

Smart V2I Alert System for Hairpin Bends

Adithya David M, Arvin Joseph, Ms Aswathy Ramakrishnan, Akash Babu, DhanushA

Dept. of Computer Science & Engineering Toc H Institute of Science & Technology Kerala, India

Abstract—Road accidents on mountain roads with steep slopes and sharp hairpin bends are a serious safety concern, mainly due to poor visibility and difficult driving conditions. Drivers approaching such bends often have no information about oncoming vehicles until it is too late to react. To address this problem, this paper proposes a Vehicle-to-Infrastructure (V2I) based alert system that improves driver awareness and reduces the risk of collisions at blind hairpin turns.

The proposed system uses a roadside unit (RSU) equipped with a camera and edge computing hardware to continuously monitor traffic near the bend. Vehicles are detected and classified in real time as light or heavy vehicles using on-device processing, avoiding delays caused by cloud dependency. Once a vehicle is detected, the RSU generates a compact warning message containing key information such as vehicle type, speed, and estimated time of arrival. This alert is transmitted to vehicles approaching from the opposite direction, where visibility is limited.

For reliable and low-latency communication, the system employs Cellular Vehicle-to-Everything (C-V2X) technology over 4G/5G or private 5G networks, achieving end-to-end latency of approximately 50–100 ms. Lane-specific alert delivery is ensured through camera-based lane detection, geographic filtering, and directional broadcasting. Receiving vehicles validate the alert using GPS position and heading before presenting visual or audible warnings to the driver.

The proposed solution is cost-effective, scalable, and suitable for real-world deployment on hazardous mountain roads. Future enhancements include AI-based collision risk prediction, improved GPS accuracy, and roadside display units for vehicles without on-board communication systems. Overall, the system demonstrates a practical approach to enhancing road safety at dangerous hairpin bends through the integration of perception, edge computing, and low-latency V2I communication.

Index Terms—V2I communication, Hairpin bends, Edge computing, YOLO vehicle detection, C-V2X, Collision avoidance, Intelligent transportation systems

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I. INTRODUCTION

Hairpin bends on mountainous roads pose significant safety risks due to sharp curvature, narrow carriageways, and complete obstruction of the line of sight between vehicles traveling in opposite directions. Traditional safety measures such as convex mirrors and static warning signboards are largely passive and unable to adapt to real-time traffic conditions, often resulting in delayed driver reactions and a high probability of severe collisions.

Recent developments in Intelligent Transportation Systems (ITS) have enabled real-time sensing, processing, and communication between vehicles and roadside infrastructure [7], [9]. Vehicle-to-Infrastructure (V2I) communication facilitates continuous monitoring of hazardous road segments by roadside

units and allows timely dissemination of warning messages to approaching vehicles. When integrated with edge computing and artificial intelligence, such systems are capable of delivering rapid, low-latency responses essential for accident prevention in visually constrained environments [2], [10].

This paper presents a Smart V2I Alert System that combines camera-based vehicle detection, edge-level AI inference,

and ultra-low-latency communication to provide early hazard warnings at blind hairpin bends. The proposed decentralized architecture eliminates reliance on cloud processing, thereby ensuring consistent real-time performance, enhanced reliability, and scalability for deployment across accident-prone mountainous regions [8], [9].

II. LITERATURE REVIEW

Several studies have explored collision avoidance and intelligent road safety systems using sensing, artificial intelligence, and vehicular communication technologies [3]. Early approaches largely relied on low-cost sensors such as ultrasonic and infrared modules for obstacle detection. While these systems offer ease of deployment, they suffer from limited detection range, poor environmental robustness, and the inability to classify vehicle types, reducing their effectiveness in complex traffic scenarios.

Recent research has shifted toward camera-based perception combined with deep learning techniques for accurate vehicle detection and classification [4], [14]. Convolutional neural network models such as YOLO have demonstrated high real-time performance across varying environmental conditions, enabling reliable identification of vehicles on curved and visually obstructed road segments. However, many vision-based systems depend on cloud computing for processing, introducing network latency that is unsuitable for safety-critical applications.

Edge computing integrated with next-generation cellular networks has emerged as a promising solution to overcome latency limitations [2], [10]. Studies on 5G-enabled edge architectures highlight their capability to perform localized AI inference with ultra-low response times,

significantly improving real-time vehicular safety operations. These systems reduce bandwidth consumption while enhancing privacy and reliability by processing data closer to the sensing source.

