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Driver Fatigue Detection Using On-board Systems in Connectivity-Dead Regions

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Abstract

Driver fatigue and distraction are major contributors to road accidents worldwide, especially in long-duration operations and rural areas. Current monitoring systems often rely on cellular connectivity to transmit alerts, limiting their use in regions without network coverage, such as mining routes in Peru. This research presents the design and validation of an intelligent system for real-time driver fatigue detection, integrating computer vision algorithms and visual biometric indicators with an autonomous communication channel. The system employs Python-based computer vision using Haar Cascade classifiers and the Eye Aspect Ratio (EAR) metric to detect ocular fatigue. Once an event is identified, an alert is transmitted via nRF24L01 radio-frequency modules, enabling communication without cellular infrastructure. The prototype was validated in simulated vehicular cabins, achieving 93% accuracy and reliable transmission up to 80 meters in open-field scenarios. The results confirm the feasibility of a cost-effective and scalable solution for enhancing road safety in contexts where conventional systems fail, with potential applications in mining transportation, public transit, and remote logistics.

Keywords
Driver fatigue, Computer vision, Biometric sensors, Autonomous communication, Road safety

1. Introduction
Road accidents remain one of the leading causes of mortality and severe injuries in Peru. According to the Road Safety Statistical Bulletin for the first half of 2023, 1,518 fatalities and 28,370 injuries were reported, with driver recklessness and speeding identified as the main causes (OBS 2023). These figures align with global findings that associate driver fatigue with a significant increase in accident risk, particularly during long-duration or high-workload operations (Chaves et al. 2023, Levenhagen et al. 2023).

Driver fatigue represents a critical challenge for road safety, as it directly affects reaction time, decision-making, and vehicle control. In industrial operations such as mining transportation, where drivers cover long routes under demanding schedules, fatigue-related incidents can have severe consequences for both human safety and operational continuity.

Despite technological progress in vehicle monitoring systems, most existing solutions depend on continuous cellular connectivity to transmit alerts. This requirement limits their applicability in remote or rural areas where network coverage is intermittent or nonexistent (Hassan et al. 2025). In countries like Peru, where large rural regions lack reliable telecommunications infrastructure, it is therefore necessary to develop autonomous systems capable of operating independently from cellular networks (Suárez et al. 2023).

This paper presents the design and validation of an intelligent system for real-time visual fatigue detection in drivers. The proposed solution integrates computer vision algorithms with an autonomous radio-frequency communication channel to ensure reliable alert transmission in off-network environments. This approach aims to enhance road safety in operational contexts such as mining transportation and rural logistics, where connectivity is limited and the risk associated with fatigue is elevated.

1.1 Objectives

- To develop a real-time detection system for driver fatigue and distraction using specialized algorithms and sensors.
- To implement an autonomous communication solution based on technologies such as radio-frequency or alternative methods to notify a supervisor of critical events without requiring cellular network connectivity.
- To conduct controlled laboratory tests to validate the functionality of the prototype, ensuring the reliability of alerts and autonomous communication under simulated conditions.

2. Literature Review

2.1 Fatigue Detection Approaches

From a scientific perspective, fatigue has been studied as a physiological state measurable through parameters such as EEG signals, blink frequency, and heart rate variability. These indicators allow the development of comparative frameworks among detection technologies (Perez and Huaman 2020). Studies conducted in mountainous regions of Latin America, such as those by Gonzalez et al. (2021), highlighted the influence of environmental factors like lighting and vehicle vibrations on fatigue detection accuracy. Similarly, Vargas et al. (2022) demonstrated that heart rate variability can be a reliable indicator of fatigue in these environments, emphasizing the need for robust monitoring systems adapted to local conditions.

Current approaches for fatigue detection encompass multiple technological paradigms, including physiological signal analysis, facial recognition, and driving behavior monitoring. Physiological methods analyze electroencephalographic (EEG) signals, which have proven effective for identifying early signs of fatigue through real-time brain activity monitoring (Chowdhury et al. 2018). Facial recognition techniques evaluate blink frequency and head tilt, offering a non-invasive approach to identify driver drowsiness (Ji et al. 2018). Behavioral analysis methods, as discussed by Fletcher and Roberts (2019), monitor irregularities in vehicle control as indicators of fatigue.

