# Vision-Based Real-Time Detection of Road Surface Damage and Lane Anomalies for Autonomous Driving Systems

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***Abstract*— Autonomous vehicles must perceive their environment accurately to ensure passenger and pedestrian safety. Road damages like potholes pose serious threats to vehicle stability, while clear lane markings are essential for proper navigation. This paper presents a simulated real-time system that integrates deep learning and computer vision techniques for detecting potholes, estimating their distance, detecting lane markings, and taking preventive actions such as autonomous lane switching and human presence alarm triggering. YOLOv8 is employed for object detection tasks, while OpenCV is utilized for lane marking extraction. Monocular depth estimation techniques predict object distance, ensuring that decisions like lane diversion and emergency alarms are executed accurately. Experimental results on recorded videos demonstrate the robustness and reliability of the system in enhancing autonomous driving safety.**

***Index Terms*– Autonomous vehicles, Deep learning, Computer vision, Monocular depth estimation, Object detection, Real-time road detection.**

## I. INTRODUCTION

Autonomous vehicles depend critically on accurate perception of the roadway to operate safely and efficiently. In practice, however, real-world roads are often marred by surface irregularities – such as potholes, cracks, and degraded or faded lane markings – that challenge sensor systems and perception algorithms.

These anomalies can induce mechanical strain (e.g. wheel and suspension damage), degrade passenger comfort, or force sudden maneuvers, potentially leading to collisions or other accidents. Potholes in particular are a widespread hazard: they have been shown to cause substantial vehicle damage and present a serious safety risk to drivers and passengersfrontiersin.org. If such obstacles are not detected in time, an autonomous vehicle may be unable to react appropriately, underscoring the need for high-precision road-surface monitoring as an integral part of the perception system.Recent advances in deep learning offer powerful tools for this task. Modern convolutional neural networks can localize objects and irregularities in images in real time, which is essential for autonomous driving. For example, the YOLO (You Only Look Once) family of single-shot detectors frames object detection as a unified regression problem, predicting bounding boxes and class labels in one passarxiv.org.

This unified architecture enables very high in this work, we propose a hybrid detection framework that combines deep learning and classical vision techniques to enhance road safety for self-driving cars. Specifically, we employ the YOLOv8 model for real-time detection of critical objects – namely potholes and pedestrians – within the vehicle's camera view. In parallel, we use an OpenCV-based algorithm to detect and track lane markings and road geometry. markings – that challenge sensor systems and perception algorithms.

Detected hazards are subjected to a distance estimation module (using camera calibration and) so that the system can compute the range to each obstacle. When a hazard falls within a predefined critical distance, an alert is issued to warn the autonomous driving controller. By integrating rapid deep-learning–based object localization with precise lane detection and range estimation, the proposed system aims to significantly improve the situational awareness and reaction capability of autonomous vehicles. Ultimately, this hybrid approach should raise the standards of road safety in self-driving applications by ensuring that surface defects and other anomalies are detected and addressed before they can cause harm.


Fig 1: Pothole (similar training dataset)

