Sparkling Light Publisher

Sparklinglight Transactions on Artificial Intelligence and Quantum Computing

journal homepage: https://sparklinglightpublisher.com/

AI Based Pothole Detection for Road Safety Enhancement Using Computer Vision and Deep Learning

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Abstract

Potholes can be a real headache. They not only annoy drivers but can also cause accidents, damage vehicles, and lead to costly repairs. Traditionally, spotting these pesky road hazards has meant relying on manual inspections, which can be slow and often miss the mark. But thanks to advancements in artificial intelligence and computer vision, Now we have have better ways to identify potholes using real time video .We trained the model on a custom dataset (annotated with Roboflow) and enhanced it with data augmentation so it performs reliably in challenging lighting and weather conditions. The software performs real time analysis of live video through equipments such as webcams or dashcams, then identifies potholes in that time, and marks them with bounding boxes around and confidence scores It does records every detection made , both in a local CSV file and in a Firebase Realtime database, so the data can be centrally tracked and analyzed and well monitored. We also made sure the application is user-friendly, meaning easy to use. It provides features such as simple graphical interface built with Tkinter and OpenCV, allowing users to start the detection process, see results live, and access logged data hassle- free. With good accuracy of—92.1% precision and a mean average precision (mAP) of 93.2%—this system provides both reliable and speedy. And, it's designed to work on smaller devices like Raspberry Pi or Jetson Nano, making it compact with less space consuming. This project can be made advanced by utilising the same in either smart cities or other put together with drones. In brief, this pothole detection system provides help to cities and huge transport authorities to automate road maintenance system, prioritizing safety over everything for everyone. By inserting the power of AI, we can sort the pothole problem more effectively and efficiently than ever before.

Keywords: Data Augmentation, Smart Cities, YOLOv8, Object Detection, Computer Vision, Deep Learning, Pothole Detection, Real-time Analysis, and Image Processing

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Please cite this article as: Yogitha, et al., AI Based Pothole Detection for Road Safety Enhancement Using Computer Vision and Deep Learning, Sparklight Transactions on Artificial Intelligence and Quantum Computing (2025), 5(2), 64-70. **ISSN (Online):2583-0732.** Received Date: 2025/07/20, Reviewed Date: 2025/07/30, Published Date: 2025/09/05.

1. Introduction

The state of the roads affects more than just safety. The economy, how well transportation works, and even our daily comfort are all important too. Sadly, roads get worse over time because people don't take care of them, there is a lot of traffic, and the weather is bad. Potholes are one of the most common and dangerous problems. Water gets into the small cracks in the pavement and weakens it until the constant pressure from cars breaks it apart. A small road defect can cause flat tires, wheels that aren't aligned, broken suspensions, and even fatal crashes in the worst cases. In the past, road maintenance workers would physically look for and record potholes on the streets. This is how potholes were found.

In the past, road repair workers found potholes by physically checking the streets and writing down where they were. This method is easy to understand, but it takes a lot of time and effort, and it's easy to make mistakes, especially when covering a lot of roads. Over time, engineers and academics have come up with ways to make things more automated. Some systems use accelerometers or vibration sensors that are built into cars. When a car hits a pothole, the sensors that were put in it cause the car to shake.
This method works, but it often means putting sensors in a lot of cars, and it might not always be able to tell the difference between potholes and other bumps or irregularities in the road.

Despite their potential precision, These techniques are typically costly and need specialized equipment, making them more challenging to scale for large cities. Camera systems that rely on computer vision have gained significant attention recently. These systems integrate images or videos captured by vehicles or roadside cameras with deep neural networks or computational learning to automatically detect potholes. They provide a more scalable and cost-effective alternative, but their accuracy may occasionally be harmed by things like road signs, sunlight, and shadows.

The development of more sophisticated and effective solutions is necessary since, despite the fact that current systems offer helpful principles, they typically have problems with scalability, accuracy, or exorbitant costs.