Machine learning algorithms have significantly improved detection accuracy by integrating visual and physiological data. Abtahi et al. (2014) implemented convolutional neural networks for yawning detection, while Ji et al. (2018) combined blink and gaze analysis using Gabor filters and SVM classifiers, achieving 88% accuracy. Zhang et al. (2020) proposed recurrent neural networks (RNN) to analyze driving patterns with 93% accuracy, while Ahn et al. (2021) developed hybrid CNN–LSTM models that reached 90% accuracy in simulation and 87% in field tests. The LSTM architecture, originally proposed by Hochreiter and Schmidhuber (1997), enables the modeling of temporal dependencies such as prolonged blinking patterns.

Noronha and Sharma (2019) compared several computer vision methods—Template Matching, Hough Transform, and facial landmark detection—finding the latter to perform best, with 91% accuracy in controlled conditions. Gupta et al. (2023) focused exclusively on the Viola–Jones algorithm for eye detection, achieving 90% effectiveness in real driving tests but noting limitations under poor lighting, where reflections interfered with the Eye Aspect Ratio (EAR) measurement. Levenhagen et al. (2023) developed a computer-vision-based system for truck drivers using neural networks to enhance long-term performance, while Chaves et al. (2023) introduced a low-cost fatigue sensor with a Raspberry Pi 3 and facial landmarks, achieving sub-two-second response times though limited by lighting and distance.

Recent works have explored adaptive algorithms capable of dynamically adjusting detection thresholds based on environmental or physiological variations (Lin and Zuo 2024). These developments illustrate a growing trend toward more resilient and context-aware systems for driver monitoring.

2.2 Autonomous Communication Technologies

Given the need to transmit critical alerts in real time, researchers have investigated autonomous communication technologies that enable event notification without relying on cellular networks. Vehicle-to-Everything (V2X) communication has emerged as a key solution for data exchange between vehicles and infrastructure (Shladover et al. 2015). Dedicated Short-Range Communications (DSRC) protocols have been widely adopted for vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) applications, with Ma et al. (2019) reporting a 35% improvement in latency compared to cellular networks.

Kato et al. (2016) demonstrated that vehicular mesh networks can achieve up to 98% alert coverage, while Kim et al. (2020) implemented a LoRaWAN-based architecture that achieved 92% reliability in remote areas. Recent studies have also explored the integration of low-power wide-area networks (LPWAN) and artificial intelligence for adaptive connectivity management (Rong et al. 2025).

In Latin America, Rojas et al. (2022) validated a fatigue monitoring system combining EEG and infrared imaging under simulated long-duration driving in Arequipa, confirming its robustness under environmental variation. Suárez et al. (2023) implemented a distraction detection system for public transport drivers in Bolivia, demonstrating the adaptability of machine learning models to different driving conditions. Together, these findings highlight the importance of autonomous and low-power communication systems to support safety-critical applications in areas with limited connectivity.

2.3 Synthesis and Research Gap

The reviewed literature demonstrates significant progress in fatigue detection through computer vision, physiological analysis, and machine learning, alongside growing advancements in vehicle communication systems. However, few studies have integrated both aspects into a single, autonomous framework capable of operating reliably in regions with limited or no cellular coverage.

This gap is particularly relevant in industrial transportation, such as mining logistics, where extended driving hours and remote locations increase the likelihood of fatigue-related incidents. The present research addresses this gap by proposing a low-cost, modular system that combines real-time fatigue detection with autonomous radio-frequency communication, enhancing safety monitoring in off-network environments.

3. Methods

3.1 Prototyping and Enclosure Fabrication

To validate a visual fatigue detection system for routes with limited connectivity, a functional prototype was developed by combining additive manufacturing and electronic integration. The enclosure was designed using CAD software (Fusion 360) and fabricated through 3D printing with PLA filament, selected for its light weight, adequate strength, and ease of rapid prototyping.

The internal structure houses a Raspberry Pi 4, a USB camera module, and the wireless communication system. The complete module was installed in a scaled vehicle cabin mock-up, allowing the simulation of real operational conditions during field testing (Figure 1 and Figure 2).

