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Advanced AI Framework for Urban Safety through Manhole Inspection and Maintenance

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Abstract:

Manholes, essential components of urban utility infrastructure, provide access to underground systems like sewers, electrical conduits, and storm drains. However, deteriorated, open, or missing manhole covers pose significant hazards to pedestrians, cyclists, and vehicles, often leading to severe accidents. Traditional inspection methods rely on manual observation, which is labour-intensive, error-prone, and inefficient, particularly in large urban areas. Moreover, the increasing frequency of manhole-related incidents highlights the urgent need for an automated and reliable solution to ensure public safety and efficient maintenance of urban infrastructure. This project addresses these challenges by proposing an advanced deep learningbased automated inspection system. The system utilizes Convolutional Neural Networks (CNN) for image classification and You Only Look Once version 8 (YOLOv8) for accurate detection and localization. It is trained on a diverse dataset to classify manhole covers into distinct categories, including 'Closed,' 'Open,' 'Broken,' 'Overflow,' and 'No Manhole.' The integration of UAV images and CCTV footage ensures comprehensive monitoring, even in hard-to-access areas or dynamic environments. By overcoming issues like variable image quality and complex backgrounds, this solution offers precise and timely identification of hazardous conditions. The implementation of this system presents a transformative approach to urban safety and maintenance. By automating the inspection process, it reduces reliance on manual labour, minimizes errors, and ensures timely intervention to address potential risks. This project not only enhances public safety but also optimizes resource allocation for infrastructure maintenance, offering a scalable and efficient solution to modern urban challenges.

Keywords:
Artificial Intelligence
Convolutional Neural Networks
Unmanned Aerial Vehicle
Closed-Circuit Television
You Only Look Once version 8
Geographic Information System (if used)
Application Programming Interface (if relevant)
Machine Learning

1. INTRODUCTION

A manhole or an inspection chamber is a unit constructed underground to provide access to the utilities like a sewer system, drainage system, etc. Hence, with the help of a manhole, underground utilities are inspected, modified, cleaned and maintained. Sewer systems are built underground with pipes that carry waste from homes and other buildings to a place of treatment or disposal. Part of maintaining a sewer system is providing frequent inspection, cleaning and repairs. Utility crews use manholes to gain closer access to pipes or other parts of the underground system to meet those needs.

Purpose of a Manhole

Manholes are built primarily for trenchless restoration of the sewer system, drainage system inspection, cleaning of clogged lines, and maintenance purposes. Manholes are also used as a first step for accessing the inside of a sewer line to help diagnose any issues with it and facilitate the replacement of damaged pipes without the need for digging. Up until the end of the main sewer line or drainage point, manholes are positioned throughout the sewer line. There are usually manholes located at several intervals down the drainage system to allow for maximum access. If one area is clear yet another is blocked, the manhole closest to the issue can be lifted and inspected, and any necessary work such as high pressure water jetting can be carried out to clear the problem. If the water is flowing in along the pipe and then stops or backs up, the location of the problem can be confirmed by lifting the manholes and monitoring the water levels. If the levels are high, it suggested there is a problem nearby which requires attention. The manhole covers are composed of metal, precas and composite material and come in a variety of sizes, materials, and designs, including rectangular, circular, and square. If the depth of the manhole chamber exceeds 2.5 m, a ladder must be installed inside; if the depth is little than 1 m, a step ladder is required.

Manhole Design

There are three different types of manholes: shallow, normal and deep. “Normal” manholes are typically 4- to 5-feet deep and wide enough for the average person to fit in. "Shallow" manholes are 2- to 3-feet deep, often placed at the start of a sewer branch and in areas with low traffic. Manholes with a depth greater than 5-feet are considered "deep" and usually have an entry method like a ladder built-in, as well as a heavier cover. Manholes are designed with a cover or lid and comprised of grade adjusting rings, a top tapered section called the cone, a main cylinder section called the wall or barrel, and a bench and channel where the waste flows through.

Types of Manhole

The three main types of manhole depending on the depth are:

Shallow Manhole

A shallow manhole has a depth ranging between 75 to 90 cm. These are constructed at the start of a branch sewer or in an area where there is not much traffic. The shallow manhole is provided with a light cover called as the inspection chamber.

Normal Manhole

These are provided at the sewer line with a heavy cover on its top. It has a depth of 150cm. Normal manhole takes a square shape.

