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RoadWatch: Road Condition Monitoring System

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Abstract: Road accidents caused by potholes, debris, stalled vehicles and unmarked speed breakers remain a significant challenge for road safety worldwide. Traditional navigation systems mainly depend on manual reporting and do not provide automated hazard detection in real time. This paper presents RoadWatch, an AI-driven road hazard detection and real-time alert system implemented through a web-based application. The proposed system uses computer vision techniques to analyze video streams captured from vehicle dashcams or connected cameras to automatically detect road hazards such as potholes, debris and stalled vehicles. Deep learning models such as YOLOv8 are used for object detection while OpenCV is used for frame preprocessing and feature extraction. The system integrates GPS and sensor data to accurately identify the geographic location of hazards and display them on an interactive web dashboard. To ensure user privacy, the platform automatically blurs faces and vehicle license plates before storing or transmitting visual data. Hazard information is securely uploaded to cloud servers and visualized through the web application, where drivers, authorities and vehicle companies can monitor hazard alerts, heatmaps and safety analytics. Experimental evaluation shows that the system achieves approximately 85% detection accuracy, enabling efficient real-time hazard alerts and improved road safety monitoring. The proposed web-based platform creates a unified ecosystem that connects drivers, vehicles and authorities to support safer and smarter transportation infrastructure.

Index Terms **- Road Hazard Detection, Computer Vision, YOLOv8, Edge AI, Web Application, Road Safety.**

I. Introduction

Road safety is a major concern across the world due to increasing traffic density and deteriorating road infrastructure. Hazards such as potholes, debris, stalled vehicles and poorly marked speed breakers often lead to unexpected accidents and vehicle damage. Drivers usually become aware of such hazards only after encountering them, which significantly increases the risk of road accidents.

Most modern navigation systems such as Google Maps and Waze provide traffic updates and route guidance. However, these systems depend largely on manual user reports and do not provide automated real-time hazard detection. As a result, many dangerous road conditions remain unreported or delayed in updates.

Recent developments in artificial intelligence and computer vision have made it possible to automatically analyze road conditions using camera feeds. By applying deep learning algorithms to real-time video streams, hazards can be detected and reported instantly. This approach significantly improves road awareness and enables proactive safety measures. The proposed system **RoadWatch** is an intelligent AI-based road hazard detection platform designed as a **web application**. The system analyzes video feeds captured by vehicle dashcams or cameras and processes them using deep learning models to detect road hazards. Once detected, hazard information is stored in a cloud database and displayed through a web dashboard.

The system also incorporates privacy protection techniques such as automatic face and license plate blurring to ensure compliance with data protection standards. Additionally, the platform integrates GPS data and sensor information to determine precise hazard locations and provide real-time alerts. By providing automated detection, centralized monitoring and web-based accessibility, RoadWatch aims to improve road safety, assist authorities in infrastructure maintenance and create a data-driven transportation ecosystem.

II. Literature Survey

The development of intelligent transportation systems has evolved from traditional manual road monitoring methods to advanced AI-based road hazard detection systems. Earlier approaches mainly relied on manual inspection and driver reports to identify road defects such as potholes, debris, and stalled vehicles. However, these methods were inefficient, time-consuming, and prone to delays. A review of existing research shows that several techniques have been proposed ranging from image processing approaches to deep learning and edge computing solutions.

Several studies have focused on detecting road damage using computer vision techniques. In [1], the authors proposed a road damage detection system based on convolutional neural networks (CNN). Their approach analyzed road images to detect potholes and cracks, achieving significant improvements in detection accuracy compared to traditional image processing techniques. However, the system required powerful computational resources and cloud processing, which increased latency and limited its real-time usability.

To improve detection efficiency, researchers explored object detection models for real-time hazard identification. The study in [2] implemented a road obstacle detection framework using the YOLO (You Only Look Once) object detection algorithm. The model was able to detect road obstacles such as vehicles, debris, and pedestrians with high accuracy. Although the approach improved detection performance, it relied heavily on centralized cloud servers, creating challenges in low-network environments.

