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SMARTPAVE: A YOLOV8-POWERED INTELLIGENT POTHOLE DETECTION AND ALERT SYSTEM FOR URBAN ROAD SAFETY

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Abstract: Potholes are areas of road surface that have cracked, worn away, and eventually formed a hole. Potholes make a ride bumpy and potentially dangerous. They can damage vehicle tires and even affect the alignment of a vehicle's wheels. With advancing urbanization, roads serve as a most important way of communication. But the increasing potholes on the roads pose a bigger danger towards public safety. Identifying and locating road potholes promptly has become a major challenge for urban construction. To address the need for improved infrastructure management, the aim of the project is to propose a pothole detection and alert system using the YOLOv8 object detection algorithm on urban road images. To enable accurate segmentation of fine-grained features, this project optimized the PothNet, which enables the segmentation head to generate high-quality masks for more accurate prediction. The proposed system serves a dual purpose, providing timely alerts to both car drivers traversing the same route and municipal authorities responsible for road maintenance. By leveraging intelligent algorithms, the system not only detects potholes but also identifies road segments in urgent need of repair. This holistic approach helps address imbalances in infrastructure maintenance efforts across cities, promoting a more equitable distribution of resources. The intelligent Pothole Detection and Alert System contribute significantly to enhancing road safety and fostering a smoother driving experience.

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

I. INTRODUCTION

Vehicular correspondence has been widely explored determined to empower the vehicles to trade data among themselves and with the framework. Vehicular adhoc network (VANET) [1] addresses an arising innovation, which works with in further developing the rush hour gridlock wellbeing and travel productivity. It permits vehicles, furnished with indispensable, sealed On-Board Unit (OBU) [2], to gather constant street condition data and offer this data with different vehicles through Side of the road Units (RSUs) [3], introduced along the streets. Street condition checking limits or forestalls street mishaps, diverts traffic away from mishaps, alarms crisis administrations utilizing the gathered data, diminishes fuel utilization, and so on [4]. Poor people and risky street conditions looking for high consideration, e.g., some geologic peril, mishaps, landslides, recognition of water over street surfaces, and so on, should be checked by a power, in particular, root authority (RA) to make ideal reactions. In CVCC [5], based street condition checking framework, VANET is joined with the distributed computing innovation and assuming that a negative street condition is distinguished, the on-street vehicles can report street condition data to the cloud server, connected by RA. Fig. 1 shows the key substances generally utilized in a CVCC system. Be that as it may, there are numerous security and protection challenges, which should be appropriately tended to for the wide sending of such system.

II. Related Works

Y. Bhatia, R. Rai, V. Gupta, N. Aggarwal and A. Akula [1] developed a system that Convolutional neural networks based potholes detection using thermal imaging .

R. Fan, U. Ozgunalp, Y. Wang, M. Liu and I. Pitas [2] developed a system that Rethinking road surface 3-D reconstruction and pothole detection From perspective transformation to disparity map segmentation.

S. Gupta, P. Sharma, D. Sharma, V. Gupta and N. Sambyal [3] developed a system that Detection and localization of potholes in thermal images using deep neural networks.

R. Fan and M. Liu [4] developed a system that Road damage detection based on unsupervised disparity map segmentation.

L. Luo, M. Feng, J. Wu and R. Leung [5] developed a system that Autonomous pothole detection using deep region-based convolutional neural network with cloud computing.

R. Ravi, H. Ayman and D. Bullock [6] developed a system that Pothole mapping and patching quantity estimates using LiDAR-based mobile mapping systems.

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.

III. EXISTING SYSTEM

This existing presents a method and evaluation results to monitor and detect road conditions (ice, water, snow and dry asphalt). The developed device bases on light polarization changes when reflected from road surface. The recognition capability has been improved with texture analysis which estimates contrast content of an image. Test drives were performed with a vehicle equipped also with a commercial solution from Vaisala which was used as the reference sensor. The results show that the proposed solution does not currently adapt to different conditions perfectly well. Therefore, further development targets have been identified to include not only more adjustable classifier but externally lighting to stabilizing ambient illumination. IcOR has earlier provided good detection results.. Unfortunately, it did not work as well during tests described here. The poor results are mainly explained by the fact that the classifier was not optimised for these specific test conditions because of limited time resources. Originally the classification parameters were modified for similar lighting and weather conditions but apparently the measurements of two different test sites varied too much. Also, the different measuring regions of the reference sensor and IcOR have some effect on the results. IcOR monitors the whole lane and its condition whereas Vaisala’s sensor was aimed to measure merely a part of the lane directly behind the left back wheel.

IV. METHODOLOGY

A. Data collection

The dataset collection module is tasked with assembling a diverse and extensive collection of pothole images. This dataset must encompass various conditions, including holes, cracks and instances of no Pothole. To achieve this, the module employs two primary components. Firstly, a web scraper automates the retrieval of pothole 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 Pothole 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 pothole images for further analysis.

C. Segmentation

The Segmentation module plays a critical role in pinpointing the region of interest (ROI) within the pothole 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 pothole image, facilitating subsequent processing within the Feature Extraction module.