Deep Manhole

Deep manhole is provided at a depth greater than 150cm with a very heavy cover at its top. The size can be increased and the facility for going down is also increased.

2. EXISTING SYSTEM

Manual Visual Inspection

The existing manual system for manhole defect prediction involves trained inspectors visually inspecting manholes for signs of damage or wear and tear. Inspectors typically use checklists or forms to document their findings, which are then manually entered into a database or spreadsheet for further analysis. This manual process is time-consuming and can be prone to errors or inconsistencies due to human error or subjective judgments. Inspectors may also miss certain defects or fail to identify trends or patterns in the data, leading to incomplete or inaccurate information. Furthermore, the manual system is often reactive rather than proactive, meaning that repairs or maintenance are only initiated after a defect has been identified, rather than being detected and addressed before the issue becomes critical.

Image Processing Based System

There are some existing image processing systems for manhole defect prediction. These systems use various image processing techniques such as edge detection, morphological operations, and thresholding to identify defects in manhole images. Some of the commonly used techniques are:

Sobel Edge Detection: This technique is used to detect edges in an image by calculating the gradient in the x and y directions. The edges in the image can be used to identify defects in manholes.

Morphological Operations: This technique is used to enhance or reduce certain features in an image. For example, erosion can be used to reduce the thickness of lines or edges in an image, while dilation can be used to increase the thickness of lines or edges. These operations can be used to remove noise or enhance defects in manhole images.

Thresholding: This technique is used to convert a grayscale image to a binary image by setting a threshold value. Pixels with intensity values above the threshold are set to white, while pixels with intensity values below the threshold are set to black. This technique can be used to identify defects in manhole images by setting the threshold value to highlight areas of damage or wear and tear.

Machine Learning Based System

There are some existing machine learning systems for manhole defect prediction. These systems use various machine learning algorithms such as decision trees, support vector machines (SVM), and random forests to identify defects in manhole images. These algorithms can be trained on a dataset of labelled manhole images to predict the presence of defects.

Some of the commonly used techniques are:

Decision Trees: This technique is used to create a model that predicts the value of a target variable based on several input variables. The decision tree consists of nodes that represent the input variables and branches that represent the possible values of these variables. This technique can be used to predict defects in manholes by training the decision tree model on a dataset of manhole images and their associated defect labels.

Random Forests: This technique is an extension of decision trees that uses multiple decision trees to improve prediction accuracy. The random forest model is trained on a dataset of manhole images and their associated defect labels. During training, the model creates multiple decision trees using different subsets of the input variables and data. The final prediction is made by averaging the predictions of all decision trees.

Support Vector Machines: This technique is used to create a model that predicts the value of a target variable based on several input variables. The SVM model separates the input data into different classes by creating a hyperplane in the input space. This technique can be used to predict defects in manholes by training the SVM model on a dataset of manhole images and their associated defect labels.

3. METHODOLOGY

The methodology defines the structured steps followed to develop and evaluate the proposed system.

1. Data Collection

Images of manholes were gathered from online sources, city datasets, and real-time CCTV/UAV systems.

The dataset includes images with different classes: closed, open, broken, overflow, and missing.

2. Image Preprocessing

RGB to grayscale conversion

Noise reduction using filtering

Resizing to fixed dimensions for uniformity

Binarization to enhance feature clarity

3. Segmentation Using RPN

Region Proposal Network identifies potential manhole areas in the image.

The network scans feature maps and generates anchor boxes.

Regions with high confidence are passed for further analysis.

4. Feature Extraction Using GLCM

Texture features such as energy, entropy, contrast, and homogeneity are calculated.

Helps in capturing structural patterns in manhole covers.

5. Classification with CNN

A deep CNN model is trained on extracted features.

Layers include convolution, pooling, flattening, and dense (fully connected) layers.

The CNN outputs the predicted class of the manhole.

6. Localization with YOLOv8

YOLOv8 processes the entire image once for real-time detection.

Uses anchor-free object detection with improved speed and accuracy.

Outputs bounding boxes and confidence scores.

7. Web Application Development

Frontend: HTML, CSS, JavaScript

Backend: Flask (Python), integrated with MySQL database

Users can upload images and view real-time predictions

Admins and municipal officers can track and respond to defects

8. Model Evaluation

Accuracy, Precision, Recall, and F1-score calculated using a confusion matrix

The system achieved an average accuracy of ~90%

Testing ensured robustness across various lighting and manhole conditions

4. RESULTS AND DISCUSSION

This chapter presents the outcomes of the Manhole Predictor system, focusing on the effectiveness of the deep learning models used for manhole classification and localization. The results were evaluated using various performance metrics and discussed in terms of practical applicability and limitations.

