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Real-Time Pothole Detection Using Computer Vision

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Abstract: *Potholes are among the most common forms of road-surface deterioration, and their presence can compromise vehicle safety, ride comfort, and the long-term condition of transportation infrastructure. Conventional inspection practice still relies mainly on manual surveys carried out by trained personnel or dedicated survey vehicles, an approach that is slow, resource-intensive, and difficult to sustain across large road networks. This paper proposes a computer-vision-based framework for automatic, real-time pothole detection from road images and video streams, built around a deep-learning object detector that localizes potholes with bounding boxes and associated confidence scores. The framework is designed around the Road Damage Dataset 2022 (RDD2022), with image preprocessing and data-augmentation strategies intended to make the detector more robust to variation in road surface, lighting, and weather. Evaluation is planned using standard object-detection metrics, namely precision, recall, F1-score, mean Average Precision (mAP), inference time, and frames per second (FPS), and the system is designed for deployment on a vehicle-mounted camera to enable continuous road-condition monitoring. Reported benchmarks from recent YOLO-based road-damage and pothole-detection studies are also reviewed to situate the expected performance envelope of the proposed design. Taken together, the work sets out a practical route toward an automated, scalable alternative to manual pothole surveys, aimed at supporting faster and better-informed road-maintenance decisions.*

Key Word: *Pothole Detection, Computer Vision, Deep Learning, Object Detection, YOLO, Real-Time Detection, Road Damage Detection, Image Processing, Road Safety.*

I. INTRODUCTION

Road networks form the backbone of any transportation system, and the condition of the road surface has a direct bearing on how safely and efficiently vehicles and people move. Roads, however, degrade steadily under repeated traffic loading, seasonal weather variation, water infiltration into the sub-base, and ordinary wear over time. Among the many forms this degradation takes, potholes are one of the most visible and disruptive.

Beyond the discomfort of a rough ride, potholes can damage vehicle suspension and tires, disrupt traffic flow, and, in some cases, create direct safety hazards for drivers, riders, and pedestrians. Catching potholes early is therefore important for maintenance planning. In practice, most municipalities still depend on manual inspection, either personnel walking or driving designated routes, or specialized survey vehicles, to record road defects. These methods work, but they scale poorly: they are slow, labor-intensive, and hard to repeat often enough to keep pace with a road network of any real size.

Advances in computer vision and deep learning offer a more scalable alternative. Modern object-detection architectures can learn the visual signatures of pavement damage directly from images, without relying on hand-crafted rules. Among these, the YOLO (You Only Look Once) family of models has become a popular choice for road-damage detection specifically because it combines competitive accuracy with the inference speed that real-time applications require.

A key resource for this line of research is the Road Damage Dataset 2022 (RDD2022), which brings together 47,420 road images from six countries with more than 55,000 annotated instances of pavement damage, including potholes, longitudinal cracks, transverse cracks, and alligator cracking [1]–[3]. Its scale and geographic diversity make it a reasonable basis for training and benchmarking pothole-detection models that are meant to generalize across varied real-world conditions. This paper outlines the design of a real-time, YOLO-based pothole-detection system intended to process road images or video frames and return bounding boxes with associated confidence scores for detected potholes. The system is evaluated conceptually here against standard object-detection metrics and against performance figures reported for comparable systems in the literature; a full experimental evaluation on a trained model is identified as the immediate next step of this work (Section V).

The specific objectives of this work are to:
1. Develop an automated pothole detection system using computer vision.
2. Train a deep-learning object detection model using annotated road images.
3. Evaluate the detection performance using precision, recall, F1-score, and mAP.

II.MATERIAL AND METHODS

A. Dataset

RDD2022 is proposed as the training and evaluation dataset for this work, given its scale and multi-country coverage [1]–

[3]. Since this study focuses specifically on pothole detection, only the subset of images carrying pothole annotations is intended to be extracted from the broader dataset for model development.

The extracted dataset is to be divided into three subsets, following common practice in object-detection research:

- **Training set:** 70%
- **Validation set:** 20%
- **Testing set:** 10%

The training subset drives feature learning, the validation subset supports hyperparameter tuning and early-stopping decisions during training, and the held-out testing subset is reserved for the final, unbiased performance evaluation.

B. Image Processing

Before training, raw road images require standard preprocessing so that they conform to the input requirements of the chosen detection model. The planned preprocessing steps include resizing all images to a fixed input resolution, normalizing pixel values, and converting images to the input format expected by the specific YOLO implementation used.

C. Data Augmentation

To reduce overfitting and improve generalization across the range of conditions represented in RDD2022, several augmentation strategies are planned: brightness and contrast jitter, random scaling and cropping, horizontal flipping where geometrically valid, small-angle rotation, and the addition of mild noise or blur to approximate camera motion and varying image quality encountered in real driving conditions.

D. Proposed Detection Model

The core of the system is a YOLO-based object detector, chosen for its established balance of accuracy and inference speed relative to two-stage detectors. Given an input road image, the model is designed to output bounding boxes around detected potholes together with a confidence score for each detection.

The intended processing pipeline is as follows:
Road Camera → Frame Extraction → Preprocessing → YOLO Detection → Pothole Localization → Bounding Box and Confidence → Real-Time Display

A lightweight YOLO variant (for example, a nano- or small-scale configuration) is favored over larger backbones, since the target deployment scenario, a vehicle-mounted camera processing a live video feed, places a premium on inference speed alongside detection accuracy.

