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MANHOLE VISUAL INSPECTION SYSTEM USING DEEP LEARNING

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Abstract: A Manhole is a covered opening in a street or public area that provides access to a utility or maintenance vault underground. Manholes are often located in public areas, and their covers need to be secure to prevent accidents. The increasing risk of traffic accidents due to the deterioration of manhole covers necessitates a more efficient and reliable inspection method. The traditional approach to monitoring manhole covers, faces challenges such as labor shortages and ethical concerns. Identifying open or broken manholes using image processing algorithms faces challenges related to variable image quality, complex backgrounds, scale changes, and dynamic environmental conditions. In response to this difficulty, the aim of this project is to propose an automated system architecture based on deep learning models to replace the manual examination process. The project involves the development of a deep learning model capable of analyzing images of manhole covers. The model undergoes training using a diverse dataset to accurately classify covers into categories such as 'Close', 'Open', 'Broken', 'Overflow' and 'Object detection'. Additionally, the system incorporates advanced techniques, including Convolutional Neural Network (CNN) for image classification and You Only Look Once version 8 (YOLOv8) for accurate prediction and localization using UAV (Unmanned Aerial Vehicle) images. The implementation of this deep learning-based architecture offers a promising avenue for enhancing urban safety and streamlining infrastructure maintenance processes.

Index Terms -Deep Learning, CNN, YOLOv8, UAV.

I. INTRODUCTION

The manhole visual inspection system can reduce the risk of accidents caused by damaged manholes, which can lead to injuries or even fatalities. This system can reduce the need for manual inspection, save costs for municipalities and other organizations responsible for maintaining manholes and improve the maintenance schedule of manholes. The system can classify manhole images accurately and quickly, making the maintenance process more efficient and reducing the amount of time required to inspect and repair manholes. The system can collect a large dataset of manhole images, which can be used to improve the accuracy of the model and identify patterns and trends in manhole condition. The web-based interface of the system makes it easy for maintenance personnel to access and use the system, improving the overall usability and accessibility of the system. The system can be easily adapted to different types of manholes and environments, making it scalable and useful for a variety of organizations responsible for manhole maintenance.

II. Related Works

Om Khare, Shubham Gandhi, Aditya Rahalkar and Sunil Mane [1] developed a system capable of accurately detecting road hazard in real-time, demonstrating the effectiveness of YOLOv8 for this task.

Apurva Kumari, P. Ashrani, Mudasar Basha and B. Sri Anjan Kumar [2] developed a system that can detect manholes and provide timely alerts or assistance to visually impaired individuals, enhancing their safety during navigation.

Ravi. M, Parvesh Ahmed. K. M and Sengottaiyan. P [3] implemented an IoT-based system for proactive monitoring of manhole status, enabling timely maintenance interventions to prevent accidents and infrastructure damage.

Yue Liang, Li Chen and Bingshi Xu [4] developed an intelligent management system that improves the efficiency and effectiveness of manhole cover maintenance, reducing the risk of failures and enhancing urban infrastructure resilience.

Xiaolin Zhang, Zanqin Wang, Hang Yu, Mei Liu and Baiqiang Xing [5] development of visual inspection technology capable of ensuring the quality and precision of manhole cover assembly, meeting the stringent safety requirements of applications like rocket fuel tank construction.

Kriti Thakur, Anikait Adhya and Chinmay Bajpai [6] uses a robust system for manhole management that leverages image processing and data analytics to improve maintenance efficiency and infrastructure resilience.

Habib Shahorier Tasin, Md Shad Sarkar and Md Asif Rahman [7] developed a detection system that effectively identifies uncapped manholes in waterlogged road conditions, reducing the risk of accidents and damage to vehicles and infrastructure, particularly during adverse weather conditions.

Liyuan Qing, Ke Yang, Weikai Tan and Jonathan Li [8] developed an automated detection system that achieves high accuracy and efficiency in detecting manhole covers in large-scale MLS surveys, enabling rapid infrastructure mapping and management.