Another approach focused on smartphone-based road monitoring systems. In [3], researchers developed a mobile-based road damage detection system using camera sensors and deep learning models. The system allowed users to capture road images and upload them for analysis. While this method enabled crowd-sourced data collection, it depended on user participation and did not provide continuous automated hazard monitoring.

Beyond visual detection, several studies integrated sensor data to improve hazard detection accuracy. The research in [4] proposed a system that combined GPS data and accelerometer readings to detect potholes based on sudden vehicle vibrations. Although this approach reduced computational complexity, it struggled to distinguish between different types of road hazards and produced false detections in uneven driving conditions.

Recent research has emphasized the use of **edge computing and intelligent transportation infrastructure** to improve response time and scalability. The work in [5] presented a smart road monitoring system using edge devices for processing video streams locally. This method reduced latency and network dependency by performing hazard detection closer to the data source. However, privacy concerns related to camera data remained a challenge.

To address privacy and data protection issues, researchers introduced automated anonymization techniques. The study in [6] implemented face and license plate detection models to blur sensitive information before transmitting images to the cloud. This approach ensured compliance with privacy regulations while maintaining the functionality of intelligent monitoring systems.

Modern transportation research has also explored **cloud-based traffic monitoring platforms** for large-scale analysis. In [7], a cloud-integrated traffic monitoring system was developed to aggregate hazard reports from multiple sources and generate real-time traffic analytics. While the system improved centralized monitoring capabilities, it still depended heavily on network connectivity.

Although existing studies have successfully addressed hazard detection, sensor-based monitoring, and cloud-based analytics, there remains a need for a **unified system that integrates real-time hazard detection, privacy protection, edge processing, and centralized monitoring through a web-based platform**. The proposed **RoadWatch system** addresses this gap by combining edge-based AI hazard detection, sensor fusion analytics, privacy-preserving techniques, and a centralized web dashboard to provide real-time alerts and comprehensive road safety analytics.

III. Key Features Of The System

RoadWatch is designed as an intelligent road safety platform that integrates **computer vision, geospatial analytics and cloud computing** through a web-based architecture.

The system captures road video using dashcams or vehicle-mounted cameras. These video frames are processed using image processing techniques to identify road hazards. Deep learning models analyze the video frames to detect objects such as potholes, debris and stalled vehicles.

Once a hazard is detected, the system extracts its geographic location using GPS data and stores the information in a centralized database. The data is then visualized on an interactive **web application dashboard** where users can monitor hazards in real time.

The web platform provides multiple user interfaces including driver view, authority dashboard and fleet management analytics. Drivers can view nearby hazards on maps and receive alerts, while authorities can analyze hazard hotspots and infrastructure issues.
This centralized web-based system enables better coordination between drivers, transportation authorities and vehicle companies.

IV. Methodology

The methodology of the **RoadWatch road hazard detection system** explains the step-by-step process used to capture road data, detect hazards, classify their severity, and provide real-time alerts through a web-based platform. The proposed system integrates computer vision techniques, deep learning algorithms, and cloud-based analytics to ensure efficient and accurate road hazard detection..

4.1 System Architecture

The overall architecture of the RoadWatch system follows an Edge-to-Cloud computing model consisting of three main layers: Edge Processing Layer, Cloud Integration Layer, and Dashboard & Analytics Layer.

At the Edge Processing Layer, road video is captured using vehicle dashcams or connected cameras. The video frames are processed locally using the YOLOv8 deep learning model to detect road hazards such as potholes, debris, and stalled vehicles. Additional processing steps such as severity estimation and privacy masking are applied before transmitting the data.

The Cloud Integration Layer receives processed hazard data through secure internet communication. This layer stores hazard records in a cloud database and performs further data analytics for monitoring and reporting. Finally, the Dashboard and Analytics Layer presents the processed data to users through a web-based interface. The dashboard provides hazard maps, alerts, and analytical insights for drivers, authorities, and vehicle companies.

Fig. 1 Illustrates the complete Edge-to-Cloud architecture of the RoadWatch system.