In parallel, Vehicle-to-Infrastructure (V2I) communication frameworks have been proposed to extend driver awareness beyond onboard sensors [7], [8]. Roadside units equipped with sensing and communication modules can detect approaching vehicles and broadcast hazard alerts, particularly in regions with limited visibility such as tunnels, sharp curves, and mountainous terrain. Empirical evaluations indicate that infrastructure-assisted alerts substantially reduce collision risk by enabling early driver response [3].

Despite these advancements, existing solutions often address perception, computation, or communication in isolation. Few systems offer an integrated edge-based AI perception framework combined with low-latency V2I communication specifically designed for blind hairpin bends. This gap motivates the development of a decentralized Smart V2I Alert System that unifies real-time vehicle detection, edge processing, and rapid hazard dissemination to enhance safety in visually constrained road environments [9].

III. METHODOLOGY

A. Proposed System Architecture

The proposed Smart V2I Alert System follows a decentralized edge-enabled architecture designed to provide real-time hazard awareness at blind hairpin bends. The framework integrates localized perception, on-device intelligence, and low-latency communication to enable proactive collision prevention.

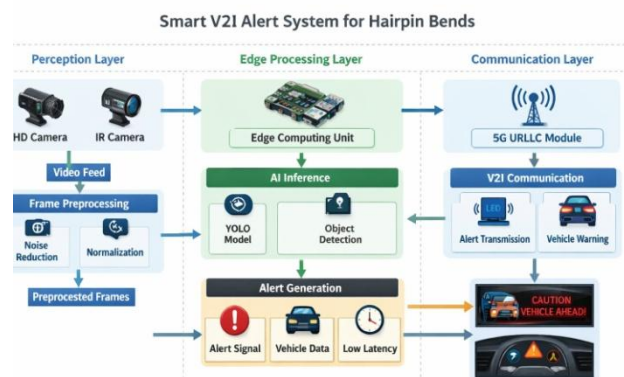


Fig. 1. Layered architecture of the proposed Smart V2I alert system showing the perception, processing, and communication layers.

The architecture is organized into three functional layers: Perception Layer, Processing Layer, and Communication Layer.

1) *Perception Layer*: The Perception Layer serves as the sensing interface of the system and is responsible for continuous traffic monitoring at the hairpin bend. A camera unit is positioned to capture both ascending and descending lanes with wide-angle coverage.

Captured video frames undergo basic preprocessing including noise reduction, illumination normalization, and motion segmentation to enhance detection robustness. These processed frames are forwarded to the edge processing unit for real-time analysis.

2) *Processing Layer*: The Processing Layer performs real-time vehicle detection, classification, and tracking. An edge processing unit executes a YOLOv8 deep learning model optimized for fast inference [14].

Detected vehicles are classified into light and heavy vehicle categories. Bounding box coordinates and confidence values are generated for each detected object. Temporal filtering techniques are applied to maintain detection continuity and estimate vehicle movement.

Essential vehicle parameters including vehicle type, direction, and timestamp are converted into compact metadata packets to minimize communication overhead.

3) *Communication Layer*: The Communication Layer enables low-latency V2I message exchange between roadside infrastructure and approaching vehicles [7],[15]. Vehicle metadata is transmitted wirelessly to opposite-lane vehicles through ESP32 microcontroller-based communication.

Received alerts are validated based on vehicle direction and lane relevance before triggering visual or audio warnings. Lane-specific filtering reduces false alerts and ensures contextual accuracy.

4) *System Workflow*: The operational flow of the system follows four sequential stages:

- Continuous video acquisition at the hairpin bend
 - Edge-based vehicle detection and classification
 - Metadata generation and hazard evaluation
 - Real-time alert transmission through V2I communication
- This closed-loop framework enables early hazard awareness before direct visual contact between vehicles.

B. System Implementation

The system was implemented using a combination of computer vision-based vehicle detection and ESP32-based wireless communication.



Fig.2. Experimental prototype setup showing the hairpin bend model.

A mobile phone camera mounted on a tripod was used to simulate a roadside surveillance unit. The main processing application was executed on a laptop acting as the edge computing platform, where real-time vehicle detection was performed using the YOLOv8 model.

ESP32 microcontrollers were deployed for wireless alert transmission between infrastructure and vehicle nodes. Supporting components including power modules and connecting circuits ensured stable system operation.

The complete workflow involved image capture, lane identification, lead vehicle detection, and alert message delivery through ESP32 communication.

C. Data Collection



Fig.3. Sample vehicle images used for dataset creation, including car and truck classes captured from different angles.

A controlled prototype environment was created using a scaled hairpin bend road model constructed from cardboard. Toy cars and toy trucks were used to represent light and heavy vehicles.

