SEP 799-C01 M.Eng. Project Part 2

Vehicle-mounted Image acquisition device for infrastructure asset management

Final Report

Team

Karan Patel, Parthkumar Patel, Manmohit Chung

> Faculty Lead Ishwar Sing Seyedeh Alavi

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Abstract

Many industries are developing and deploying computer vision to improve productivity. For several applications, including travel convenience, safety, and urban sensing, efficient and economical data collection from smart cities, sensors are essential. However, to effectively utilize computer vision in these areas, efficient and cost-effective data collection methods are very crucial. Infrastructure asset management (IAM) is a challenging field where the acquisition of images of infrastructure assets is critical. Currently, IAM requires the use of photographs or videos taken to record information about the state of their infrastructure assets. This can be time-consuming and laborious, and it limits the rate of deferring issues with infrastructure assets. To address this issue, a vehicle-mounted image acquisition device must be developed to quickly collect images of infrastructure assets for analysis. The existing solution of using cameras on vehicles is the best coverage of the sidewalk. This report involves various low-cost methods to collect data and different methodologies to label the dataset and then predict the defects from the pavements.

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Background Study

As more people use mobile phones while walking, sidewalk accidents occur more frequently. Also, to improve the sidewalk in an effectively timely manner, approaching the method to detect the defects on sidewalks and take appropriate steps to mitigate the defects. (Sun, Su, Ren, & Guan, 2019). Manual inspections, photographic documentation, video surveys, LiDAR (Light detection and ranging) scanning, aerial surveys, sensor networks, and citizen reporting were traditionally used to collect infrastructure data. These approaches incurred labor, equipment, transportation, data processing, and maintenance costs. In response to these obstacles and expenses, the development of vehicle-mounted image-capturing systems offers a viable option for efficient and cost-effective data collection. Such devices can expedite the process, improve coverage, and enable more proactive infrastructure asset management by integrating computer vision and machine learning. (Group, 2023)

Project Description

The aim is to utilize computer vision for comprehending infrastructure asset conditions through the deployment of a vehicle-mounted camera equipped with onboard processing, network connectivity, and cloud storage. The hardware designated as data mules will gather both static and mobile sensor data, access roadside units, and transmit data to a cloud server. Data collection will be facilitated by employing high-resolution cameras mounted on the Robo Car assembly, ensuring optimal coverage of sidewalk pavement and above-ground assets. To enhance the data collection process, robust AI (Artificial Intelligence) algorithms will be utilized, leveraging Raspberry Pi technology. This report encompasses the utilization of raspberry pi hardware and Roboflow API for data collection, as well as methodologies for dataset labeling and processing. The effectiveness of ML (Machine Learning) algorithms incorporating computer vision will be harnessed to enhance accuracy in detecting crucial features such as potholes and signs. The goal is to determine the optimal hardware combination for vehicle-mounted data collection and explore the feasibility of incorporating additional sensors (Vibration sensor, High-Resolution Cameras, etc.) to enhance comprehension of infrastructure conditions. (Kim, et al., 2022)

Project Overview

The aim of this project is to develop a vehicle-mounted image acquisition device for infrastructure asset management. The device will utilize computer vision techniques to analyze images captured by a camera mounted on a vehicle. By deploying onboard processing, network connectivity, and cloud storage, we will create a system that can efficiently collect data, label the data for tagging sidewalk defects, and facilitate the understanding of infrastructure asset conditions.

Objectives

The primary objectives of this project are as follows:

- I. Develop a hardware implementation for the vehicle-mounted image acquisition device.
- II. Design and implement computer vision algorithms for fault detection, identification, and localization.
- III. Integrate vibration sensors with the device to enhance fault detection capabilities.
- IV. Train a neural network model to accurately classify and tag sidewalk defects.

V. Establish a reliable network connectivity and cloud storage system for data transmission and storage and create a dashboard for real time tracking of defects.



