models), making it particularly suitable for locating non-metallic pipelines like concrete and PVC pipes. The maximum detection depth reaches 5-10 meters (depending on soil conductivity and antenna frequency). However, detection effectiveness may be affected by groundwater levels, metallic interference, or dense clay layers. Data interpretation requires geological data integration, typically serving as supplementary tools for drainage pipeline surveys and hazard prediction.

Analysis of the aforementioned drainage pipeline inspection technologies reveals that while numerous methods exist for pipeline evaluation, most suffer from limitations such as high costs and inaccurate results. Table 2 summarizes these detection techniques, enabling engineers to strategically select appropriate methods for practical applications.

Table 2 Comparison of drainage pipe detection technology

|  |  |  |  |
| --- | --- | --- | --- |
|  measurement technique  |  operational principle  |  working load  |  boundedness  |
| CCTV check  | Optical capture | High (referring to defect interpretation) | It takes a long time, the efficiency is low, the detection effect is unstable and the labor cost is high |
| Laser detection | Optical capture |  tall  | Suitable for dry and clean pipeline detection, unable to identify internal structural defects |
| QV check  | Optical capture |  low  | The detection distance is short and the information below the water flow cannot be detected |
|  ultrasonic inspection  | Ultrasound scanning imaging |  same as  | The detection efficiency is low and it cannot be used in a large range of pipelines |
| Ground-penetrating radar detection | Radar scanning and imaging |  tall  | Due to the limitation of the material of the object under test, the internal information of the pipeline cannot be effectively detected |

**3. Research status of drainage pipeline defect identification method**

In recent years, with economic development and accelerated urbanization, the scale of drainage networks has been expanding significantly. Consequently, pipeline inspection technologies have gained widespread application. During inspections, substantial amounts of video footage and images are generated, which require extensive manual interpretation and classification of defect types. However, due to human subjectivity and the enormous workload involved, this process often results in inaccurate interpretations and low efficiency. To address these challenges, numerous scholars have integrated machine vision and deep learning techniques into drainage pipeline inspection systems.

**3.1. Drainage pipeline defect identification based on traditional machine learning**

Machine learning is the process where computers extract data features from massive datasets, learn through model training to solve specific problems. While it doesn't rely on fixed rules, it requires humans to define learning features first, then automatically map relationships to identify and classify defects[15]. Common traditional machine learning classifiers include Decision Tree (DT) algorithm[16], Support Vector Machine (SVM) algorithm[17-18], K-Nearest Neighbor (KNN) algorithm[19], and Naive Bayes algorithm[20]. The DT algorithm classifies new data using tree structures derived from historical data, extracting a tree-like classification model from unordered training samples. The SVM algorithm works by mapping feature vectors into higher-dimensional space, transforming nonlinear problems into linear ones in high-dimensional space. By maximizing classification margins, it obtains the optimal hyperplane for classification while enhancing the model's generalization ability. The KNN algorithm is a supervised machine learning method that uses labeled training sets and unlabeled test sets. It identifies the K nearest training samples in the training set and assigns the test set's category based on the majority class among these samples. Naive Bayes algorithm mainly uses probability knowledge to classify, which requires the prior probability to be clear and assumes that attributes are independent of each other. Therefore, it can only be used in specific scenarios.

The research titled "Moradi S[21]" proposes a machine learning method for real-time automatic defect detection in CCTV surveillance videos of drainage pipelines. By leveraging computer vision technology to extract pipeline image features and employing machine learning algorithms, the system effectively identifies common defects such as cracks, corrosion, and tree roots. Experimental results demonstrate that this approach meets real-time detection requirements while significantly improving accuracy compared to manual inspection methods. This study provides a practical solution for intelligent inspection of urban underground pipelines

Zhen Zhen [22] Based on the classification complexity of machine learning, two supervised learning-based classification models were introduced and constructed: a traditional machine learning model combining SVM-KNN and a deep learning classification model based on the VGG16 backbone. The optimized VGG16 convolutional neural network model was ultimately determined to be most suitable for underground drainage pipeline defect image classification. Its classification accuracy significantly outperformed human visual recognition, enabling accurate and rapid identification of defective images while demonstrating considerable scalability and generalization potential.

Sinha S K[23] proposed a pipeline scanning image classification method that integrates feature extraction with neural fuzzy algorithms. By extracting key visual features from images and employing a neural fuzzy system for pattern recognition, this approach achieves automated classification of pipeline defects such as cracks and deformations. Experimental results demonstrate that compared to traditional neural networks, this method exhibits higher classification accuracy and robustness while effectively handling image uncertainties and noise. This provides a reliable technical solution for early-stage pipeline defect detection.

Zheng Maohui et al. [24] proposed a drainage pipeline defect diagnosis model based on GA-ELM for intelligent identification of pipeline defects. By optimizing the initial weights and thresholds of ELM through genetic algorithm (GA), the model's classification performance for detecting pipeline cracks, leaks, and other defects was significantly enhanced. Experimental results demonstrated that GA optimization of ELM network parameters achieved higher diagnostic accuracy, with test set precision increasing from 65.59% to 82.96%. The GA-ELM model exhibits superior diagnostic accuracy and stability, providing an effective solution for intelligent inspection of urban drainage networks.

