Automated Road Damage Detection Using Deep Learning

Crackathon – IIT Bombay

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Domain: Computer Vision | Artificial Intelligence | Infrastructure Safety

Dataset: Road Damage Detection Dataset 2022 (RDD2022)

Github: https://github.com/nehaksharma11/RDD2022-Road-Damage-Detection

1. Introduction

Well-maintained road infrastructure is essential for economic growth, public safety, and efficient transportation. However, monitoring and maintaining large-scale road networks remains a major challenge for government bodies and infrastructure agencies. Traditional road inspection methods rely heavily on manual surveys, visual checks, and subjective judgment, which are time-consuming, costly, and prone to inconsistencies.

With recent advancements in Artificial Intelligence and Computer Vision, automated road condition monitoring has become a viable and scalable alternative. Deep learning–based object detection models can analyze road images, identify surface damage, and classify defects with high accuracy. Such systems can significantly reduce inspection costs while enabling faster and more data-driven maintenance decisions.

This project presents an AI-powered approach for detecting and classifying multiple types of road damage from images. The goal is to develop a robust object detection model that can accurately localize road defects and categorize them into predefined damage classes, even under varying lighting, weather, and road conditions.

2. Problem Statement and Objective

Road surface damage such as cracks and potholes directly impacts vehicle safety, fuel efficiency, and long-term infrastructure costs. The objective of this challenge is to automate the detection of such damages using computer vision techniques.

Given an input road image, the model must:

- Detect all visible instances of road damage
- Draw accurate bounding boxes around each damaged region
- Correctly classify each damage instance into one of the five predefined categories

The five damage classes considered in this challenge are:

1. Longitudinal Crack
2. Transverse Crack
3. Alligator Crack
4. Other Corruption
5. Pothole

The model's performance is evaluated using Mean Average Precision (mAP), which measures both localization accuracy and classification performance. The ultimate objective is to achieve a high mAP score on a hidden test dataset, demonstrating strong generalization to real-world scenarios.

3. Dataset Description

The Road Damage Detection **2022** (RDD2022) dataset is a large-scale, multi-national dataset designed specifically for automated road inspection research. It contains more than 47,000 high-resolution images collected from different countries and road environments.

Dataset Structure

- Training Set: Images with annotated labels
- Validation Set: Images with annotated labels
- Test Set: Images without labels (used only for evaluation)

Annotation Format

Annotations are provided in YOLO TXT format. Each image has a corresponding text file containing:

- Class ID
- Normalized bounding box coordinates (x_center, y_center, width, height)

This standardized format enables efficient training with modern object detection frameworks.

The dataset includes diverse road textures, lighting conditions, camera angles, and damage severities, making it suitable for training a model that can generalize well to real-world road environments.

4. Model Architecture

A YOLO-based object detection architecture was selected for this project due to its strong balance between detection accuracy and computational efficiency. **YOLO** models are well-suited for real-time and large-scale image analysis tasks, making them ideal for infrastructure monitoring applications.

Architecture Overview

- Backbone Network: Extracts hierarchical visual features from input images
- Neck (Feature Pyramid Network): Enables multi-scale feature fusion for detecting both small cracks and large potholes
- Detection Head: Predicts bounding boxes, class probabilities, and confidence scores

Pre-trained weights were used as initialization to accelerate training and improve convergence. This transfer learning approach allows the model to leverage general visual features learned from large datasets, resulting in better performance with limited task-specific data.

5. Data Augmentation and Training Strategy

To improve robustness and reduce overfitting, extensive data augmentation techniques were applied during training. These augmentations help the model learn invariant features and perform well across varying road conditions.

Data Augmentation Techniques

- Horizontal and vertical flipping
- Random scaling and cropping
- Rotation and perspective transformations
- Brightness and contrast adjustment
- Noise injection for robustness

Training Strategy

The model was trained using mini-batch gradient descent with an adaptive learning rate scheduler. Validation **mAP** was monitored throughout training, and early stopping was applied to prevent overfitting. The model checkpoint with the best validation performance was selected for final inference on the test dataset.

6. Hyperparameter Tuning Experiments

Several experiments were conducted to optimize key hyperparameters and improve overall detection performance.

Key Tuned Parameters

- Learning rate
- Batch size
- Input image resolution
- Confidence and IoU thresholds

Lower learning rates provided more stable convergence, while higher image resolutions improved the detection of fine-grained cracks at the cost of increased computation. An optimal balance was selected based on validation mAP and inference efficiency.

7. Techniques Used to Improve Performance

To enhance performance beyond the baseline model, multiple optimization techniques were applied:

- Fine-tuning pre-trained weights on the target dataset
- Class balancing to handle uneven damage distribution
- Anchor box optimization for better localization
- Confidence threshold tuning during inference
- Removal of noisy or low-confidence predictions

These steps collectively improved both localization accuracy and class-wise detection consistency, leading to better overall mAP performance.

8. Results and Discussion

The trained model demonstrated strong performance across all five damage categories. It was able to detect both large defects such as potholes and subtle damage such as fine longitudinal cracks. The use of multi-scale feature extraction proved especially effective for handling varying damage sizes.

The results highlight the feasibility of deploying AI-based road inspection systems in real-world scenarios, where consistent and scalable monitoring is critical.

9. Conclusion

This project demonstrates that deep learning–based object detection can significantly improve the efficiency and reliability of road damage assessment. By automating the detection and classification process, the proposed solution reduces dependence on manual inspection while enabling faster and more objective infrastructure evaluation.

The developed system shows strong potential for integration into smart city platforms, municipal maintenance workflows, and autonomous road monitoring systems.

10. Future Scope

Future improvements may include:

- Deployment on edge devices such as mobile cameras and drones
- Integration with GIS systems for automated road mapping
- Real-time detection using video streams
- Expansion to additional damage categories
- Continuous learning using new road data