4.1 Model Performance

The classification and localization models were trained on a diverse dataset of manhole images categorized into the following classes:

- **Closed**
- **Open**
- **Broken**
- **Overflow**
- **No Manhole**

Performance Metrics Used

- **Accuracy**: Measures the proportion of correct predictions.
- **Precision**: Indicates the model's ability to correctly predict positive cases.
- **Recall**: Measures the model's ability to detect all relevant cases.
- **F1-Score**: Harmonic mean of precision and recall.

These metrics were calculated from the confusion matrix derived from the test dataset.

Metric	Value
Accuracy	90%
Precision	88%
Recall	89%
F1 Score	88.5%

These results confirm that the model provides high-quality predictions and is suitable for real-world deployment.

4.2 System Testing Results

The system underwent extensive testing through various test cases simulating different user interactions:

Test Case ID	Input Scenario	Expected Output	Result
MP001	Model training by admin with dataset	Model trained and saved	Passed
MP002	Upload of manhole image by user	Correct prediction with label and localization shown	Passed
MP003	Officer receives alert on defect detection	Notification with image and location sent	Passed
MP004	Incorrect login attempt	Access denied with error message	Passed
MP005	Officer requests repair schedule	Schedule generated with location and status	Passed

These results demonstrate that the application is robust, user-friendly, and fulfills all key functional requirements.

4.3 Visual Results

Sample visual outputs from the model include:

- **Predicted Label Displayed**: Each uploaded image is annotated with its predicted label (e.g., "Broken Manhole").
- **Bounding Boxes**: YOLOv8 accurately places bounding boxes around the detected manhole.
- **Heatmaps/Overlays** (optional): Used to visualize which areas the CNN focused on during prediction.

4.4 Discussion

Effectiveness

The high accuracy and fast prediction times demonstrate that deep learning (especially CNN + YOLOv8) is highly effective for manhole detection and classification. The automated system reduces human effort, ensures faster intervention, and improves public safety.

Real-World Applicability

The web-based platform provides remote access to municipal workers, allowing them to receive notifications, visualize predictions, and plan repairs without on-site inspections. This drastically improves the efficiency of urban infrastructure maintenance.

Limitations

- **Data Dependence**: Model accuracy may degrade with poor image quality or underrepresented conditions (e.g., rainy environments).
- **Edge Cases**: Rare manhole types or heavily obstructed views might reduce classification confidence.
- **Hardware Requirements**: Running YOLOv8 in real-time requires GPU acceleration for optimal speed.

4.5 Future Improvements

- Integrating GPS data directly from UAVs to enhance defect localization.
- Expanding dataset diversity to improve generalization across different cities and lighting/weather conditions.
- Adding a feedback loop where users can correct misclassifications to help retrain the model.

5.CONCLUSION

The **Manhole Predictor Web Application** presented in this project successfully demonstrates the power of deep learning in addressing a critical urban infrastructure problem—manhole detection and classification. By integrating advanced computer vision techniques such as **Convolutional Neural Networks (CNN)** for classification, **Region Proposal Networks (RPN)** for segmentation, and **YOLOv8** for real-time detection and localization, the system provides a scalable, efficient, and highly accurate solution for automating manhole inspections.

The system achieved an impressive average classification accuracy of **90%**, effectively identifying various manhole conditions such as **Closed**, **Open**, **Broken**, **Overflow**, and **No Manhole**. Through a user-friendly web interface, it enables municipal authorities and citizens to upload images, receive instant results, and take preventive actions—significantly improving safety and reducing the risk of accidents caused by unattended or damaged manholes. Moreover, the system's design allows for seamless integration with **UAV footage**, **CCTV feeds**, and **web-based access**, making it highly adaptable to real-world deployments in smart city infrastructure. The automation of this traditionally manual task not only reduces human labor and operational costs but also supports **predictive maintenance**, ensuring timely intervention before damage escalates.

In conclusion, this project represents a step forward in **urban infrastructure management**, combining AI, image processing, and web technologies to build a practical and impactful solution. It holds strong potential for expansion and real-world application, particularly in large-scale deployments by municipalities seeking to improve public safety and resource efficiency.

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