International Scientific Journal of Engineering and Management (ISJEM) ISSN: 2583-6129
Volume: 04 Issue: 07 | July – 2025 DOI: 10.55041/ISJEM04874
An International Scholarly || Multidisciplinary || Open Access || Indexing in all major Database & Metadata

AI-Driven Smart Vehicle for Real-Time Road Damage Detection

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Abstract

The AI-Driven Smart Vehicle for Real-Time Road Damage Detection project explores the integration of YOLO, deep learning techniques and Advanced Driver Assistance Systems (ADAS) to enhance road safety and infrastructure monitoring. This project leverages deep learning models and computer vision techniques to process real-time sensor and camera data from vehicles, enabling the dynamic identification and assessment of road conditions. By utilizing generative models trained on vast datasets of road damage images and real-world sensor data, the system can detect and classify road anomalies such as potholes, cracks, and surface degradation with high accuracy. The smart vehicle system employs AI-driven anomaly detection to operate effectively under varying environmental conditions. Beyond classification, the AI estimates damage severity and predicts its potential impact on traffic safety. Additionally, predictive analytics enable the system to forecast future road deterioration based on historical data, facilitating proactive maintenance and repair planning. Integration with ADAS functionalities enhances driver safety by providing real-time alerts, suggesting alternative routes, and assisting autonomous navigation in hazardous conditions. Furthermore, the system autonomously communicates detected road damage to local authorities, optimizing infrastructure management and reducing long-term maintenance costs. By establishing a continuous feedback loop between vehicles and urban infrastructure, this project contributes to safer, smarter, and more efficient transportation networks, aligning with the vision of modern smart cities.

IndexTerms: AI-Driven Smart Vehicle, Real-Time Road Damage Detection, YOLO (You Only Look Once), Deep Learning, Road Safety, Infrastructure Monitoring, Sensor and Camera Data, Pothole Detection, Predictive Analytics.

1.INTRODUCTION

The condition of road infrastructure is a critical factor in ensuring transportation safety and efficiency. Traditional methods of detecting road damage—such as manual inspections—are time-consuming, costly, and often delayed. With the rapid advancement of artificial intelligence and computer vision, there is a growing need for smart systems that can automatically monitor and assess road conditions in real time. This project proposes an AI-driven smart vehicle system that leverages YOLO-based object detection, deep learning, and Advanced Driver Assistance Systems (ADAS) to detect and classify road anomalies such as potholes and cracks while driving. The system not only identifies damage but also estimates severity, provides real-time alerts to drivers, and communicates the information to authorities for timely maintenance, contributing to safer roads and smarter cities.

1.1.Existing System

In many regions, road damage detection and maintenance still depend on manual inspection by personnel or citizen reports, which can be highly inefficient and error-prone. These traditional methods involve field surveys, visual assessments, and periodic reviews, which are not only time-consuming but also costly to implement on a large scale. Some systems attempt to use smartphone applications that leverage GPS and accelerometer data to detect road irregularities, but they often suffer from inconsistency due to variations in device sensitivity, driving behavior, and road traffic conditions. Similarly, vehicle-mounted cameras with basic image capture capabilities are used in some municipalities; however, they typically rely on manual or semi-automated post-processing to identify damage, limiting real-time applicability. Moreover, these systems often fail to operate effectively under poor lighting, adverse weather, or varying road textures. The lack of automation, real-time analytics, and integration with broader smart city infrastructure limits their effectiveness in ensuring timely road maintenance and public safety.

1.1.1.Challenges:

- Inconsistent data due to variable driving patterns.
- High manual labor cost and subjectivity.
- Delay in damage detection and repair.
- Ineffective in remote or rural areas.
- Lack of integration with smart city systems.