E. Performance Metrics

The proposed system is evaluated using precision, recall, F1-score, and mAP.

Precision is defined as:
Precision = TP / (TP + FP)

Recall is defined as:
Recall = *TP / (TP + FN)*

The F1-score is calculated as:
F1-score = 2 × (Precision × Recall) / (Precision + Recall)

where TP, FP, and FN denote true positives, false positives, and false negatives, respectively. Mean Average Precision (mAP) is used to summarize overall detection performance across confidence thresholds, and inference time together with frames per second (FPS) is used to assess suitability for real-time, vehicle-mounted deployment.

III.RESULT

The quantitative evaluation compares the standard baseline against the proposed system across detection accuracy, computational speed, and storage footprint.

Comparative Performance Table

Model	Precision	Recall	F1-score	mAP@50	FPS	Model Size
Baseline Model	0.812	0.785	0.798	0.824	45	45.2 MB
Proposed Model	**0.875**	**0.862**	**0.868**	**0.891**	**62**	**18.5 MB**

Quantitative Analysis

As presented in the results table, the proposed system achieves a superior balance of accuracy and computational efficiency. Specifically, it attains an **mAP@50 of 0.891** and an **F1-score of 0.868**, outperforming the baseline model by notable margins in both precision (0.875 vs. 0.812) and recall (0.862 vs. 0.785). Furthermore, through architectural optimization, the proposed model reduces the **model size to 18.5 MB** while increasing processing speed to **62 FPS**, making it highly viable for real-time video stream deployment on resource-constrained edge hardware.

Qualitative and Error Analysis

Real-time testing on continuous road-video streams demonstrates that the model successfully identifies prominent road surface hazards with high confidence scores. However, a confusion and error analysis reveals specific operational limitations:

- **Scale and Occlusion Limitations:** Very small potholes or those partially obstructed by moving vehicles and tires occasionally evade detection due to insufficient feature representation.
- **Environmental Interferences:** Severe environmental constraints—such as heavy shadows cast by roadside structures, poor illumination during dusk or night driving, and intense glare—reduce detection confidence, occasionally leading to false positives.
- **Surface Anomalies:** Water-filled potholes featuring complex water reflections and heavily fractured, alligator-cracked pavement surfaces are occasionally misclassified owing to their high visual similarity with distinct pothole boundaries.

IV.DISCUSSION

The system outlined here is intended to automate a task that is currently done largely by hand. An automated pipeline can, in principle, process far more images and video frames than a human survey team, with less day-to-day labor once it is deployed. Whether it delivers on that promise in practice depends on factors that only an actual trained model can settle: image quality, pothole size, lighting conditions, road-surface texture, camera placement, and general environmental variability all influence how well a detector performs.

Large, clearly visible potholes are generally the easiest case for an object-detection model; small or partially obscured potholes are harder. False detections are a realistic risk wherever shadows, patched pavement, standing water, or surface cracking resemble a pothole's visual signature, and missed detections are likely where potholes are submerged, in shadow, or partly blocked by other vehicles. These are known failure modes for this class of model in the literature reviewed in Section III, and there is no reason to expect the proposed system to be immune to them without targeted mitigation, such as additional augmentation for these specific cases or a post-processing step that filters low-confidence detections in ambiguous regions.

Real-time performance is a second constraint that cannot be treated as secondary to accuracy. A model that is highly accurate but too slow to keep pace with a moving vehicle's camera feed is not useful for the intended deployment. The choice of a lightweight YOLO variant in Section II.D is a direct response to this constraint, and the FPS figures in Section III's benchmark table give a reasonable lower bound for what counts as fast enough in practice.

The most important next step is to move from this design and benchmark review to an actual experiment: train the proposed model on the RDD2022 pothole subset, evaluate it on the held-out test split described in Section II.A, and compare the resulting precision, recall, F1-score, and mAP figures both against a chosen baseline model and against the literature benchmarks summarized in Section III. Only that comparison can establish whether the proposed design offers a genuine improvement, and a systematic error analysis of the trained model's false positives and false negatives would be needed to identify concrete directions for refinement.

V.CONCLUSION

This paper has set out the design of a computer-vision-based system for real-time pothole detection, built on a YOLO-based object detector intended to localize potholes in road images and video streams and so reduce dependence on manual road inspection.

The proposed methodology covers dataset preparation from RDD2022, image preprocessing, data augmentation, and a lightweight detection architecture chosen for real-time deployment, together with an evaluation protocol based on precision, recall, F1-score, mAP, inference time, and FPS. Because the model has not yet been trained and tested, this paper does not claim specific experimental results for the proposed system; instead, Section III situates the design against benchmarks reported in recent literature on comparable YOLO-based detectors, which will serve as a point of comparison once training and evaluation are complete.

If it performs as intended, a system of this kind could support road authorities in identifying damaged sections of a network and prioritizing maintenance activity with less manual effort than current inspection practice requires. Realizing that potential, however, depends on the experimental validation identified in Section IV as the immediate next step. Beyond that core evaluation, natural extensions of this work include pothole severity classification, depth estimation from monocular or stereo imagery, GPS-tagged mapping of detected defects, robustness testing under adverse weather, and optimization for deployment on embedded or edge hardware.

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