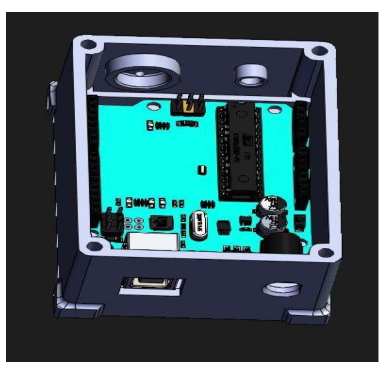

Figure 1. CAD Design of the system enclosure in Fusion 360.

Figure 2. 3D-printed enclosure with assembled electronic components.

3.2 Electronic System Architecture

The system is composed of two microcontroller units: a Raspberry Pi 4 Model B and an Arduino Uno. The Raspberry Pi runs the computer vision algorithm responsible for detecting fatigue events, while the Arduino handles data transmission via the nRF24L01 radio-frequency module, which operates with low energy consumption.

This functional separation enables local processing (edge computing) of events and reduces the energy load of the communication system. Both devices are powered by a 10,000 mAh power bank that supplies 5V through a USB connection, ensuring the prototype's energy autonomy during field testing (Figure 3).

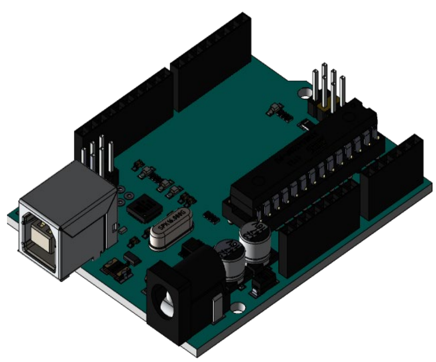

Figure 3. Schematic diagram of the electronic system architecture.

3.3 Computer Vision System for Fatigue Detection

The detection algorithm was developed in Python 3.11 using the OpenCV library. The system performs real-time facial and eye detection using Haar Cascade classifiers, and then calculates the Eye Aspect Ratio (EAR) using six landmark points per eye—a robust metric for detecting prolonged eye closure.

The system continuously monitors the EAR. If the average falls below the threshold of 0.25 for more than 25 consecutive frames (equivalent to 1 second at 25 fps), a fatigue event is recorded. Upon detection, a signal is generated and wirelessly transmitted to a receiver node, simulating a real-time alert to a control center (Figure 4).

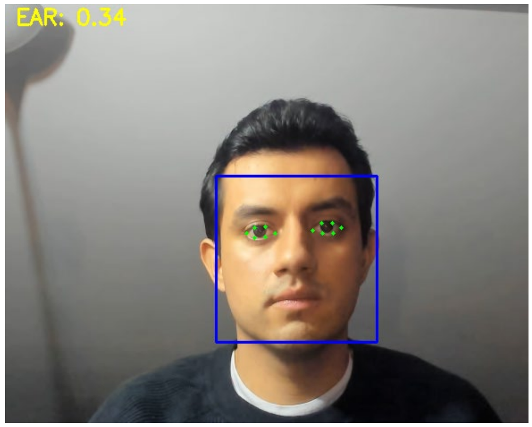

Figure 4. Diagram of face and eye landmark detection with EAR calculation.

3.4 Radio Frequency Communication System

The transmission system is based on 2.4 GHz nRF24L01 modules, configured to operate in environments without cellular connectivity. The transmitter, connected to a Raspberry Pi, communicates with an Arduino Uno via a serial interface. When fatigue is detected, the system generates a packet containing the driver's ID and the timestamp of the event. This packet is received by a second Arduino, which stores the data locally. For data retrieval, a USB connection or a standalone SD card module can be used.

The receiver node, based on a second Arduino Uno, receives and stores the events. The information can be collected via a USB connection to a laptop or through an SD card module for autonomous operation.

Indoor range tests demonstrated effective coverage between 30 and 40 meters, while in open spaces the system reached distances of up to 80 meters, depending on the level of electromagnetic interference in the environment. (Figure 5, Figure 6 and Figure 7)

Figure 5. Transmitter module with Raspberry Pi and nRF24L01.