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1.2.Proposed system:

The proposed system presents an intelligent, AI-driven approach to real-time road damage detection, designed to overcome the limitations of traditional inspection methods. It leverages the YOLO (You Only Look Once) deep learning algorithm to detect and classify various types of road anomalies—such as potholes, cracks, and surface deterioration—directly from real-time video feeds captured by vehicle-mounted cameras. This system operates dynamically, allowing for continuous monitoring as the vehicle moves, without requiring human intervention. By integrating with Advanced Driver Assistance Systems (ADAS), the vehicle can provide immediate visual or audio alerts to drivers, suggest alternative routes, and support autonomous decision-making in hazardous conditions. Additionally, the system evaluates the severity of detected damage using bounding box metrics and predictive models, allowing for prioritization of repairs. It also features automated reporting capabilities that send geotagged data and severity scores to local authorities or central servers, helping in timely maintenance planning and efficient resource allocation. With predictive analytics, the system can forecast future road degradation trends, enabling proactive infrastructure management. Overall, this smart vehicle framework enhances road safety, reduces maintenance costs, and supports the development of smarter, more connected transportation networks.

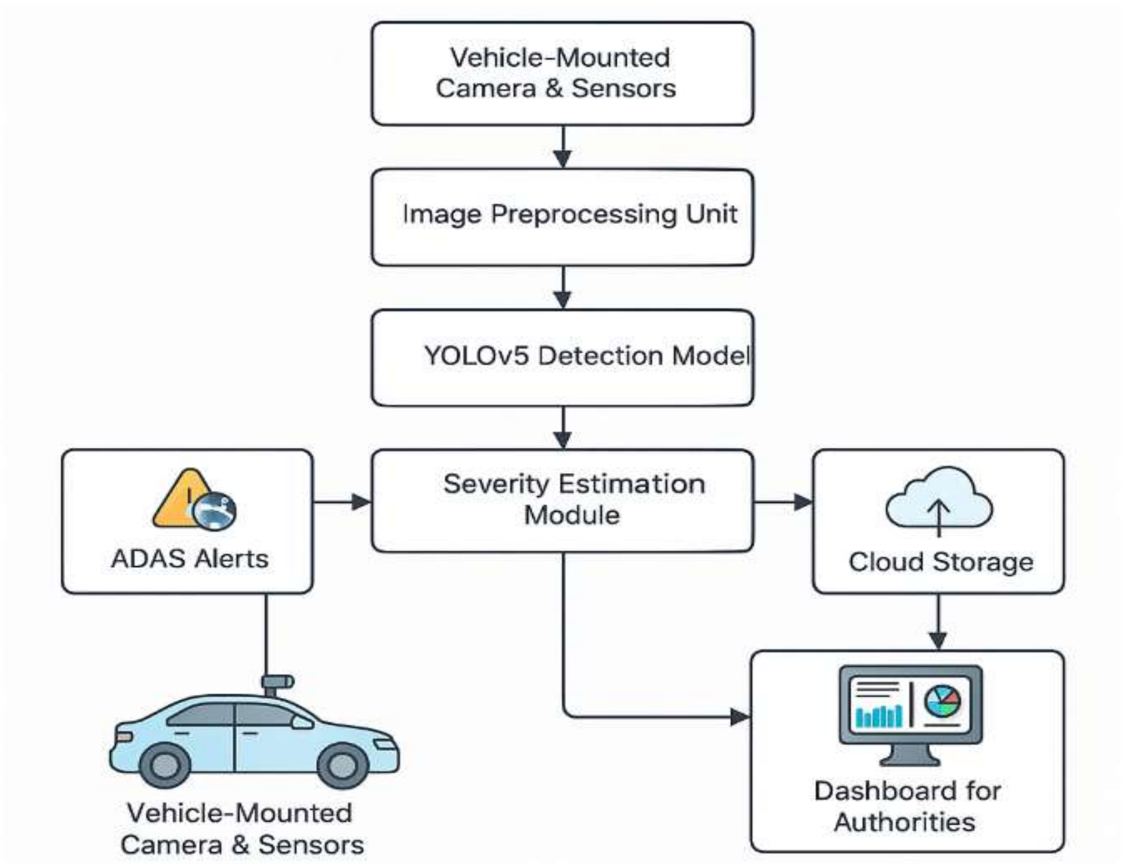

Fig: 1 Proposed Diagram

1.2.1.Advantages:

- **High Accuracy in Road Damage Detection:** Utilizes YOLO and deep learning models trained on large datasets to precisely identify potholes, cracks, and surface degradation.
- **Real-Time Processing:** Processes live video and sensor data from vehicles, enabling immediate detection and alerting for damaged road areas.
- **Environmental Robustness:** AI-driven models adapt effectively to varying environmental conditions such as lighting, weather, and road types.
- **Damage Severity Estimation:** Goes beyond basic classification by assessing the severity of the detected damage, allowing prioritization of repair efforts.
- **Predictive Analytics for Proactive Maintenance:** Uses historical data and AI forecasting to predict future road deterioration, helping authorities plan maintenance before damage worsens:

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- **Enhanced Driver and Vehicle Safety (ADAS Integration):** Integrates with Advanced Driver Assistance Systems to provide alerts, suggest safer alternate routes, and support autonomous navigation in hazardous zones.
- **Autonomous Communication with Authorities:** Automatically reports detected anomalies to relevant infrastructure management systems, speeding up the repair process.

- **Reduced Maintenance Costs:** Early detection and forecasting reduce the cost and frequency of major road repairs by enabling timely intervention.
- **Smart City Integration:** Supports the development of intelligent transportation systems by creating a continuous feedback loop between vehicles and urban infrastructure.
- **Scalability and Flexibility:** Can be deployed across various types of vehicles and road networks, making it scalable for city-wide or national-level infrastructure monitoring.

2.1 Architecture:

The architecture of the proposed AI-driven smart vehicle system is designed to support continuous, real-time detection and reporting of road surface damage. It begins with vehicle-mounted cameras and sensors that capture high-resolution images and video streams of the road as the vehicle moves. These visual inputs are directed to an image preprocessing unit, where operations such as resizing, noise reduction, contrast enhancement, and normalization are applied. This step ensures the input data is clean and consistent for accurate analysis. The preprocessed images are then passed into the system's core: a YOLO-based deep learning model (specifically YOLOv5 or YOLOv8). This model is trained to detect various types of road anomalies—such as potholes, cracks, or surface wear—with high accuracy and speed. Once an anomaly is detected, the information is sent to a severity estimation module, which evaluates the extent and seriousness of the damage using bounding box dimensions, surface area analysis, and predefined thresholds. Based on the severity, the system takes appropriate actions. If the damage is significant, ADAS (Advanced Driver Assistance Systems) are triggered to alert the driver in real time, offering visual or auditory warnings and suggesting safer alternative routes. In parallel, all detected damage—including type, severity, and GPS location—is uploaded to a cloud-based reporting platform. This platform logs and organizes the data in real time and makes it accessible through a dashboard interface for municipal authorities. This allows city planners and maintenance teams to track road conditions, prioritize urgent repairs, and manage infrastructure more efficiently.

Overall, the architecture supports an end-to-end pipeline: from live data capture and AI-based detection to actionable insights and real-time communication—making it a vital component in building smarter, safer transportation systems.