Different Types of Sidewalk Defects

Sidewalks can develop several types of defects over time due to factors like weather, usage, and material deterioration. Some common types of sidewalk defects include:

Cracks: Longitudinal, transverse, or diagonal fissures in the pavement surface caused by factors like freeze-thaw cycles, settling, or tree root growth.

Potholes: Depressions or holes formed when the pavement surface erodes or breaks down, often due to repeated stress from traffic and weather conditions.

Crumbling Edges: Deterioration of the edges of the sidewalk, leading to potential safety hazards and reduced overall structural integrity.

Uneven Settlement: Differential settling of the ground beneath the sidewalk, resulting in uneven surfaces and trip hazards.

Surface Wear: Gradual erosion of the sidewalk's surface due to foot traffic, weather, and other environmental factors. (Redmon, 2013)

However, the report focuses only on two defects that is Potholes and cracks.





Hardware Used

The following hardware components are essential for the successful implementation of this project:

- I. Raspberry Pi 4 (or higher) for onboard processing and network connectivity.
- II. High-resolution camera module compatible with Raspberry Pi for image acquisition.
- III. Vibration sensors capable of detecting road defects and communicating with the Raspberry Pi.
- IV. Storage device (e.g., microSD card) for data storage.

- V. Power supply and necessary cables for connecting the components.
- VI. Raspberry pi camera mounting encloser.

Design of Raspberry PI Enclosure

A conclusive result has been reached after a thorough and rigorous analysis of numerous enclosure designs, pointing to the provided design as the best option for the project's unique requirements. The Raspberry Pi project's spirit is effectively captured by this carefully chosen container design, which also perfectly complements its main goals.

The main goal of this Raspberry Pi enclosure design is to give the Raspberry Pi board and the Pi camera module a safe and functional housing. It provides a safe cocoon through careful engineering that not only securely encloses the components but also guarantees their proper placement. In turn, this design protects against the potentially harmful impacts of outside factors, effectively extending the lifespan of the parts and the system's overall operational effectiveness. The project's mobility and adaptability are increased by the portable nature of this enclosure design, allowing for simple deployment across a variety of locations without sacrificing the functionality and safety of the encased components.

The objective of the Raspberry Pi enclosure is to house and safeguard the Raspberry Pi board and the Pi camera module. Assuring that the components are arranged and protected from outside factors, it offers a safe and portable solution. The chosen enclosure design effectively combines utility, security, and portability into a seamless whole, capturing the very core of the project's goals.

Several beneficial aspects of the selected enclosure design increase its utility. It is specially made to perfectly fit the Raspberry Pi board and Pi camera module, ensuring a tight fit and perfect alignment. This customized construction helps to retain the integrity of the components and makes installation easier.

This enclosure design's focus on accessibility is one of its main advantages. The Raspberry Pi's vital ports and connectors are easily accessible thanks to the clever arrangement. This thoughtful design decision not only makes networking simple but also makes configuration quick and easy. The sturdy design of the casing also serves as a shield, preserving the delicate interior parts from any harm and inadvertent impacts. The integrated system's overall lifetime and dependability are improved by its robust makeup. Additionally, the design's provision of flexible mounting choices enhances its usefulness. These mounting components provide versatility in positioning, catering to a wide range of applications and situations, whether they are attached to a surface or connected to a tripod.





Standards Used

Following Road Maintenance standards are used:

Inspections shall be carried out as per MQS-551. (Maintenance Office, 2003)

1. Potholes

The maintenance rules mandate immediate repair for concrete surface potholes deeper than 20mm. To ensure road safety and stop future deterioration, these potholes, which are identified as depressions or openings in the pavement, need to be fixed right away. Particularly, potholes having an area of at least 0.04m2 and a depth of more than 50mm must be repaired under a strict 3-day time constraint. Potholes within the same area range but with depths between 25mm and 50mm must be repaired within a longer 7-day window. To maintain the quality of the roads, guarantee commuter safety, and reduce potential interruptions brought on by road problems, it is essential to stick to these clearly established dates.