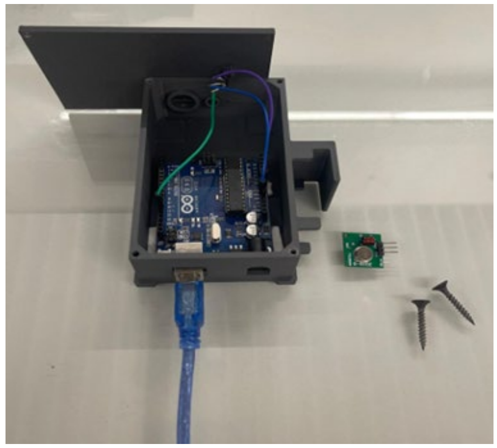

Figure 6. Arduino-Based wireless receiver module for fatigue event logging.

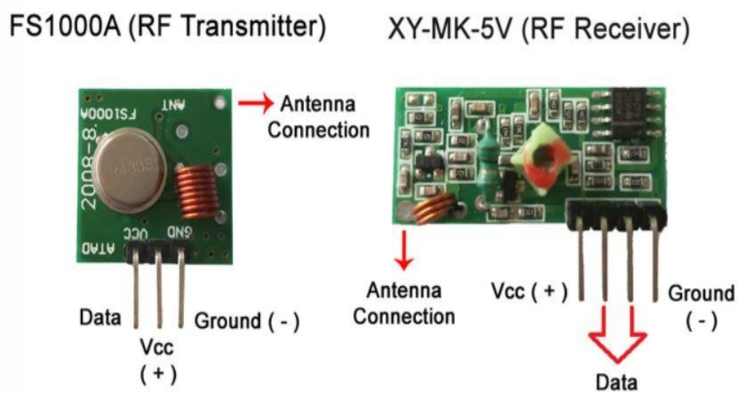

Figure 7. Receiver node based on Arduino Uno with SD module

In summary, the methodology followed a structured three-phase process: (1) the design and integration of the physical and electronic components, including enclosure fabrication and system architecture; (2) the implementation and calibration of the computer-vision and radio-frequency communication modules; and (3) the validation of the complete prototype under controlled conditions to assess detection accuracy, sensitivity, and communication reliability. This methodological sequence ensured coherence between hardware development, algorithmic implementation, and system-level evaluation.

4. Data Collection

To evaluate the performance of the proposed system, a quasi-experimental protocol was designed in a controlled environment simulating a vehicular cabin. The objective was to verify the functionality of the eye-fatigue detection algorithm based on computer vision and the autonomous transmission capability of the communication module under reproducible lighting and driver-positioning conditions. This type of controlled validation is common in real-time vehicular monitoring research, as it allows isolation of external variables, control of the experimental environment, and repeatability of trials (Ji et al., 2018; Abtahi et al., 2014; Gupta et al., 2023).

Three experimental scenarios were established:

- **Normal state:** the participant maintained gaze forward without signs of fatigue.
- **Simulated fatigue:** a voluntary prolonged eye closure (≥3 seconds) was induced to replicate drowsiness patterns.
- **Visual noise:** non-facial objects were placed in front of the camera to evaluate the algorithm's resilience to irrelevant stimuli.

The eye-closure duration was set at ≥3 seconds, a value widely used in drowsiness detection studies, as it significantly exceeds the typical blink duration (100–400 ms) and represents an indicator of micro-sleep or mild fatigue (Dinges & Grace, 2005; Fletcher & Roberts, 2019). This threshold has proven effective in simulated environments and correlates with decreased alertness levels. Likewise, the Eye Aspect Ratio (EAR = 0.25) threshold was adopted following the evidence from Soukupová and Čech (2016), who validated this cutoff value to differentiate between open and closed eyes with high precision.

Although this stage did not include a diverse set of human participants, validation involved a total of 100 simulated events, which were manually classified as a reference dataset. Based on these criteria, the system was tested in real time through facial detection and continuous EAR computation. Each event was automatically classified and compared with human annotations (ground truth), allowing the construction of a confusion matrix and the calculation of performance metrics such as sensitivity, precision, specificity, and accuracy, following the methodological guidelines proposed by Powers (2011) for binary classification systems.