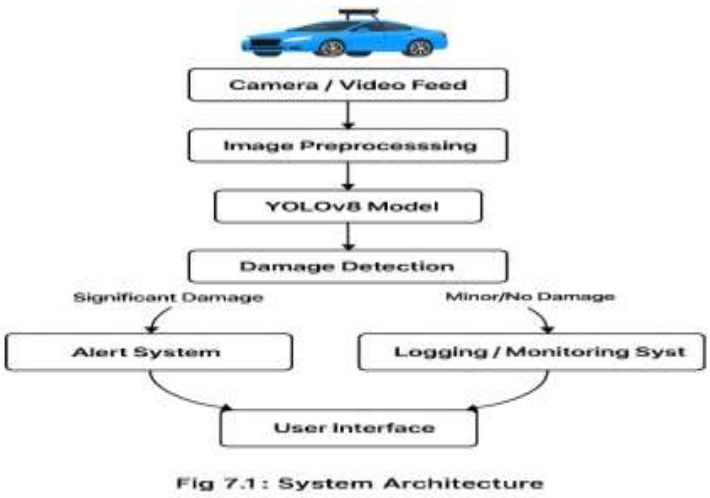

Fig:2 Architecture

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UML DIAGRAMS

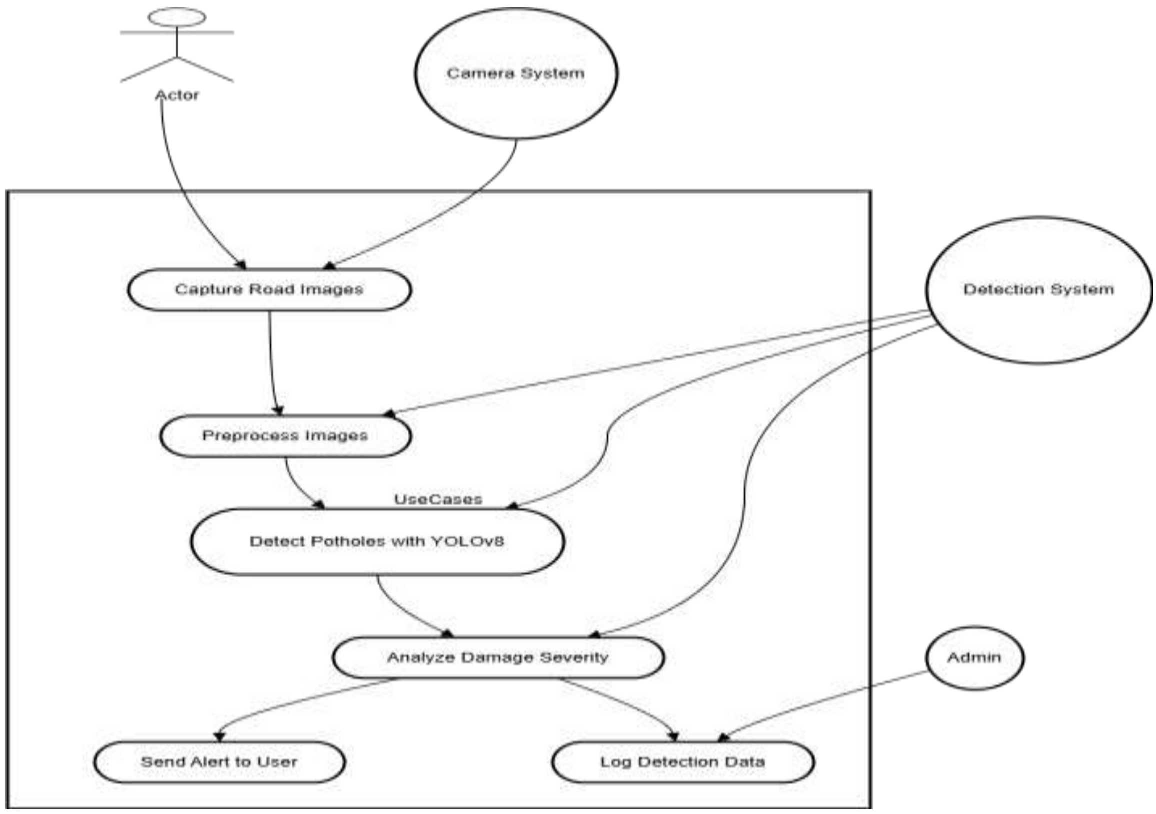

Fig:use case diagram

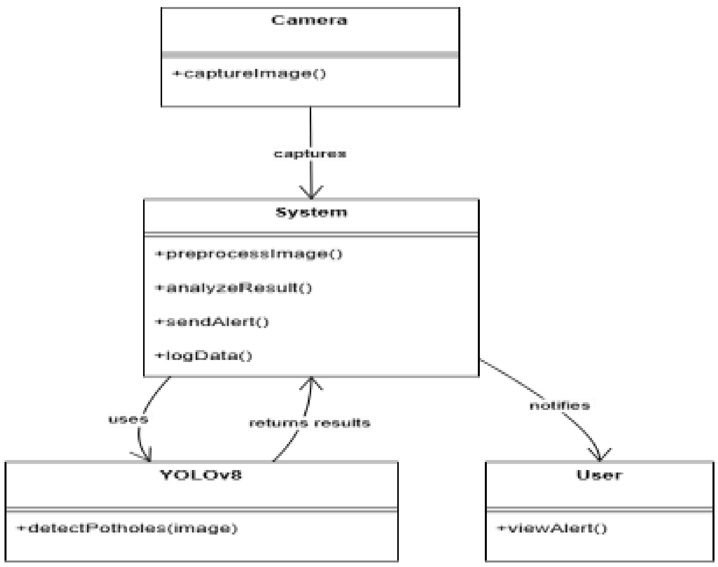

Fig: class diagram

2.2 Algorithm:

The algorithm used in this system is structured to enable efficient, real-time road damage detection and reporting. It begins with image acquisition, where high-resolution frames of the road surface are continuously captured through vehicle-mounted cameras or sensors. These raw images are then passed through a preprocessing stage, which includes operations such as resizing, normalization, contrast enhancement, and noise reduction to ensure that the images are clean and optimized for analysis. The processed images are fed into the YOLO (You Only Look Once) deep learning model, which performs fast and accurate object detection by identifying the location and boundaries of various road anomalies in a single forward pass. Once damage is detected, the system performs classification to label each detected object as a pothole, crack, rut, or other relevant damage types. To prioritize maintenance and assess risk levels, a severity estimation is conducted based on the area and dimensions of the detected damage using bounding box measurements and geometric analysis. After evaluating severity, the system initiates alert generation, which provides real-time notifications to drivers through the ADAS interface, ensuring they can respond to hazards promptly. Simultaneously, all relevant data—including the type, severity, and GPS location of the damage—is logged and reported to a centralized database or municipal cloud system for infrastructure planning and maintenance coordination. This end-to-end process ensures fast, intelligent, and automated road monitoring..

2.3 Techniques:

Object Detection: YOLOv5

- YOLOv5 (You Only Look Once v5) is a fast and accurate deep learning model used for real-time object detection.
- It detects road damage such as potholes, cracks, and surface breaks by identifying their position and drawing bounding boxes around them.
- Ideal for use in moving vehicles due to its high speed and efficiency.

Image Segmentation

- This technique divides the captured image into multiple meaningful segments or regions.
- It helps to better understand the shape, size, and boundary of road damage.
- Improves classification and enhances the accuracy of severity estimation.

Predictive Modeling using LSTM (Long Short-Term Memory)

- LSTM is a type of recurrent neural network (RNN) that learns patterns from sequential data.