Images were captured using the mobile camera under varying orientations and lighting conditions to improve dataset diversity. The dataset was self-collected to maintain consistency in environmental conditions.

Two vehicle classes were formed:

- Car
- Truck

D. Preprocessing and Model Training

More than 300 images were manually annotated using bounding boxes through the Roboflow platform. The annotated dataset was exported in YOLO format. Training was performed on Google Colab using the YOLOv8 training pipeline, which automatically handled image resizing and normalization. The trained model was saved in .pt format for real-time inference.

E. System Testing

Testing was conducted on the prototype hairpin bend model by positioning vehicles alternately across both lanes.

Initial tests revealed classification and lane overlap issues, which were resolved through algorithm refinement. A virtual lane separation mechanism was introduced to distinguish vehicle direction.

Lead vehicle prioritization logic was implemented to determine alert triggering.

ESP32 communication was optimized through repeated testing, resulting in stable low-latency message

transmission.

IV. RESULTS AND DISCUSSION

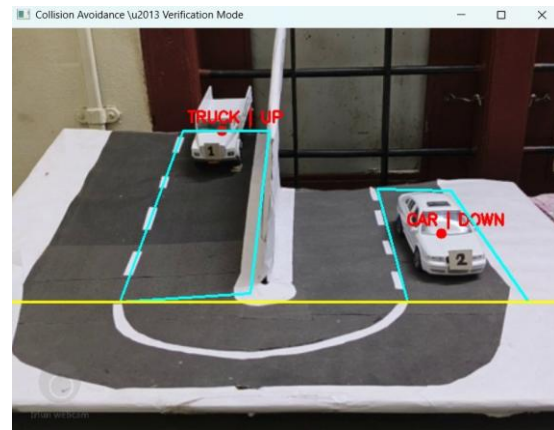


Fig.4. Output

The proposed Smart V2I Alert System was evaluated using the scaled hairpin bend prototype environment to assess detection performance, system responsiveness, and communication reliability. The layered architecture integrating perception, edge processing, and wireless communication demonstrated effective real-time operation [9].

The YOLOv8-based vehicle detection model consistently identified car and truck classes across multiple test scenarios. Vehicles approaching from both lanes were accurately localized using bounding box detection, enabling effective lane-wise separation and lead vehicle identification. The preprocessing techniques improved detection stability under varying illumination conditions.

Edge-based inference ensured minimal processing delay [2], [10], allowing hazard assessment and alert generation to occur in near real time. The conversion of detection outputs into compact metadata packets significantly reduced communication overhead while preserving essential safety information.

ESP32-based V2I communication achieved stable wireless transmission of alert messages after iterative optimization. Message delivery exhibited negligible latency and high reliability, ensuring timely warning dissemination to receiving nodes.

The combined system performance validates the feasibility of decentralized edge-enabled safety frameworks for blind curve accident prevention. The prototype demonstrated proactive hazard awareness before direct visual contact between vehicles, highlighting its effectiveness for real-world mountainous road scenarios.

However, the current experimental setup was limited to a scaled physical model. Environmental

factors such as heavy fog, rain, and long-range detection were not fully represented. These aspects will require enhanced sensing hardware in real-world deployments.

Overall, the results confirm that integrating computer vision with low-latency V2I communication offers a practical and scalable solution for improving road safety at hazardous hairpin bends.

V. CONCLUSION AND FUTURE WORK

This paper presented a decentralized, edge-enabled Smart V2I Alert System designed to enhance road safety at blind hairpin bends through real-time perception and low-latency communication. The proposed layered architecture effectively combined camera-based sensing, edge AI processing, and ESP32-

enabled wireless alert transmission to provide proactive hazard awareness.

The implemented prototype successfully demonstrated accurate vehicle detection, lane-wise separation, lead vehicle prioritization, and reliable alert delivery within a controlled environment. Edge-based processing minimized latency while maintaining high detection performance, validating the practicality of localized intelligence for real-time traffic safety applications.

Although the system was tested on a scaled model, the obtained results indicate strong potential for real-world deployment. Future work will focus on integrating higher-resolution cameras, weather-resilient sensors, and long-range communication modules to enhance robustness under diverse environmental conditions.

Further enhancements will include multi-sensor fusion combining radar, GPS, and vision data to improve detection reliability and enable predictive collision risk assessment. The addition of roadside visual display units may also support vehicles lacking onboard communication systems.

The proposed framework contributes toward intelligent transportation safety solutions and offers a scalable approach for accident prevention in challenging roadway environments.

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