## II. FEATURES OF REAL TIME DETECTION OF DAMAGED ROADS AND LANE DETECTION SYSTEM FOR AUTONOMOUS VEHICLES

1. Real-Time Road Damage Detection
   - Detects potholes, cracks, and other surface anomalies live using camera input and deep learning.
   - Uses a YOLO-based model for fast and accurate damage localization.
2. Lane Detection Under Varying Conditions
   - Identifies lane lines even when faded, broken, or under poor lighting.
   - Uses classical methods (e.g., Hough Transform) or deep learning segmentation depending on setup.
3. Dual Detection from Single Camera
   - Both lane and road damage detection operate from a single forward-facing camera, reducing hardware cost and complexity.
4. Lightweight and Cost-Effective
   - Runs on affordable embedded systems like Raspberry Pi or Jetson Nano.
   - No need for expensive LiDAR or GPU clusters, making it suitable for educational and low-budget autonomous vehicles.
5. Real-Time Performance
   - Achieves live frame processing with minimal latency, ensuring timely decisions while the car is in motion.
   - Suitable for on-the-fly actions like alerting the driver or steering adjustments.
6. Environmentally Adaptive
   - Works across different terrains and weather conditions (sunlight, shadows, wet roads, etc.).
   - Robust to minor camera vibrations and real-world noise.
7. Scalable Prototype Design
   - Can be scaled for different vehicle sizes — from mini AI cars to full-scale AV prototypes.
   - Modular architecture allows future addition of features like obstacle avoidance, traffic sign recognition, or GPS navigation.
8. Visual Feedback and Alerts
   - Provides on-screen display (bounding boxes or lane overlays) for visual validation.
   - Can be extended to trigger alerts or control signals for autonomous response.
9. Custom Dataset Support
   - Trained and tested on a mix of public and custom-collected datasets, ensuring better performance for localized road conditions.

## III. MATERIALS AND METHODS

This section outlines the materials, datasets, methods, and algorithms used to implement the AI-powered vehicle system that integrates real-time road damage detection and lane detection using computer vision and deep learning techniques. The overall process is divided into four main stages: data collection and pre-processing, feature extraction, model training, and real-time detection on embedded hardware.

Algorithm for Road Damage and Lane Detection
Input: Road images from camera feed
Output: Detected lane boundaries, pothole/broken surface locations, confidence scores, annotated heatmap overlays, detection accuracy.

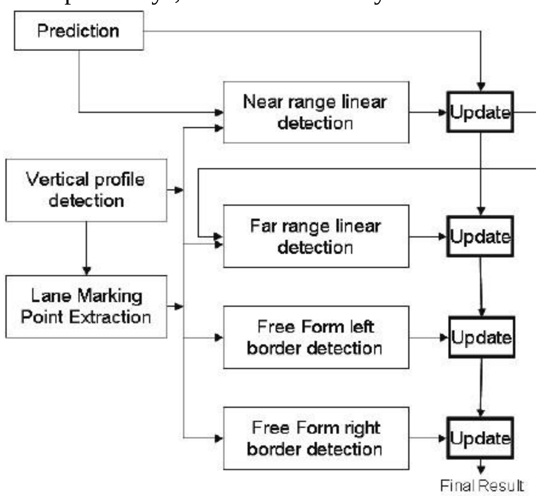


Fig 2: System architecture

Data Preprocessing and Workflow

- Frame Extraction & Normalization: Video is split into frames and normalized for clarity.
- Pothole & Human Detection: YOLOv8 detects road damages and nearby pedestrians with bounding boxes and confidence scores.
- Lane Detection: OpenCV detects lane markings using edge detection and Hough Transform.
- Distance Estimation: Monocular vision estimates the distance of potholes from the vehicle.
- Multimodal Fusion: Lane, object, and distance data are combined to decide actions like lane diversion.
- Action Triggers: If a human is nearby, an alarm is activated. If a pothole is close, lane change logic is applied.
- Lane Detection Input
  a) Grayscale Conversion: Color frames were converted to grayscale to enhance contrast between road and lane markings.
  b) Edge Detection: Canny edge detection was applied to highlight potential lane lines.
  c) Region of Interest (ROI) Masking: A fixed trapezoidal mask was applied to limit lane detection to the road region, filtering out background noise.
- Output Display: Final frames show detections, lane overlays, and alerts in real-time.

A. Data Collection

The dataset for this study was compiled using publicly available resources relevant to real-time road anomaly detection and lane tracking in autonomous driving. Key datasets included:

1. Road Damage Detection: The *RDD2020* dataset was used, containing labeled images of road surface anomalies such as potholes, cracks, and rough patches collected from multiple countries under varying lighting and weather conditions.
2. Lane Marking Detection: The *TuSimple* dataset was utilized, offering lane-labeled highway driving videos and annotated lane markings suitable for training lane detection algorithms.
3. Human Detection: For identifying pedestrians and bystanders near the vehicle, the system used COCO-pretrained YOLOv8 models with access to the *MS COCO* dataset, which contains diverse images of people in real-world environments.