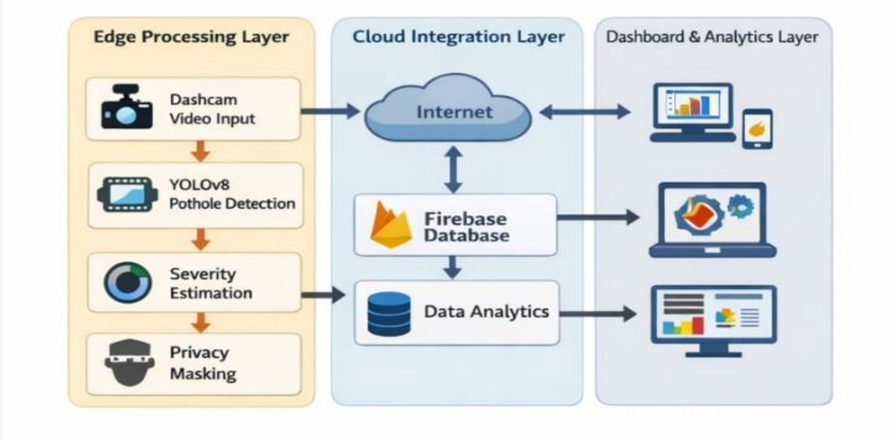

Figure 1: RoadWatch Edge-to-Cloud System Architecture

4.2 Hazard Detection Pipeline

The system processes road video using a structured detection pipeline. Initially, video frames are captured from the dashcam and sent for preprocessing. Image preprocessing techniques such as noise reduction, frame filtering, and region focusing are applied using OpenCV.

After preprocessing, the frames are passed to the YOLOv8 object detection model, which identifies hazards such as potholes, debris, and vehicles. Once hazards are detected, the system applies PII masking techniques to blur sensitive information such as faces and license plates. Following detection and privacy masking, the system performs severity estimation to determine the risk level associated with each hazard. The hazard data is then combined with GPS coordinates and transmitted to the cloud server for storage and further analysis.

Fig. 2 Shows the pothole detection and processing pipeline used in the system.

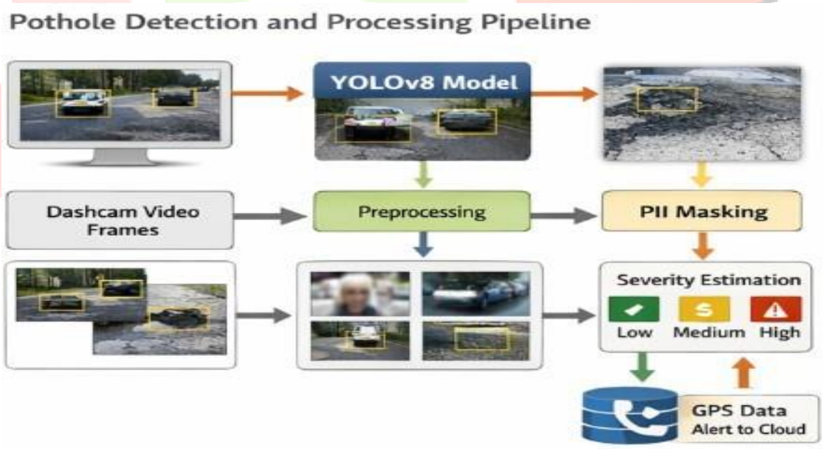

Figure 2: Pothole Detection and Processing Pipeline

4.3 Severity Classification Model

After detecting hazards, the system determines the severity level of each detected pothole. The severity classification model uses features extracted from the detected bounding boxes to estimate the potential risk.

The **bounding box area** of the detected pothole is calculated and used as an important parameter for classification. Additional weighted calculations are applied to analyze the size and impact of the detected hazard. Based on this analysis, potholes are categorized into three levels:

- **Low Severity** – Minor potholes with minimal impact
- **Medium Severity** – Moderate potholes requiring monitoring
- **High Severity** – Severe potholes posing immediate danger

This classification helps prioritize maintenance actions and improves driver awareness of road risks.