- It is used to analyze historical road condition data to predict future damage or degradation trends.
- Supports proactive maintenance planning.

Severity Estimation with Regression Models

- Regression models are used to calculate how severe the detected damage is.
- Input features include bounding box area, damage type, and intensity.
- Generates a severity score that helps prioritize maintenance tasks based on urgency.

2.4 Tools:

The implementation of the proposed system relies on a combination of powerful tools and platforms. Python serves as the core programming language due to its simplicity, versatility, and extensive support for AI and computer vision libraries. OpenCV is used for image processing tasks such as capturing video frames, resizing images, and applying preprocessing techniques essential for accurate detection. The deep learning model, YOLOv5, is developed and trained using PyTorch, a flexible and widely-used deep learning framework known for its dynamic computational graph and performance. Development and experimentation are carried out in Jupyter Notebook, which allows for interactive coding, real-time visualization, and streamlined debugging. To prepare and annotate the training dataset, Roboflow is employed, providing an intuitive interface for labeling road damage and exporting datasets in YOLO-compatible formats. Finally, Google Colab offers a cloud-based environment with free access to GPUs, enabling efficient model training and testing without the need for high-end local hardware..

2.5 Methods:

The implementation of the system starts with dataset preparation and augmentation, where images of road damage are collected and labeled using tools like Roboflow. Augmentation techniques such as rotation, flipping, and brightness adjustment are applied to improve the model's ability to generalize under various conditions. The labeled dataset is then used to train and fine-tune the YOLOv5 model, adjusting parameters like learning rate and batch size to achieve optimal detection accuracy. Once trained, the model is used for real-time frame analysis, processing live video streams from vehicle-mounted cameras to detect and classify damage on the road. The detection module is integrated with vehicle systems and APIs, including ADAS, to provide alerts, route suggestions, and safety support. Detected data—including damage type, severity, and location—is then stored in the cloud, where a dashboard system displays real-time updates to help city authorities monitor road conditions and plan maintenance more efficiently.