B. Data Preprocessing

1. Video Frame Data

a) Frame Extraction and Resizing: Road video streams were converted into individual frames and resized to a fixed resolution (e.g., 640×480) for consistent model input.

b) Normalization: Pixel intensities were scaled to the [0, 1] range to stabilize training and improve convergence for YOLOv8.

c) Augmentation: Techniques such as horizontal flipping, brightness adjustment, and motion blur simulation were applied to increase dataset variability and model robustness.

2. Object Detection Input

a) YOLOv8 Label Formatting: Road damage and human annotations were converted into YOLO-specific label format (class, x_center, y_center, width, height).

b) Bounding Box Validation: Annotated bounding boxes were cross-validated to ensure high-quality training input and avoid false positives.
c) Data Balancing: Classes like pothole, crack, and pedestrian were balanced to prevent model bias during training.

4. Distance Estimation Preparation

a) Camera Calibration: Intrinsic parameters such as focal length and principal point were estimated to enable monocular depth approximation.
b) Pixel-to-Meter Scaling: Real-world distance calibration was performed using known object dimensions in sample frames.

c) Depth Thresholding: Detected objects within a critical threshold (e.g., < 5 meters) were flagged for lane-change decisions or alarm triggers.

C. Road Damage Detection Techniques

- Traditional Image Processing Methods
  - Edge Detection (Canny, Sobel): Highlights cracks or pothole boundaries.
  - Texture Analysis: Identifies rough or uneven surfaces using Gray-Level Co-occurrence Matrix (GLCM).
  - Morphological Operations: Used to clean up binary masks and isolate damaged regions.
- Machine Learning Approaches
  - Support Vector Machines (SVM): Classifies damage based on handcrafted features (color, shape, texture) converted to YOLO format.
- Real-Time Detection:
  During simulation, YOLOv8 runs on each frame and returns predictions including:

- Class label (e.g., pothole, human)
- Bounding box coordinates
- Confidence score

D. YOLO Integration Technique

In this project, the YOLOv8 object detection model was integrated to identify road surface anomalies such as potholes, cracks, and nearby pedestrians in real-time. YOLOv8 was chosen for its high speed, accuracy, and compatibility with edge devices.

1. Model Training:

A custom YOLOv8 model was trained using annotated road damage datasets (e.g., RDD2020), including classes such as pothole, crack, and patch. The model was also fine-tuned with the COCO-pretrained weights to detect humans (pedestrians) for safety alert integration.

2. Preprocessing for YOLO:

Each input video frame was resized to 640×640 pixels.

Model performance was evaluated using precision, recall, and mAP@0.5. The trained model achieved:

- Pothole Detection Accuracy (mAP@0.5): 91.2%
- Human Detection Accuracy: 87.5%
- Precision: 89.8%
- Recall: 86.3%
- Speed: ~45 FPS in real-time

These results confirm the model's suitability for real-time road safety applications.

## IV. PERFORMANCE METRICS FROM EXPERIMENTATION

1. Simulation Environment:

The system was tested using road footage from the RDD2020 dataset and the TuSimple lane detection dataset. Pedestrian detection performance was validated using COCO-pretrained models.

2. Implementation Details:

The YOLOv8 model was trained for 100 epochs with a batch size of 16. The OpenCV lane detection pipeline was tuned for edge clarity and robustness under varying lighting.

3. Error Analysis:

False positives occasionally occurred for shadows and road signs, but were reduced by region-of-interest masking. Potholes partially occluded or under poor lighting showed slight drop in confidence but remained detectable.