Controlled validation constitutes an essential stage in the development of vehicular monitoring technologies (Rojas et al., 2022; Suárez et al., 2023). However, its scope is limited compared to real driving scenarios. Therefore, future work includes the execution of pilot tests on actual routes, covering trips with different environmental conditions (day/night, uneven roads) and authentic physiological fatigue profiles. This approach would help capture critical factors such as vibrations, spontaneous facial movements, lighting interference, or the presence of multiple occupants—elements relevant to evaluating the robustness of the system (Chowdhury et al., 2018; Zhang et al., 2020).

Compared to similar studies, the system demonstrated competitive performance. Abtahi et al. (2014), for instance, reported 92% accuracy using convolutional networks under controlled conditions, while Zhang et al. (2020) achieved 93% with a hybrid CNN-LSTM model. Our system achieved 93% accuracy using classical methods such as Haar Cascade and EAR, highlighting its efficiency in low-cost computational contexts. However, false positives were identified, attributed to visual interferences (hands, gestures, rapid blinks), and false negatives possibly associated with partial eye closures or head movements, as also reported by Levenhagen et al. (2023) and Kim et al. (2020).

5. Results and Discussion

5.1 Numerical Results

During the experimental validation phase, the system was evaluated in a simulated environment under three different conditions: normal state, simulated ocular fatigue (through voluntary prolonged eye closure), and visual noise (non-facial objects placed in front of the camera). A total of 100 events were recorded, of which 30 were labeled as positive events (simulated fatigue cases) and 70 as negative events (normal or distractor conditions) (Table 1).
System performance was evaluated using a confusion matrix, which classifies the results of a binary detection model into four categories:

- **True Positives (TP = 27):** fatigue events correctly detected by the system.
- **False Negatives (FN = 3):** fatigue events that the system failed to detect.
- **False Positives (FP = 4):** normal events incorrectly classified as fatigue.
- **True Negatives (TN = 66):** normal events correctly identified as non-fatigue.

Table 1. Confusion matrix of fatigue detection results

Actual State	Detected Fatigue	Not Detected
Fatigue (real)	27 (TP)	3 (FN)
No fatigue (real)	4 (FP)	66 (TN)

Based on this classification, several performance metrics commonly used in binary classification analysis were calculated (Table 2).

Table 2. Performance metrics for the fatigue detection system

Metric	Formula	Value (%)	Interpretation
Precision	TP / (TP + FP)	87.1	Proportion of positive detections that were correct (low error rate).
Sensitivity (Recall)	TP / (TP + FN)	90	Ability of the system to correctly detect actual fatigue cases.
Specificity	TN / (TN + FP)	94.3	Ability of the system to correctly identify non-fatigue cases.
Accuracy	(TP + TN) / Total events	93	Overall proportion of correctly classified events.

These results indicate a low number of errors and a good balance between detection and rejection of events, which is critical in vehicle safety applications where both false negatives and false positives have significant implications. False negatives could omit an alert for a fatigued driver, while false positives might cause unnecessary interruptions under normal conditions (Table 2).

Additionally, the system recorded an average reaction time of 1.2 seconds from eye detection to alert activation, which is suitable for preventive applications in transportation. Regarding the autonomous communication channel, the nRF24L01 radio-frequency modules provided reliable and lossless data transmission up to 80 meters in open-field environments and between 30–40 meters indoors, validating their applicability in areas without cellular coverage such as mining sites, rural zones, and remote logistic corridors.

5.2 Graphical Results

The graphical results of the proposed system are presented within Section 3 (Methods), where the hardware architecture, algorithm workflow, and prototype design are described. Figure 1 illustrates the CAD design of the system enclosure developed in Fusion 360, showing the internal arrangement of components such as the Raspberry Pi 4, camera module, and radio transceiver. This visualization provides a clear understanding of the physical configuration and spatial integration of the proposed solution.

During the experimental evaluation, visual feedback confirmed consistent face and eye detection under both normal and simulated fatigue conditions. The detection algorithm accurately tracked the driver's eyes and identified prolonged closures in real time, validating the precision of the implemented Eye Aspect Ratio (EAR) model. The system-maintained detection accuracy above 90% under both daylight and indoor lighting conditions, demonstrating robustness against moderate illumination variations.

