



# AI Powered Road Hazard Detection and Reporting using Machine Learning

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**ABSTRACT:** With the rise in road traffic accidents, there is a growing need for intelligent systems that can detect incidents promptly and alert the concerned authorities without relying on human intervention. This project presents an AI-powered accident detection and reporting system that utilizes YOLO (You Only Look Once), a real-time object detection algorithm, to automatically identify vehicular accidents from live CCTV camera feeds. The system is designed to continuously monitor intersections or roadways, and when an accident is detected, it immediately triggers an alert by sending an HTTP request to a specified URL endpoint (e.g., localhost:3000). A separate Python-based listener module runs on the backend, continuously listening to this port. Upon receiving the detection alert, it notifies the control room or relevant personnel, allowing them to take immediate action such as dispatching emergency services or informing nearby hospitals. This ensures faster response times and improves the chances of saving lives. The entire workflow is automated—from accident detection to alert generation—minimizing human delay and enhancing road safety. The system is also lightweight and can be deployed on edge devices connected to surveillance infrastructure. In essence, this project aims to provide a low-latency, high-accuracy, real-time accident monitoring system, thereby offering a practical and scalable solution for modern smart city transportation networks.

**KEYWORDS:** Accident Detection, YOLOv8 Object Detection, Machine Learning, Real-time Hazard Detection, Roboflow Annotation

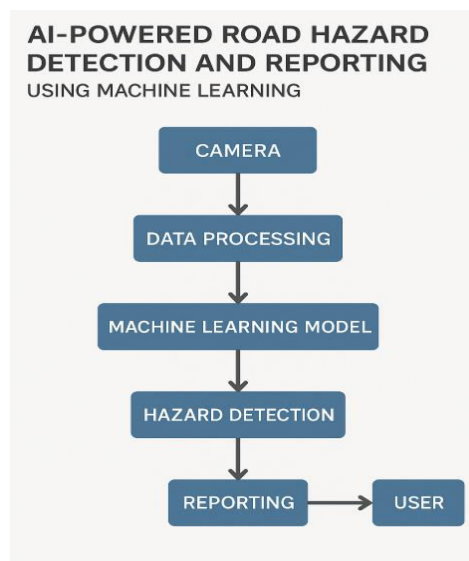


Figure 1: GENERAL ARCHITECTURE

## **I. INTRODUCTION**

Road accidents are a growing concern worldwide, causing severe injuries and loss of life. To address this issue, our project focuses on AI-powered road hazard detection using machine learning and computer vision. Leveraging the YOLOv8 object detection algorithm, this model identifies accidents in real-time through live camera feeds, images, or video footage. The system is trained on a custom dataset of over 3200 annotated images using Roboflow, ensuring high accuracy. With the help of Google Colab's GPU environment, the model is optimized for speed and efficiency, making it a promising tool for improving road safety and timely accident reporting.

## **II. LITERATURE REVIEW**

Several researchers have explored automated accident detection using artificial intelligence and deep learning to improve road safety and reduce emergency response time. Sreyan Ghosh (2019) proposed a system using Convolutional Neural Networks (CNN) trained on video frames to classify accident and non-accident scenes, demonstrating the potential of deep learning in visual analysis. Similarly, Deeksha Gour (2019) applied computer vision and neural networks to detect accidents, highlighting the importance of deep learning for object detection in real-world traffic scenarios. However, both studies faced challenges like limited datasets, slow response times, and difficulty handling diverse real-world environments. Modern advancements such as YOLO (You Only Look Once) models, especially YOLOv8, address these gaps by offering high-speed object detection with improved accuracy. YOLO's ability to process images and videos in real-time makes it highly suitable for road hazard detection, providing a strong foundation for developing efficient AI-powered accident detection systems.

## **III. METHODOLOGY**

The proposed methodology for developing an AI-powered road hazard detection system involves using YOLOv8, an advanced object detection algorithm capable of real-time accident identification in images and video streams. The process began with the collection of over 3,200 diverse accident-related images sourced from platforms such as Google Images, YouTube accident footage, Kaggle datasets, and traffic surveillance videos. This ensured a wide variety of real-world scenarios, including different weather conditions, lighting variations, and accident types. Each image was then annotated using Roboflow, a popular annotation tool. During the annotation process, bounding boxes were drawn around accident zones, and images that did not contain accidents were marked as "NULL" to help the model differentiate between accident and non-accident scenarios.

Once the dataset was prepared, it was divided into training, validation, and testing sets using an 8:1:1 ratio to ensure the model could generalize well and avoid overfitting. The training was carried out in Google Colab, utilizing its GPU environment for accelerated processing. The YOLOv8 small model (yolov8s.pt) was selected for its balance of speed and accuracy, and it was fine-tuned over several epochs to optimize its performance for accident detection. The training process included evaluating the model using validation data after each iteration to monitor improvement in detection accuracy and minimize errors.