These rules act as a command to immediately and methodically address pothole-related issues. In accordance with the degree of the damage, the standards prescribe different repair deadlines for different pothole sizes and depths. Authorities hope to maintain the integrity of the road infrastructure by enforcing these requirements and to improve everyone is driving experience overall.

2. Cracking

An essential guideline for identifying and successfully managing road surface distress is the classification of cracks. The two main fracture orientations are longitudinal cracks that run parallel to the center line and transverse cracks that run perpendicular to the center line. While corner fractures frequently form triangle patterns with transverse joints or other cracks, diagonal cracks exhibit a distinctive angular displacement from the center line. These fracture types must be recognized and understood because they shed light on the underlying causes and potential structural weaknesses of the road.

The recommendations also specify criteria for dealing with cracks based on their sizes. Cracks at joints that are wider than 40mm should be reported right away to the district office because they could indicate serious structural issues. For asphalt surfaces, cracks larger than 25 millimeters must be repaired within a fortnight to ensure that the integrity of the road is promptly restored. Similarly, concrete surfaces with cracks wider than 6 mm must be reported to the district office for more evaluation. Following these instructions helps maintain the road's quality, improve safety, and reduce any potential problems brought on by broken road surfaces.

Methodology and Approach

To achieve the project objectives, work is divided into the following four Phases. The steps involved in the process include:

Phase 1

- To conduct a thorough literature review on existing methodologies for infrastructure
- asset management using computer vision and vehicle-mounted devices.
- Familiarize with the Raspberry Pi platform and its capabilities for onboard processing and network connectivity.
- Research and select a suitable camera module for image acquisition.

Phase 2

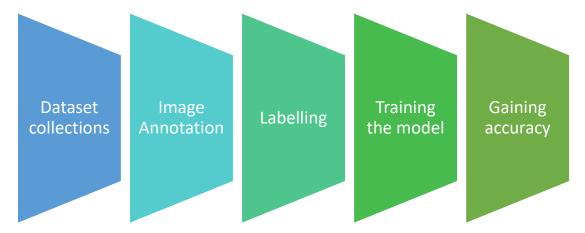
- Procure the necessary hardware components, including Raspberry Pi, camera module, vibration sensors, and any additional required components.
- Investigate and implement computer vision algorithms for fault detection in the captured images.
- Experiment with various image processing techniques such as edge detection, feature extraction, and anomaly detection to identify potential faults.

Phase 3

- Set up the Raspberry Pi environment and configure it for development purposes.
- To develop a basic data acquisition system to capture images using the camera module.

Phase 4

- Enhancing the accuracy of the model.
- Developing the final model working with the Robocar that can detect the sidewalk's defects.



Major Challenges and Solutions

- Lack of Available Dataset: At the outset, there was a notable absence of a fitting dataset for the analysis of sidewalk defects, necessitating the need for data collection.
- **Absence of Labeled Data**: The data gathered required manual labeling, a process that consumed considerable time and effort to accurately annotate the defects.
- **Identifying the Right AI Model:** The pivotal task of choosing the optimal artificial intelligence model for the detection of sidewalk defects was of paramount importance, requiring thorough evaluation and selection.
- Real-Time Interface: Establishing a real-time interface to effectively process and present the
 collected data posed its own set of challenges, demanding seamless integration and reliable
 performance.
- Varied Sidewalk Surfaces: The diverse nature of sidewalk surfaces added complexity to the
 defect detection process, demanding adaptability, and robustness in the AI model's
 performance.

- Weather & Lighting Conditions: The varying environmental conditions, encompassing diverse weather patterns and lighting scenarios, introduced challenges in maintaining consistent and accurate defect detection under different circumstances.
- Model Interpretability: Ensuring the interpretability of the AI model's decision-making process
 and its ability to provide insights into detected defects proved to be an essential factor in
 building trust and understanding.