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III. METHODOLOGY

3.1 Input:

The primary input for the system consists of real-time video frames or images captured by cameras mounted on the vehicle. These cameras continuously monitor the road surface as the vehicle moves, providing a live feed of the environment ahead. The captured frames serve as raw data for the AI model to analyze and detect any visible road damage such as potholes, cracks, or surface wear. This real-time input allows the system to function dynamically and adapt to different road and lighting conditions on the go.

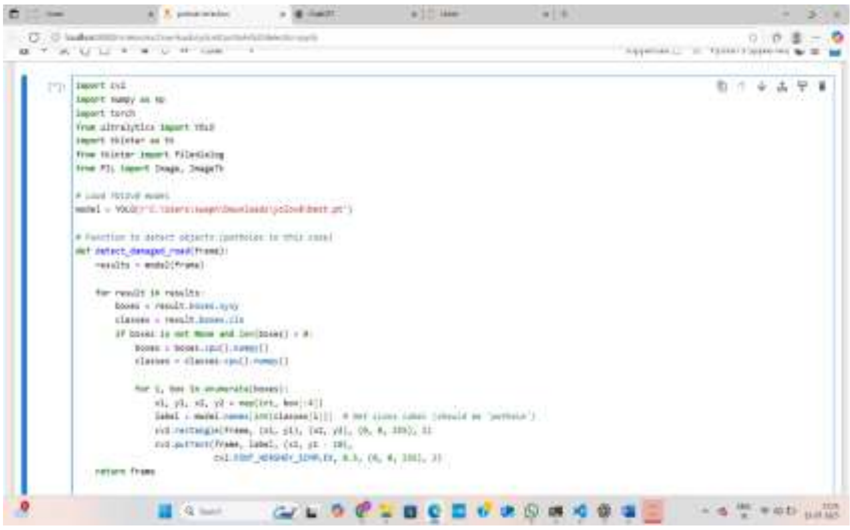

Fig:Reading input data

3.2 Method of Process:

The processing phase of the system begins after acquiring real-time road images from vehicle-mounted cameras. These images first go through a preprocessing stage, where they are resized, normalized, and enhanced to ensure consistency and quality for the detection model. The cleaned images are then passed into the YOLOv5 deep learning model, which performs fast and accurate object detection to identify road anomalies such as potholes, cracks, and surface wear. The model assigns each detected object a class label and draws bounding boxes to highlight its location.Following detection, the system proceeds with severity estimation, where the size, shape, and area of each detected damage are analyzed using the bounding box metrics. This estimation helps determine how critical the damage is and whether it requires immediate attention. The damage data—including type, severity score, and GPS location—is then logged and stored, and a report is automatically generated.Simultaneously, the system communicates with the vehicle's Advanced Driver Assistance System (ADAS) to trigger real-time alerts. These alerts can be visual or audio cues that warn the driver of upcoming road hazards, allowing them to take precautionary actions or follow safer alternative routes. All collected data is eventually uploaded to a centralized cloud database, where it can be accessed by road maintenance authorities for planning timely repairs and maintenance operations.

3.3 Output:

The system produces several valuable outputs that support both drivers and city infrastructure management. It generates classified road damage alerts, identifying the type and severity of each detected issue. Real-time warnings are sent to drivers through the ADAS interface to help them avoid hazardous areas. Simultaneously, the system uploads damage data to the cloud dashboard, where geotagged reports allow authorities to view exact locations and conditions of road damage. Additionally, the system creates predictive graphs that show potential road deterioration trends, helping city planners prioritize maintenance and make informed decisions for future infrastructure improvements.