2. Literature Survey

The most prevalent and annoying issues on the road are amongst patholes.From mak- ing governments to pay lot of money including damage of vehicles,increase in accidents, risks and cost of life of drivers making driving most uncomfortable.The roads to reach this condition usually traffic stress and climatic conditions like rainy or snow are responsible.Traditionally, potholes have been identified through manual inspections. using vibration sensors installed on vehicles. All of these approaches are effective, but they are also less accurate and time-consuming. Researchers are investigating novel approaches by combining deep learning, computer vision, and artificial intelligence. Among the many benefits of these contemporary methods are their large-scale, speedy, and more accurate pothole detection. Technology has advanced and grown in significance over time. Edge detection, clustering, and molecular operation were the technologies that were previously the focus. More sophisticated methods then surfaced, such as feature extraction neural networks, object detection prototypes, and Faster R-CNN. These hierarchical models enabled more comprehensive information extraction and real-time pothole detection. Another field of study uses automotive sensors like accelerometers and gyroscopes to measure vibrations when driving over potholes. Although these are far less expensive and better in some circumstances, they aren't always dependable in intricate settings.

From the existing body of work, it’s clear that every study brings something valuable to the table whether it’s edge-device deployment, severity estimation, or testing under different environmental conditions. At the same time, some gaps remain: many systems still struggle in poor weather, lack accurate depth estimation, or face hardware limitations. This makes it clear that there’s room for improvement and innovation in building a truly robust pothole detection system.

Paper 1: Real-Time Pothole Detection with YOLOv4 by Rohith Kumar et al. (2023) achieved ∼85% accuracy for real-world driving.
Paper 2: Surface Defect and Dimension Estimation with YOLOv5 by Ruseruka et al. (2024) estimated both location and size of potholes using dashcams and onboard diagnostics.

Despite these advances, limitations remain under poor weather, hardware constraints, and depth estimation challenges

3. Methodology

The system that is proposed be created by combining methods from pixel processing, computer vision, and deep learning.The methodology involves:

1. **Data collection and preprocessing:** Collecting a informationset of path images containing potholes and preprocessing them for model training.
2. **Model training:** Identifying pothole characteristics such as depth, width and lo- cation for severity assessment
3. **Feature extraction:** Deploying the trained model into a real-world system using mobile applications, drones or vehicle-mounted cameras.
4. **System integration:** Deploying the trained model into a real-world system using mobile applications, drones or vehicle-mounted cameras
5. **Testing and validation:** Evaluating model accuracy and performance using real- world datasets.