Uroš Andrijašević, Jelena Kocić and Vladan Nešić [9] developed an detection system that accurately identifies lid openings in manholes, enabling timely intervention to prevent accidents or security breaches.

Vinay Vishnani, Anikait Adhya and Chinmay Bajpai [10] developed an system that accurately identifies and maps manholes from Street View imagery, enabling efficient infrastructure management and urban planning.

III. EXISTING SYSTEM

The existing manual system for manhole visual inspection system 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. Inspectors may also miss certain defects or fail to identify trends or patterns in the data, leading to incomplete or inaccurate information. The maintenance are only initiated after a defect has been identified. Image processing systems use techniques like Sobel Edge Detection, Morphological Operations, and Thresholding to enhance defect identification in manhole images. Meanwhile, machine learning systems employ algorithms such as Decision Trees, Random Forests, and Support Vector Machines, trained on labeled datasets, to predict defects in manhole images. These systems aim to streamline defect detection and improve accuracy compared to manual inspection methods. Traditional method suffers from labor-intensive manual inspection prone to safety risks. Limited coverage and infrequent inspections may overlook emerging issues, leading to inefficient responses and high maintenance costs. Traditional machine learning methods struggle with complex features and may fail to generalize across different conditions. Additionally, they demand significant computational resources and training data, while prone to false positives and negatives, further hindering accurate predictions and maintenance operations.

IV. METHODOLOGY

A. Data collection

The dataset collection module is tasked with assembling a diverse and extensive collection of manhole images. This dataset must encompass various conditions, including open, closed, broken, overflow, presence of pedestrians, and instances of no manhole. To achieve this, the module employs two primary components. Firstly, a web scraper automates the retrieval of manhole images from diverse online sources, utilizing specific criteria like location, size, or date to ensure dataset richness. Secondly, users are empowered to contribute to the dataset by uploading images they encounter. These user-contributed images are stored in a database for future utilization. Together, these components facilitate the creation of a comprehensive dataset essential for training the deep learning model powering the Manhole Predictor system.

B. Data Pre-processing

The pre-processing module undertakes a series of essential steps to ready the manhole images for subsequent feature extraction and classification processes. Initially, the Red, Green, Blue (RGB) to grayscale conversion simplifies image representation by condensing the three-channel Red, Green, Blue (RGB) format into a single-channel grayscale image. This conversion not only streamlines computational requirements but also enhances processing speed. Following this, resizing ensures uniformity across all images, crucial for Convolutional Neural Network (CNN) model training, by standardizing them to a fixed dimension. Subsequently, the de-noising step employs filters to eliminate unwanted pixels and fine details, thus refining image clarity and aiding feature extraction and classification accuracy. Finally, binarization transforms grayscale images into binary form, segregating them into black and white pixels based on a specified threshold value. This transformation is imperative for isolating specific image features essential for subsequent analysis. Collectively, these meticulous pre-processing steps optimize the quality and suitability of manhole images for further analysis.

C. Segmentation

The Segmentation module plays a critical role in pinpointing the region of interest (ROI) within the manhole image. Leveraging the Region Proposal Network (RPN) algorithm, it generates object proposals or ROIs, which are subsequently refined through the Region of Interest (ROI) pooling layer to yield fixed-size feature maps. The RPN, a deep convolutional neural network, operates by traversing a small network across the convolutional feature map derived from the backbone network. It evaluates the saliency of each proposed region and refines them through bounding box regression. Subsequently, the ROI pooling layer extracts fixed-size features from these proposed regions via max-pooling, yielding feature maps of consistent dimensions. These maps are then channeled into a classifier for further analysis. By employing the RPN algorithm alongside the ROI pooling layer, the Segmentation module efficiently identifies the ROI within the manhole image, facilitating subsequent processing within the Feature Extraction module.