D. Feature Extraction

The Feature Extraction module is tasked with deriving crucial attributes from segmented pothole images, pivotal for subsequent classification tasks. Employing the Gray-Level Co-occurrence Matrix (GLCM) algorithm, this module focuses on extracting texture features from the pothole 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 pothole image. Implemented using the scikit-image library in Python, this module processes segmented pothole 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 pothole 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 cracks, damaged holes. 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 pothole images, enabling prompt identification and categorization of various damage levels within the infrastructure.

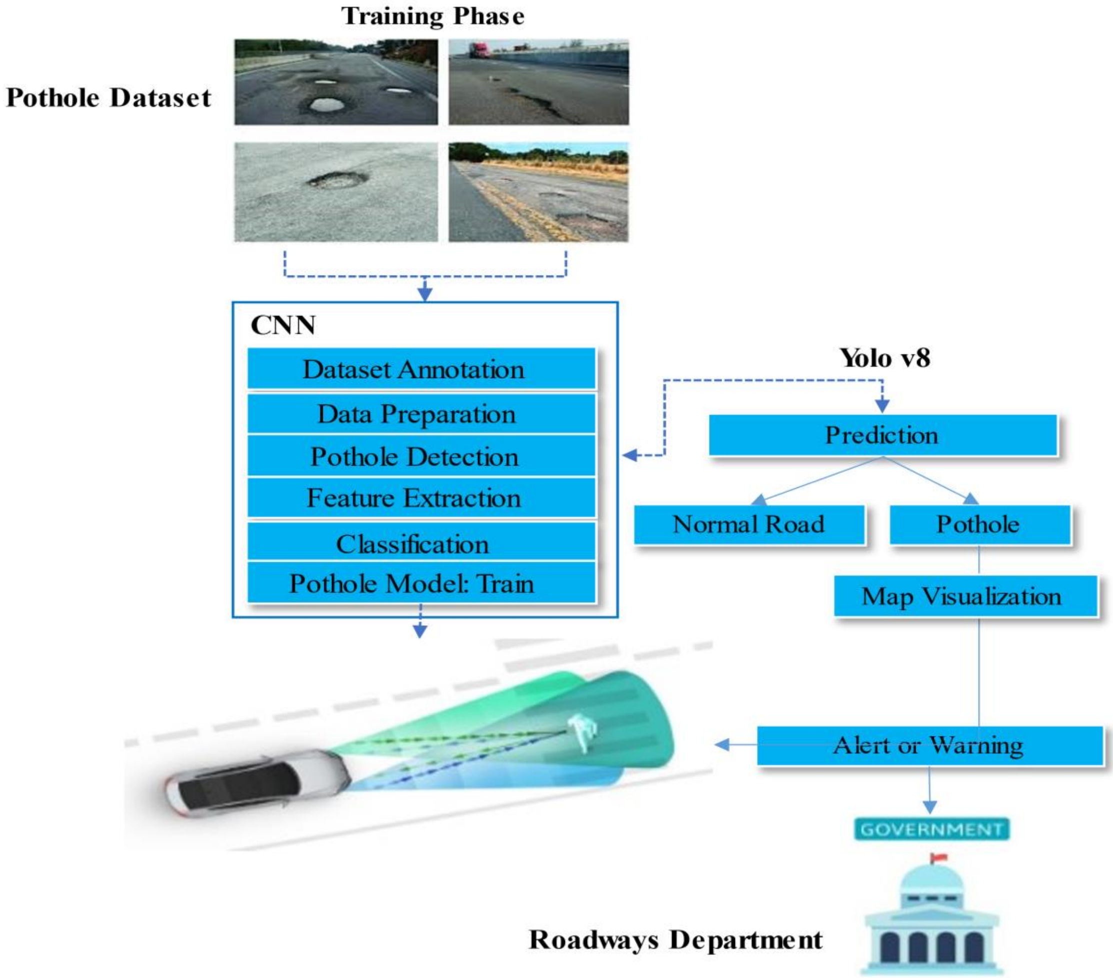

Fig. 1. Architecture diagram

V. WORKING

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 Pothole Predictor module then employs this trained model to predict the condition of Potholes. 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 pothole 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 pothole defects. Upon identification by the Pothole Predictor, a notification containing the location and image of the defective manhole is generated and sent to the administration.

VI. CONCLUSION

In conclusion, we have considered web based road condition monitoring system, where road potholes monitors real-time road conditions through a cloud server. Despite the advantages, many security and privacy threats can restrict the usefulness of this technology.. The proposed system in this paper has addressed some of these monitoring the automatically for potholes roads and report the administrations. It has useful for security purpose of the methods and it can used to any peoples are reporting to our systems .This proposed are any time monitoring to the used for survillence camera monitoring to the our location of the methods and connected to the google map so this map are identified to the reporting to road locations are identified.In addition to this, the performance of the proposed system in terms of computational cost will be evaluated to demonstrate its practicality for implementation.This are keeping to the clear roads and reduce the accidents to the vehicles then this menthods are very useful and secure of the worlds.

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