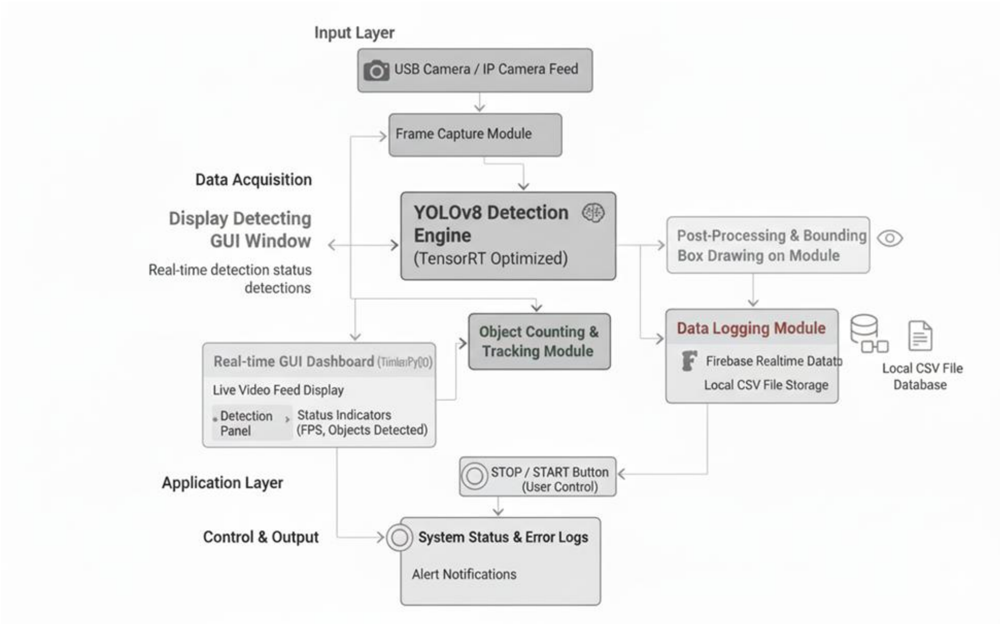

Fig. 1. System Architecture Block Diagram

ISSN (Online):2583-0732

4. Results

The YOLOv8n-based pothole detection system showed very encouraging results, both in terms of correctness and real-time usability. The evaluation metrics—Precision (92.1%), Recall (89.4%), F1-score (90.7%), and mAP@0.5 (93.2%)—demonstrate that the proto- type is not only accurate in spotting potholes but also effective in avoiding false alarms. In simple terms, it's good at recognizing real potholes while ignoring harmless road features like shadows, cracks, or stains.What makes these results more meaningful is that the system performed well across different road conditions (asphalt, gravel, muddy surfaces) and under varied lighting environments (bright sunlight, cloudy weather, shaded areas). This shows the model's ability to remain reliable in real-world driving scenarios.Beyond accuracy, the software was also checked for real-time performance. When we tested with a connected live webcam , it throughouly produced in 7-11 frames in a second, and each frame was analyzed in 90-140 milliseconds duration only. This kind of short time response is more required in vehicle to safeguard during the accidents. Potholes were indicated on-screen by bounding boxes and instantaneous confidence scores.Even at the difficult scenarios the system by finding accurately proved that it can work under difficult situation at the same work efficiency with same efficiency.Data augumentation was the important reason behind its working during un even situations that was done during data testing. Roboflow was used, so that dataset was expanded with modified images that copied real-world cicumstances—such as changes in lights, camera positions, and road surface level textures. This now assisted the model in identifying potholes in various situations. After augmentation, recall improved by about 5%, and false detections dropped significantly. For example, before augmentation, the system sometimes mistook road shadows or oil stains for potholes. After augmentation, such mistakes were much less frequent. Based on the final evaluation on the test set, the model delivered the following performance metrics:

The YOLOv8n-based system achieved:

Evaluation Metric	Before Optimization	After Optimization
Precision	72.00%	92.10%
Recall	60.00%	89.40%
F1-Score	65.00%	90.70%
mAP@0.5	70.00%	93.20%