D. Feature Extraction

The Feature Extraction module is tasked with deriving crucial attributes from segmented manhole images, pivotal for subsequent classification tasks. Employing the Gray-Level Co-occurrence Matrix (GLCM) algorithm, this module focuses on extracting texture features from the manhole images. By evaluating the spatial relationship between pairs of pixels within the image, the GLCM algorithm generates a matrix detailing the frequency of pixel pair co-occurrences across various spatial relationships and gray-level differences. From this matrix, key statistical measures such as Contrast, Energy, Homogeneity, and Correlation are computed, encapsulating the texture information inherent in the manhole image. Implemented using the scikit-image library in Python, this module processes segmented manhole images as input, generating extracted features in a tabular format. These features are subsequently stored in a database and utilized for training the classification model, thereby enhancing its predictive capabilities.

E. Data classification

The Classification module assumes the pivotal role of categorizing manhole images into distinct damage categories, employing a Convolutional Neural Network (CNN) algorithm. Comprising layers specifically tailored for learning and extracting essential features from input images, the CNN architecture encompasses convolutional layers, pooling layers, and fully connected layers. These layers collectively undertake the task of identifying critical features such as edges, corners, and blobs within the input image. Convolutional layers focus on feature detection, while pooling layers down-sample the extracted features to reduce spatial dimensions. Subsequently, fully connected layers facilitate prediction by mapping the output from preceding layers to distinct output classes, corresponding to different damage categories such as Open, Broken, Overflow, No manhole, and Human presence inside manhole. The complexity and size of the dataset dictate the configuration of layers, with weights learned during training via backpropagation and gradient descent. Once trained, the model effectively classifies new manhole images, enabling prompt identification and categorization of various damage levels within the infrastructure.