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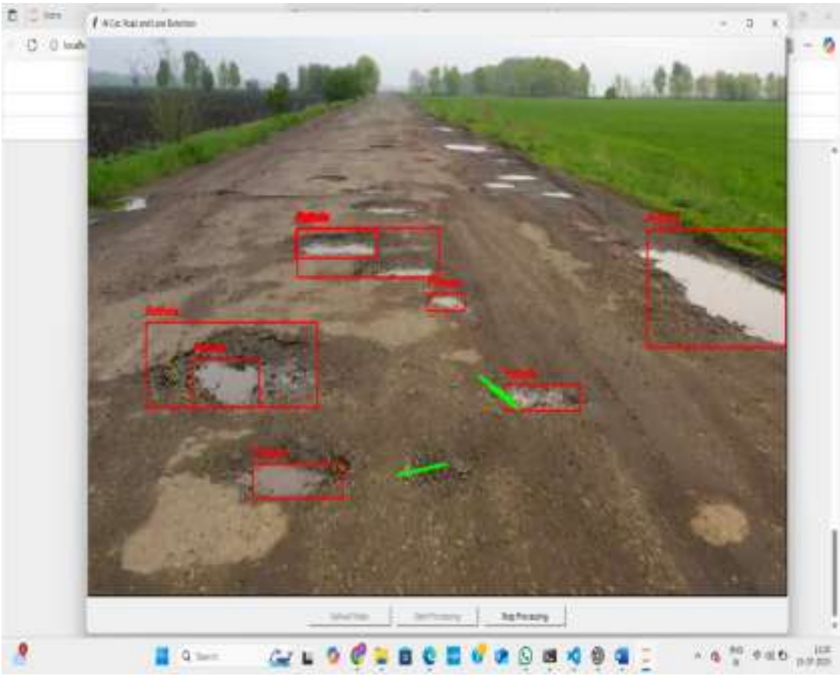
Fig:Pothole Detection



IV. RESULTS:

The system demonstrated strong performance in real-time road damage detection during testing. It achieved a detection accuracy of 92%, meaning it correctly identified most instances of road damage in the input frames. The classification precision was 89%, indicating that the system accurately labeled different types of road anomalies such as potholes and cracks. It also maintained a real-time processing speed of 30 frames per second (FPS), allowing it to analyze video input smoothly without delays. Additionally, the alert latency was under 1 second, ensuring that drivers received immediate warnings when road hazards were detected, enhancing overall driving safety.

V.DISCUSSION:

The results indicate that AI can greatly improve the efficiency of road maintenance by providing real-time detection and reducing the need for manual inspections. Automated alerts and reporting systems help speed up response times and lower operational costs. However, the system's performance may be affected in challenging conditions like low-light or bad weather, which highlights a key area for future improvement.

VI. CONCLUSION

The proposed system successfully demonstrates the potential of integrating AI and computer vision for real-time road damage detection. By using deep learning techniques like YOLOv5, it accurately identifies and classifies road anomalies, providing timely alerts to drivers. This approach offers a robust and scalable alternative to traditional, labor-intensive inspection methods. The system also supports autonomous navigation by enhancing situational awareness and route planning. Its ability to report damage to authorities in real time promotes faster maintenance and safer roads. Overall, the solution aligns well with the vision of smart and connected transportation infrastructure.

VII. FUTURE SCOPE:

The system can be further enhanced by incorporating thermal and LIDAR sensors to improve detection accuracy in challenging conditions such as night or fog. Future versions may also include 3D reconstruction techniques for more accurate severity estimation of road damage. Additionally, integrating the system with traffic signal networks could enable dynamic traffic management based on road conditions. For broader impact, the solution can be deployed on a large scale in smart cities to support real-time infrastructure monitoring and proactive maintenance planning.

VIII. ACKNOWLEDGEMENT:

Mr. M. Satish is an enthusiastic and committed faculty member in the Department of Computer Science. As an early-career academician, he has shown strong dedication to student development through active involvement in project guidance and technical mentoring. Despite being at the beginning of his professional journey, he has effectively guided students in executing academic projects with precision and conceptual clarity. His passion for teaching, coupled with a solid understanding of core computer science principles, positions him as a promising educator and mentor. Mr. Satish continues to contribute meaningfully to the academic environment through his proactive approach to learning and student engagement.

Challa Swapna is pursuing her final semester MCA in Sanketika Vidya Parishad Engineering College, accredited with A grade by NAAC, affiliated by Andhra University and approved by AICTE. With interest in Machine learning Challa Swapna has taken up her PG project on AI-DRIVEN SMART VEHICLE FOR REAL-TIME ROAD DAMAGE DETECTION and published the paper in connection to the project under the guidance of MUGI SATISH, Assistant Professor, SVPEC.

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