Traditional machine learning demonstrates significant advantages in automated detection and recognition accuracy, efficiently processing image data to achieve high-accuracy defect classification. However, practical applications still face multiple challenges, as model performance heavily depends on data quality and requires substantial annotated samples. For drainage pipeline defect detection, integrating computer vision technologies (such as CNN-based feature extraction) with intelligent optimization algorithms (like GA-ELM) can effectively enhance system performance. Yet when handling large volumes of video or image data, traditional machine learning methods prove inadequate. For instance, when processing massive high-resolution images, the computational complexity of feature extraction and model training grows exponentially, leading to significant speed degradation. Consequently, deep learning has gradually replaced traditional machine learning as the mainstream solution for large-scale visual data applications. Nevertheless, traditional machine learning remains valuable in specific scenarios where its unique strengths are evident.

**3.2. Drainage pipeline defect identification based on deep learning**

Deep Learning (DL), a subfield of machine learning, operates by simulating the human brain's hierarchical information processing mechanism through multi-layer neural networks. These systems automatically learn multi-level feature representations from data to accomplish complex tasks such as classification, regression, and generative modeling. The fundamental theory of deep learning relies on multi-layer neural network architectures that abstract and combine features through multiple hidden layers, enabling the system to learn nonlinear mappings from inputs to outputs[25].

In 1943, Warren Mcculloch et al. [26] first explicitly gave the definition of artificial neural network in their paper and established the relevant mathematical model, so artificial neural network officially entered people's vision [27]. Related research was carried out in full swing, so many scholars applied deep learning to the field of drainage pipeline defect identification.

In their study [28], KUMAR S S et al. developed an automated deep convolutional neural network (CNN) system for detecting pipeline defects (including cracks and tree roots) in CCTV surveillance footage of drainage systems. By constructing a specialized defect dataset and optimizing the network architecture, the method achieves high-precision defect identification. Experimental results demonstrate that this approach significantly outperforms traditional image processing techniques in classification accuracy while demonstrating strong adaptability to complex background interference. The solution provides a reliable framework for intelligent inspection of urban drainage networks.

In the research of LI D et al., a hierarchical classification method based on deep convolutional neural networks (DCNN) was proposed to address the issue of sample imbalance in CCTV detection data for drainage pipelines. To tackle common pipeline damages such as cracks and corrosion, the authors developed a hierarchical classification architecture that significantly improved detection performance for minority classes. Experimental results demonstrated that the method maintained high recall rates even under imbalanced sample distributions, showing clear advantages over traditional CNN and machine learning approaches. This provides an effective solution for intelligent analysis of imbalanced pipeline inspection data in practical engineering applications. The study also verified the method's generalization capability across different urban drainage pipeline defect datasets.

Lu Bing et al. [30] developed a convolutional neural network-based detection method for drainage pipeline defects in CCTV surveillance systems, conducting comprehensive research on network selection optimization and training enhancement. This innovative approach significantly elevates the intelligence and automation of defect detection, reduces manual labor requirements in field operations, while effectively addressing urban drainage infrastructure inspection needs.

Cheng J C et al. [31] first proposed the use of Faster R-CNN technology to automatically detect drainage pipe defects in CCTV images, and through experiments, it is shown that this method can accurately, quickly and accurately detect sewage pipeline defects.

He Min et al. [32] developed an intelligent drainage pipeline defect classification model using AlexNet and ResNet50 frameworks through transfer learning. After optimizing network parameters via sensitivity analysis, both models achieved 92.00% and 96.50% accuracy rates on the test set, respectively, with ResNet50 demonstrating superior performance. Engineering validation showed practical application accuracy ranging from 85.41% to 87.94%, confirming the method's effectiveness in enhancing automated pipeline defect classification accuracy and its strong engineering applicability. This research provides reliable technical support for intelligent detection of drainage networks.

In summary, deep learning technology has proven effective in pipeline defect detection, replacing manual inspection with high efficiency and stable performance. By developing a convolutional neural network (CNN)-based intelligent detection system, the technology can automatically identify various defects such as cracks, corrosion, and sediment buildup on pipe interiors, achieving over 90% accuracy rates – significantly higher than traditional manual inspections at 60%-70%. Through analyzing CCTV surveillance footage, this system enables real-time processing of multiple frames per second, reducing single-detection time by over 80% compared to manual methods, thereby substantially improving efficiency. Moreover, deep learning models maintain consistent performance without human bias or fatigue effects, ensuring reliable results. In practical engineering applications, these intelligent systems demonstrate notable advantages: they automatically generate standardized defect reports detailing location, type, and severity, while also establishing pipeline health databases to support maintenance decisions through data-driven analysis.

**4. Conclusion**

This paper discusses the classification of drainage pipeline defects and detection technologies, revealing that CCTV inspection technology proves most suitable for pipeline evaluation. A review of domestic and international defect identification techniques reveals that integrating traditional machine learning, deep learning with CCTV inspection can replace manual interpretation in practical engineering applications while avoiding misjudgments. Currently, drainage pipeline defect recognition remains in its developmental stage with immature technologies. The accuracy of defect detection using machine learning and deep learning depends on pre-trained pipeline defect datasets. Although existing databases have been established for model training, the similarity and complexity of pipeline defects necessitate continuous expansion and optimization of these databases. Establishing comprehensive training datasets remains one of the primary challenges in achieving effective drainage pipeline defect detection.

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