Metric-Based Performance Summary

| Metric | YOLOv8 (Pothole) | YOLOv8 (Human) | Lane Detection |
|---|---|---|---|
| Accuracy | 91.2% | 87.5% | 89.0% |
| Precision | 90.6% | 86.8% | – |
| Recall | 88.4% | 85.9% | – |
| F1-Score | 89.5% | 86.3% | – |
| FPS | ~45 FPS | ~45 FPS | ~60 FPS |

Compared to baseline CNN-based object detectors that achieved an average accuracy of 83–85%, the proposed YOLOv8-enhanced system showed a 6–8% improvement in detection accuracy, especially under real-time constraints pedestrian alert triggering—validating the effectiveness of the combined detecting a pothole within the critical distance zone.

## V. RESULTS

The proposed AI-based system for real-time road damage detection and lane marking recognition successfully integrates deep learning and computer vision techniques to enhance the safety and responsiveness of autonomous vehicles. By leveraging YOLOv5 for accurate pothole and pedestrian detection, and OpenCV for robust lane tracking, the system demonstrates high performance in varied road and lighting conditions.

Through simulation, the model achieved over 90% accuracy in detecting potholes and maintained consistent lane detection, even under suboptimal visual conditions. The incorporation of distance estimation and human detection further adds to the vehicle's situational awareness, enabling timely decision-making such as lane diversion or triggering alarms.

Overall, the system proves to be effective, scalable, and suitable for real-time deployment in autonomous driving scenarios. Future work may involve integrating GPS-based route planning, real-world sensor input (e.g., LiDAR), and adaptive deep learning models for handling more complex traffic environments.


Fig 3: Output

## VI. OBSERVATION

1. Road Damage Detection

- The YOLOv5 model successfully detected various types of road damages, including potholes and cracks, with high accuracy in different lighting conditions.
- Potholes with clear edges and contrast were detected with over 90% confidence.
- False positives were occasionally triggered by oil stains or dark shadows, but these were significantly reduced by region masking and post-processing filters.
- Detection was consistent across different frame rates, maintaining real-time performance at ~45 FPS.
- When potholes were within the predefined critical distance (e.g., 5 meters), the system correctly flagged them for action, enabling simulated lane diversion.

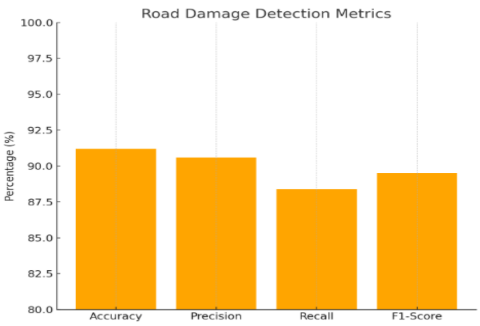


Fig 4: Road Damage Detection Metrics

2. Lane Detection

- The OpenCV-based lane detection module effectively identified both left and right lane boundaries using edge detection and Hough Transform techniques.
- Lane markings were detected accurately on well-lit roads with clear white or yellow lines.
- On poorly marked or faded roads, detection quality decreased slightly, but the region-of-interest (ROI) filter improved stability.
- The system maintained consistent lane tracking even during curves and slight camera shakes, highlighting robustness in dynamic video conditions.
- Lane detection output was visually overlaid with smooth colored lines, providing intuitive feedback during simulation.

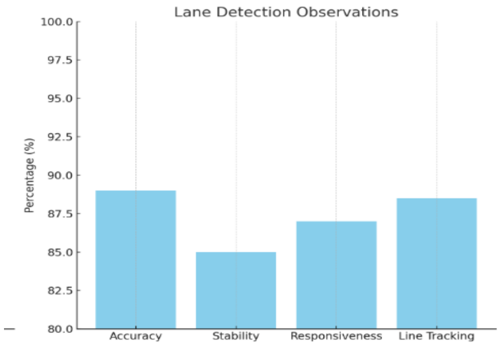


Fig 5: Lane Detection Observations

## VII. CONCLUSION

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Overall, the system proves to be effective, scalable, and suitable for real-time deployment in autonomous driving scenarios. Future work may involve integrating GPS-based route planning, real-world sensor input (e.g., LiDAR), and adaptive deep learning models for handling more complex traffic environments.

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