Addressing these challenges required a comprehensive approach, involving innovative strategies in data collection, labelling, model selection, interface development, and adapting to varying real-world conditions. Keeping this factor as a challenge in the research to find the proper platform to use computer vision, found Roboflow provides the best solutions. (Roboflow, 2021)

Roboflow:

Roboflow is a solid platform designed for computer vision researchers and developers. It streamlines the complex process of organising and preparing datasets by simplifying data administration, annotation, and augmentation. It enables the development of high-performance computer vision systems by providing innovative model training and deployment capabilities. The platform's automation features lower resource requirements, allowing for faster project completion with more accuracy. Its collaborative environment encourages collaboration and invention while providing a straightforward interface ideal for both professionals and newbies. Roboflow, in general, redefines computer vision development, establishing a new industry standard with user-centric design and robust functions.

Roboflow is a critical asset for computer vision engineers, providing a full toolkit for fast project progression. By combining user-centric design, vast capabilities, and strong functionalities, it redefines industry excellence, positioning itself as a disruptive force in the field of computer vision.

Crack detection method- CNN (Convolutional Neural Network) Algorithm (Hamishebahar, Guan, So, & Jo, 2022)

Installation and Implementation Process:

- **1. Hardware Setup:** Begin by assembling the necessary hardware components, including a Raspberry Pi, camera module, and microSD storage card.
- 2. **Install Roboflow on Raspberry Pi:** Establish an internet connection for your Raspberry Pi and open a terminal window. (Roboflow, Raspberry Pi, 2023)
- 3. **Install the Roboflow Python Library:** Execute the following command in the terminal to install the Roboflow Python library:

pip install roboflow

4. Implement the Code:

Import Libraries: Begin by importing the required libraries, including 'cv2' for image processing and 'Roboflow' from the roboflow library for API interaction.

```
import cv2
from roboflow import Roboflow
```

5. **Initialize Roboflow:** Utilize your Roboflow API key to initialize the Roboflow instance for API communication.

```
rf = Roboflow(api_key="YOUR_API_KEY")
```

6. Load Projects and Models: Load the relevant projects and models from your Roboflow workspace.

```
project = rf.workspace().project("ipd-pothole-detection")
model = project.version(7).model

project2 = rf.workspace().project("crack-and-dent-detection")
model2 = project2.version(3).model
```

7. **Define Paths:** Define the paths for the input and output videos.

```
input_video_path = "input_video.mp4"
output_video_path = "output_video.mp4"
```

8. **Initialize Video Capture and Writer:** Set up video capture and writer objects with relevant parameters.

```
cap = cv2.VideoCapture(input_video_path)
fps = int(cap.get(cv2.CAP_PROP_FPS))
width = int(cap.get(cv2.CAP_PROP_FRAME_WIDTH))
height = int(cap.get(cv2.CAP_PROP_FRAME_HEIGHT))
fourcc = cv2.VideoWriter_fourcc(*'XVID')
out = cv2.VideoWriter(output_video_path, fourcc, fps, (width, height))
```

- 9. Frame Processing: Process each frame of the input video by performing the following steps:
 - Convert the frame to RGB format.
 - Save the RGB frame as a temporary image.
 - Make predictions for pothole detection using the first model.
 - Save the prediction image.
 - Make predictions for crack and dent detection using the second model.
 - Convert the prediction image to BGR format.
 - Write the processed frame to the output video.
 - Remove temporary images.

```
while cap.isOpened():
    ret, frame = cap.read()
    if not ret:
        break
    frame_rgb = cv2.cvtColor(frame, cv2.COLOR_BGR2RGB)
    temp_img_path = "temp_frame.jpg"
    cv2.imwrite(temp_img_path, frame_rgb)
    prediction = model.predict(temp_img_path, confidence=50, overlap=30)
    prediction_img_path = "prediction.jpg"
    prediction.save(prediction_img_path)
    prediction2 = model2.predict(prediction_img_path, confidence=15)
    prediction_bgr = cv2.cvtColor(prediction2.image, cv2.COLOR_RGB2BGR)
    out.write(prediction_bgr)
    os.remove(temp_img_path)
    os.remove(prediction_img_path)
```

10. Release Resources: After processing, release the video capture and writer objects.

```
cap.release()
out.release()
```

11. **Print Completion Message:** Display a message indicating the completion of the processing and the path to the output video.