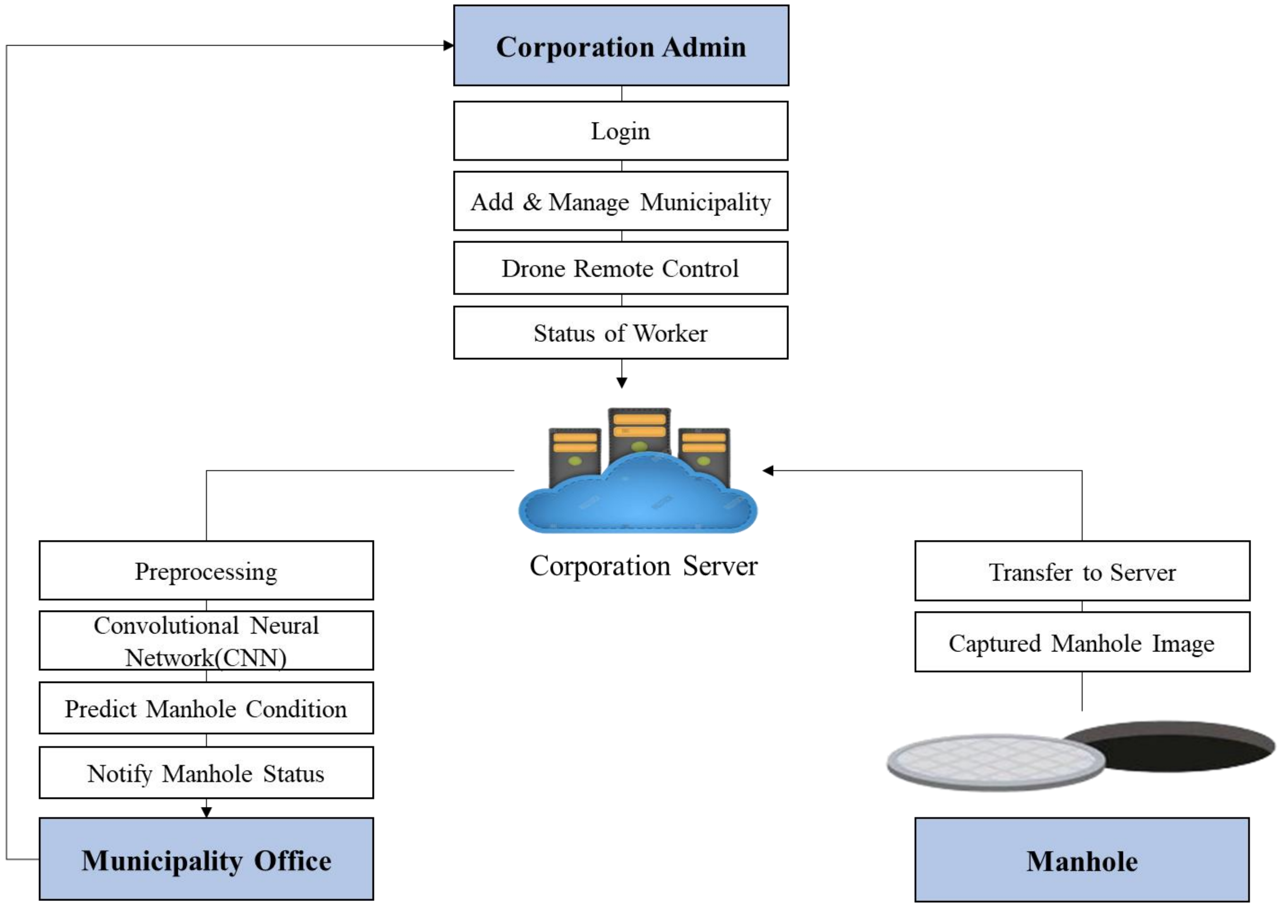

Fig. 1. Architecture diagram

V. WORKING

The fig 1 shows the architecture diagram for manhole visual inspection system workflow. The Build and Train module serves as the backbone of encompassing crucial stages from model development to deployment. Initially, the Network Architecture Definition phase crafts the model's architecture, specifying layers, activation functions, and optimization algorithms. Hyper parameter Tuning optimizes model performance by adjusting parameters like learning rate and batch size. Subsequently, Model Training utilizes prepared datasets to adjust model weights, minimizing loss. Model Evaluation assesses performance metrics like accuracy and precision using validation sets. Upon successful evaluation, models are deployed to the web application for real-world application. The Manhole Predictor module then employs this trained model to predict the condition of manholes. Beginning with the input image received from the user interface, the process undergoes pre-processing to convert RGB to grayscale, resize, de-noise, and binarize the image. Following this, Segmentation isolates the manhole cover from the background using a region proposal network

(RPN). Feature Extraction utilizes the segmented image to extract GLCM features. Classification then employs a CNN to categorize the manhole cover's condition. Predictions are made based on the output of the CNN, with the predicted class returned and displayed through the web app interface. Furthermore, the Notification module plays a vital role in promptly alerting Municipality Officers of identified manhole defects. Upon identification by the Manhole Predictor, a notification containing the location and image of the defective manhole is generated and sent to the administration.

VI. RESULT

Fig 2. Output (Overflow module)

The fig 2 shows the results for overflow classification manhole cover module and raise complaint to municipality administration.

VII. CONCLUSION

In conclusion, the development and implementation of the Manhole Predictor Web App represent a significant advancement in infrastructure maintenance practices. The proposed system of the project utilizing advanced deep learning algorithms such as Convolutional Neural Networks (CNN) for manhole classification, Region Proposal Network (RPN) for segmentation, and You Only Look Once version 8 (YOLOv8) for accurate prediction and localization, marks a significant advancement in infrastructure maintenance practices. The project has demonstrated the potential to revolutionize the inspection and maintenance of manhole covers in urban environments. The accuracy and efficiency of the prediction model showcased in the project's results underscore its effectiveness in accurately classifying manhole covers and predicting their conditions. By providing municipalities and maintenance authorities with timely and precise information about the state of manhole covers, the web app enables proactive maintenance measures, ultimately enhancing urban safety and minimizing the risk of accidents. Furthermore, the user-friendly interface and seamless communication features of the web app facilitate efficient collaboration between users and municipal officers, streamlining the maintenance process and optimizing resource allocation. Thus, this project represents a valuable tool for enhancing infrastructure management practices, contributing to safer urban environments, and laying the foundation for future advancements in smart city initiatives. With ongoing refinement and widespread adoption, the project holds the potential to significantly improve the maintenance and safety standards of urban infrastructure systems globally.

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