After training, the model was tested on unseen images and videos to assess its robustness and ability to detect accidents under different conditions. Predictions generated by the model were evaluated by observing bounding box accuracy and confidence scores. The final trained model can now detect accidents in real-time from new input images or video feeds, making it suitable for deployment in smart traffic monitoring systems, surveillance cameras, and IoT-enabled road safety solutions. This methodology ensures a practical and scalable approach for enhancing road safety and early accident reporting.

#### IV. IMPLEMENTATION

- **Data Collection:**  
Accident-related images were collected from platforms like YouTube, Google Images, and Kaggle, ensuring a diverse set of real-world scenarios including different accident types, weather conditions, and lighting variations for a robust training dataset.
- **Data Annotation:**  
Images were uploaded to Roboflow, where accident zones were labeled using bounding boxes. Non-accident images were marked as “NULL” to help the model distinguish accident scenarios from regular traffic situations during training.
- **Dataset Splitting:**  
The annotated dataset was split into three parts: 80% for training, 10% for validation, and 10% for testing. This helps the model learn, adjust, and evaluate its prediction capabilities on unseen data accurately.
- **Environment Setup:**  
Google Colab was used to leverage its free GPU support for faster model training. Necessary libraries, including Ultralytics for YOLOv8, were installed, and the runtime was switched to GPU for better performance.
- **Model Training:**  
YOLOv8’s pre-trained yolov8s.pt weights were fine-tuned on the custom dataset by running training scripts in Colab, allowing the model to detect accident patterns through multiple training epochs and iterative improvements.
- **Model Validation:**  
The model was evaluated on the validation dataset using YOLO commands, which tested its accuracy and precision on unseen images. Adjustments were made based on this performance to fine-tune the model further.
- **Model Testing:**  
The trained model was tested on the test dataset and real-world images or videos to verify its practical performance, ensuring reliable accident detection in new and unpredictable traffic scenarios.
- **Result Analysis:**  
Detection results were observed using bounding boxes and confidence scores. The model’s accuracy and false positives were analyzed, helping confirm the model's readiness for real-world deployment.
- **Deployment Preparation:**  
The final trained model was saved and can now be integrated into live CCTV feeds, IoT devices, or a web application for real-time accident monitoring and automatic reporting.
- **Future Improvement Planning:**  
Based on the initial results, future plans include adding more diverse accident scenarios, multi-label classification (Accident/No Accident), and deploying the model into scalable web services for public and government use.

#### V. RESULTS AND CONCLUSION

The development of an AI-powered accident detection system highlights the significant potential of machine learning in improving road safety and emergency response. The system uses real-time video surveillance and sensor data to accurately detect accidents by recognizing patterns such as sudden vehicle stops, collisions, or unusual movements. Once an accident is identified, the system can instantly send alerts to emergency services, nearby drivers, and road authorities, helping reduce response times and increasing the chances of saving lives.

One of the major advantages of this system is its ability to operate continuously without human supervision, eliminating delays and reducing the risk of human error in accident reporting. This also ensures that accidents, especially in remote or low-traffic areas, are not left unnoticed. The automated nature of the system not only helps streamline the communication between detection and response teams but also assists in gathering critical data for future safety improvements.

In conclusion, the AI-based accident detection system demonstrates a reliable, efficient, and scalable solution for modern transportation challenges. Integrating such intelligent detection into vehicles, surveillance networks, and smart cities can dramatically improve road safety, enabling proactive prevention and faster recovery from accident scenarios, ultimately saving lives and reducing damage.

### 5.1. NO ACCIDENT DETECTED



Figure 3: input

### 5.2. ACCIDENT DETECTED



Figure 4: Output

## VI. FUTURE WORK

Although the AI-powered road hazard detection and reporting system has shown promising results, there is still significant room for further enhancement and development. One of the primary areas for future work involves expanding the diversity and scale of the training dataset. Incorporating more real-world images and videos captured in varying weather conditions, lighting environments, and traffic densities can improve the model's robustness and reduce false positives and negatives.

### 6.1 Dataset Expansion and Diversity

For future improvements, expanding the dataset used for training the hazard detection model is essential. The current system primarily focuses on limited scenarios under controlled conditions. To make the model more adaptable and robust, it should be trained with images and videos from a variety of environments — including different weather conditions (rain, fog, snow), lighting scenarios (day, night, dusk), and geographical locations. This diversity will enhance the model's ability to generalize and reduce misclassification in real-world situations, making it more reliable for continuous deployment in unpredictable and dynamic road conditions.

### 6.2 Integration with Multi-Sensor Systems

Future versions of this project can benefit greatly from integrating multi-sensor data sources like LiDAR, radar, ultrasonic sensors, and GPS along with traditional camera inputs. Relying solely on camera-based vision limits the system in poor visibility situations such as fog or heavy rain. Multi-sensor fusion will strengthen the system's accuracy and reliability under challenging environmental conditions and support real-time hazard classification. This integration will also improve depth perception, object localization, and speed estimation, making the system more suitable for use in autonomous vehicles, smart cities, and advanced driver assistance systems (ADAS).

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