Fig. 3 Illustrates the severity classification model used for pothole risk estimation.

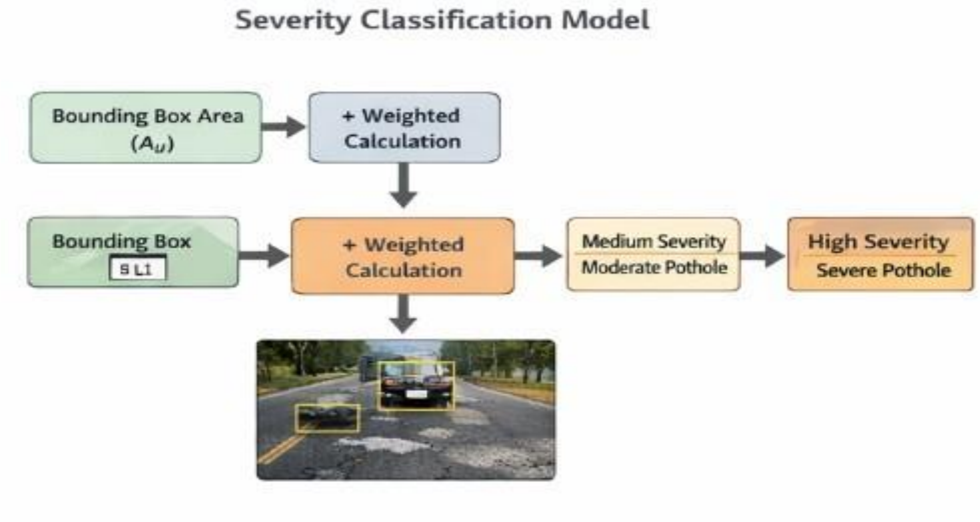

Figure 3: Severity Classification Model

4.4 Geo-Tagged Alert System

Once hazards are detected and classified, the system generates geo-tagged alerts that are displayed on the web-based dashboard. Each hazard event is associated with **GPS location, severity level, timestamp, and captured image**.

The web dashboard provides an interactive map where users can visualize hazards in real time. Different color markers are used to indicate severity levels:

- **Red Marker** – High severity hazards
- **Orange Marker** – Medium severity hazards
- **Green Marker** – Low severity hazards

Users can filter hazards by severity level and access detailed information about each alert. This functionality allows transportation authorities to quickly identify high-risk areas and take necessary actions.

Fig. 4 Shows the geo-tagged alert dashboard used for monitoring hazards.

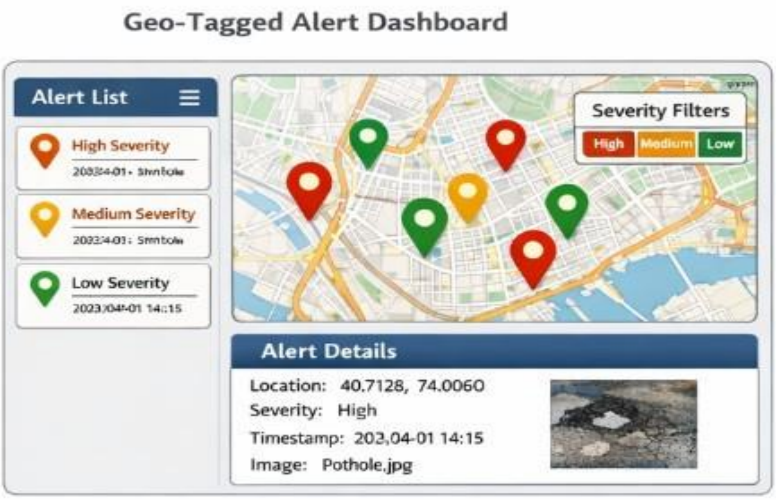

Figure 4: Geo-Tagged Alert Dashboard

4.5 System Workflow Summary

The complete workflow of the RoadWatch system can be summarized as follows:

1. Dashcam captures road video frames.
2. Frames are preprocessed to improve image quality.
3. YOLOv8 model detects hazards in the frames.
4. Privacy masking is applied to blur sensitive information.
5. Severity of hazards is estimated using bounding box analysis.