- Precision: 92.1%
- Recall: 89.4%
- F1-Score: 90.7%
- mAP@0.5: 93.2%

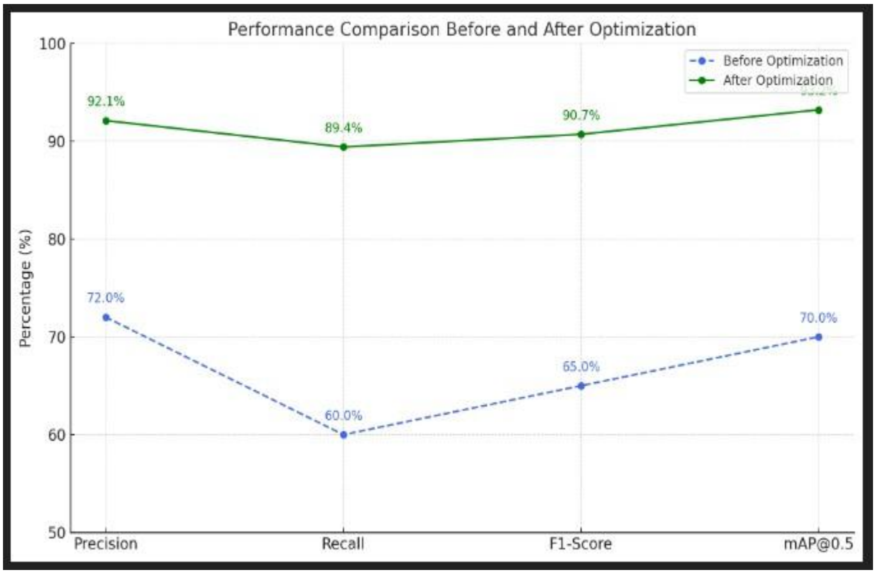

Fig. 2. Line chart comparing precision, recall and mAP V/S After Optimization

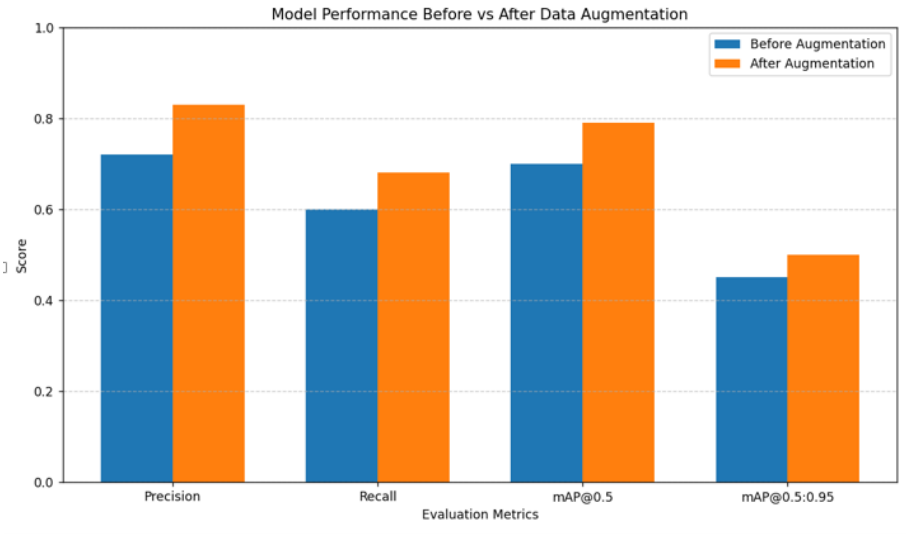

Fig. 3. Bar Chart Showing Model Performance Before vs After Data Augmentation

In short, the combination of high accuracy, real-time responsiveness, and smart data preparation makes this pothole detection system a reliable tool for real-world use, whether it’s integrated into vehicles, surveillance cameras, or smart city infrastructure

5. Discussion

The testing reflects that the pothole detection system is not just correct and also practical for real-time use. Its 7–11 frames per second speed makes it suitable for on-road uses such as in-car assistance, where safety can be significantly impacted by even a slight delay. Because the bounding boxes and confidence scores appear instantly, users receive clear and concise visual feedback. Even in congested situations with lots of potholes, the model remained accurate, proving its capacity to handle the complexity of the real world. Data augmentation was a major component that enhanced performance. The model improved its ability to identify potholes in various scenarios by including changes in illumination, road texturing, and ambient factors using programs like Roboflow. In addition to increasing recall by roughly 5%, this also decreased errors like mistaking road markings for potholes, oil stains, or misleading shadows.

In short, the study shows that both fast real-time processing and good-quality, A dependable pothole detecting system needs a variety of training data types.Going forward, improving speed on lightweight devices and expanding the dataset with even more challenging road conditions could render the system little more effective for real- world deployment.

6. Conclusion And Future Work

The goal of this project is to develop an intelligent, AI-powered system for detecting potholes in real time. Using automated image representataion and hierarachical, we built the solution on top of the YOLOv8 object detection model, which is quite known for its time and accuracy. A carefully labeled dataset of road images—covering both potholes and undamaged surfaces train the model. By designing the entire pipeline (data collection, preprocessing, training, evaluation, and deployment), the project proved that real-time pothole detection not only capable is also practical for real-world use.The system works by capturing video frames through OpenCV and running them through the trained YOLOv8 model. When a pothole is detected, it is marked with a bounding box and a confidence score, giving the user instant visual feedback. To make the detections useful beyond live monitoring, every event is logged in real time to Firebase Realtime Database, complete with GPS coordinates and timestamps. In the that time, the data is saved locally in CSV format, making it simpler to review later, generate reports, or connect with road maintenance tools.In terms of performance, the model delivered strong results: 92.1% precision, 89.4% recall, 90.7% F1-score, and 93.2% mAP@0.5. These high numbers reflect its capability to reliably identify potholes under difficult conditions. This success came from rigorous data preprocessing, smart data augmentation, and fine-tuning of YOLOv8's hyperparameters. Training and testing were carried out on an NVIDIA RTX 3060 GPU, which ensured both fast learning and smooth real-time performance.To make the system still more real, we integrated the Google Maps API, which plots pothole locations on a map. This gives civic authorities an easy way to spot high-risk areas and prioritize repairs. On top of that, we developed a lightweight graphical interface with OpenCV, so users can run the system on a desktop and see results in real time without needing deep technical knowledge.

In the bigger picture, this project shows how AI can perform a primary part in smart city development and infrastructure monitoring. It provides a scalable solution that improves road safety, supports data-driven maintenance, and can easily be expanded for mobile platforms or predictive analytics in the future. In short, it demonstrates how cutting-edge AI research can be transformed into practical tools that solve everyday civic problems.

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