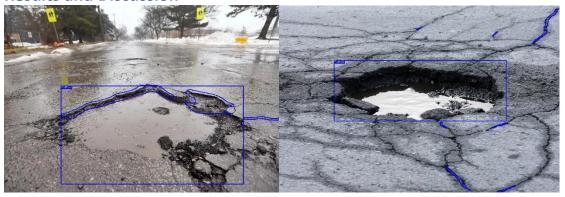
```
print("Processing complete. Output video saved at:", output_video_path)
```

Model Training Links:

For pothole detection model: https://universe.roboflow.com/project-ckcli/detect-hole

For crack and dent detection model: https://universe.roboflow.com/fyp-n53kb/pcd_v1

Results and Discussion



The current study integrated vehicle-mounted image acquisition technology and robust computer vision algorithms to achieve promising outcomes in infrastructure asset management. The primary focus of the investigation was the accurate identification and classification of sidewalk defects, including potholes and cracks, utilizing advanced machine learning techniques.

Comparison with Existing Methods

A comprehensive comparative analysis was undertaken to assess the efficacy of the proposed approach relative to established methodologies within the domain of infrastructure asset management. The findings of the study exhibited distinct advantages. The implemented solution not only displayed heightened efficiency and precision but also demonstrated superior cost-effectiveness. Notably, the velocity at which data was gathered through the utilization of the vehicle-mounted device outperformed traditional manual methods.

Discussion of Challenges

The study encountered notable challenges that contributed to its developmental trajectory. In the initial stages, the model's performance was hindered, resulting in a modest 15% accuracy in detecting defects. This initial setback shed light on the intricacies inherent in the task, emphasizing the pivotal role of dataset quality and size in influencing model performance.

To address this limitation, a deliberate expansion of the dataset was undertaken. A meticulously annotated set of 2500 images were incorporated, encompassing diverse conditions and defect variations. The subsequent model retraining using this augmented dataset yielded significant improvements. The accuracy rates achieved ranged between 65-70%, contingent upon the quality of input images. This experience underscores the critical importance of incorporating diverse and substantial datasets during the machine learning model training process. Moreover, it underscores the efficacy of persistence and iterative refinement in progressively enhancing accuracy and overall performance This experience serves to underscore the critical importance of incorporating diverse and substantial datasets during the machine learning model training process. Moreover, it underscores the

efficacy of persistence and iterative refinement in progressively enhancing accuracy and overall performance.

Conclusion

In the present report, a solution involving a vehicle-mounted image acquisition device for infrastructure asset management has been proposed. Through the integration of cost-effective hardware and advanced computer vision techniques, the system efficiently collects data, accurately identifies sidewalk defects, and extracts critical features using machine learning methods in alignment with MQS-551 regulations.

By incorporating real-time data analysis and cloud storage, the solution enables expedited and well-informed decision-making processes for infrastructure maintenance. Including a dedicated Raspberry Pi enclosure ensures safeguarding components and convenient accessibility.

This undertaking underscores the transformative potential of technology in elevating infrastructure management, ultimately leading to safer and more efficient urban environments. Moving forward, ongoing efforts will encompass the refinement of algorithms and the execution of field trials to validate the practical utility of the proposed solution. Embracing the concept of intelligent data collection holds the promise of reshaping infrastructure maintenance practices and enhancing travel experiences for all stakeholders

Future Work

Subsequent efforts will involve refining the neural network architecture, exploring advanced augmentation techniques, and further enriching the dataset. This iterative strategy aims to bolster the model's robustness and its capacity for generalization.

While the achieved accuracy range of 65-70% is commendable, forthcoming work will prioritize the enhancement of the neural network architecture. Additionally, investigations into advanced augmentation techniques and potential utilization of transfer learning will be conducted to further elevate accuracy levels.

The ongoing commitment to diversify the dataset with an expanded array of images will remain a focal point. This continuous iterative approach underscores the objective of reinforcing the model's robustness and extending its proficiency in accurately detecting defects.

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