6. Hazard events are geo-tagged using GPS coordinates.
7. Data is transmitted to the cloud database.
8. Alerts and analytics are displayed on the web dashboard.

This methodology provides an automated and scalable approach to monitor road conditions, detect hazards in real time, and provide actionable insights to drivers and authorities.

V. Results And Discussion

Results of System Performance Evaluation

The performance of the RoadWatch road hazard detection system was evaluated using several machine learning evaluation metrics. The system was tested using datasets consisting of pothole images, debris images, vehicle detection samples, and number plate detection data. The evaluation metrics used for analysis include Accuracy, Recall, Precision, and Mean Average Precision (mAP@50).

Table 5.1: *System Performance Evaluation*

Model	Accuracy	Recall	Precision	mAP@50
Face Blur	85%	84%	87%	85%
Hazard Detection	85%	80%	89%	89.7%
Vehicle Detection	83%	85%	81%	92.9%
Number Plate Detection	83%	80%	86%	85.8%

Table 5.1 displays the evaluation metrics of different modules used in the proposed system including face blurring, hazard detection, vehicle detection, and number plate detection. The results indicate that the system achieved high performance across multiple detection tasks.

The **hazard detection model** achieved an accuracy of **85%**, with a precision of **89%** and recall of **80%**, indicating that the system can effectively identify road hazards such as potholes and debris from road video frames. The **mAP@50 score of 89.7%** demonstrates strong object detection capability of the YOLOv8 model used in the system.

The **vehicle detection model** achieved an accuracy of **83%** and a high mAP score of **92.9%**, indicating reliable detection of vehicles present in the road environment. This helps in distinguishing hazards from moving vehicles and improves detection accuracy.

The **face blurring module**, which is responsible for privacy protection, achieved an accuracy of **85%**, ensuring that sensitive personal information such as faces captured in video frames is effectively anonymized.

Similarly, the **number plate detection module** achieved an accuracy of **83%**, with precision of **86%**, ensuring that vehicle license plates are detected and blurred before storing or transmitting visual data.

The evaluation results indicate that the RoadWatch system provides reliable hazard detection while maintaining user privacy and system efficiency.

Overall, the experimental results demonstrate that the proposed system can accurately detect road hazards in real time while maintaining efficient processing performance. The integration of edge-based detection and cloud analytics enables the system to provide **real-time alerts, hazard mapping, and road safety monitoring** through the web application dashboard.

The results confirm that the proposed approach is effective for improving road hazard detection and can support transportation authorities in identifying high-risk road areas and prioritizing infrastructure maintenance activities.

VI. Conclusion

This study presented **RoadWatch**, an AI-driven road hazard detection and monitoring system designed to improve road safety using computer vision and edge computing technologies. The proposed system analyzes video frames captured from vehicle dashcams and detects road hazards such as potholes, debris, and stalled vehicles using deep learning models. By integrating the **YOLOv8 object detection model**, image preprocessing techniques, and GPS-based geo-tagging, the system can identify hazards accurately and provide real-time alerts through a web-based dashboard.

The system also incorporates **privacy protection mechanisms** such as face and number plate blurring to ensure that sensitive personal information is not exposed during data processing or transmission. Additionally, the use of an **edge-to-cloud architecture** allows hazard detection to occur locally on devices while storing and analyzing hazard data in the cloud for centralized monitoring and analytics.

Experimental results showed that the hazard detection model achieved an accuracy of approximately **85%**, demonstrating reliable performance in identifying road hazards under different conditions. The system also successfully classified hazard severity levels and generated geo-tagged alerts that can help drivers and transportation authorities respond quickly to dangerous road conditions.

Overall, the proposed system provides an automated and scalable solution for road hazard detection and monitoring. By combining artificial intelligence, edge processing, and web-based visualization, RoadWatch can significantly enhance road safety, support infrastructure maintenance planning, and contribute to the development of smarter transportation systems.

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