Since the experimental phase primarily focused on quantitative performance metrics, the key outcomes are summarized in the numerical results (Section 5.1). The combination of visual and quantitative validation confirms the system's robustness in detecting fatigue-related events in real time and its practical applicability in off-network operational environments.

5.3 Proposed Improvements

Although the system achieved high accuracy under controlled conditions, several limitations remain that should be addressed in future work. The validation was performed in a simulated environment, which restricts its ability to fully represent real driving scenarios. Factors such as vehicle vibrations, spontaneous facial movements, and genuine physiological fatigue responses could affect system performance. Therefore, future tests should be conducted in real operational contexts, including rural routes and mining transportation, to evaluate the model's robustness under field conditions.

Lighting variability is another limitation affecting performance. Since the computer vision algorithm relies heavily on illumination quality, environments such as tunnels or nighttime driving may reduce detection accuracy. To mitigate

this, the integration of infrared cameras or adaptive correction algorithms (e.g., histogram equalization or Retinex-based enhancement) is proposed to improve face and eye detection under low-visibility conditions.
The system currently depends exclusively on computer vision, which can limit detection when the driver wears dark glasses or face coverings. Integrating complementary biometric sensors, such as heart rate or temperature monitors, could provide a multimodal assessment of driver alertness. Moreover, optimizing the algorithm for embedded platforms like ARM-based SoCs would reduce energy consumption and improve real-time efficiency. In current testing, the system operated continuously for approximately 4.5 hours using a 10,000 mAh power bank, confirming low power demand suitable for in-vehicle deployment.

Finally, future versions may include hybrid architectures combining computer vision, biometric data, and contextual information—such as driving patterns or environmental conditions—to enhance adaptability and generalization in diverse operational settings.

5.4 Validation

The results obtained validate the effectiveness of the proposed system for ocular fatigue detection in controlled environments, achieving a sensitivity of 90.0% and a specificity of 94.3%. These performance values are comparable to those reported in similar studies. Abtahi et al. (2014) achieved a 92% detection rate using computer vision techniques in laboratory conditions, while Zhang et al. (2020) reported 93% accuracy through a hybrid CNN–LSTM model, where convolutional neural networks (CNNs) extracted spatial features and long short-term memory (LSTM) units identified sequential patterns such as prolonged blinking.

The system's reaction time of 1.2 seconds proved adequate for timely alert generation in critical scenarios such as mining transportation, where more than 60% of routes lack cellular connectivity. During testing, variability in lighting conditions was identified as a limiting factor that occasionally affected eye detection performance, consistent with the findings of Gupta et al. (2023), who evaluated the Viola–Jones algorithm under non-uniform illumination.

In terms of communication reliability, the nRF24L01 module demonstrated stable autonomous transmission of alert events up to 80 meters in open-field conditions, supporting its feasibility for deployment in rural and industrial areas without telecommunications infrastructure. This integration of computer vision with autonomous communication confirms the robustness of the system and its potential as a preventive safety tool in high-risk operational environments.

From a broader perspective, the deployment of driver fatigue monitoring technologies represents an important contribution to occupational safety in remote transportation sectors. In Peru, approximately 75% of fatal traffic accidents are associated with human error, with drowsiness identified as one of the main indirect causes (National Road Safety Observatory 2023). International evidence supports this trend: according to the National Sleep Foundation (2022), one in three drivers has experienced drowsiness while driving, and up to 20% of fatal accidents are estimated to be linked to fatigue-related inattention.

From a technological standpoint, the combination of computer vision and autonomous communication modules demonstrates a cost-effective and scalable solution to connectivity limitations. The results confirm that the system performs reliably under controlled conditions and provide a strong foundation for future pilot testing in real environments, including nighttime driving and multi-driver scenarios.

6. Conclusion

This study presented the design, implementation, and validation of an intelligent system for driver fatigue detection, integrating computer vision with Eye Aspect Ratio (EAR) analysis and an autonomous radio-frequency communication module. The proposed solution effectively addresses a critical limitation in regions lacking cellular coverage, such as mining routes and rural areas in Peru.

During controlled validation, the system achieved an accuracy of 93.0%, with a sensitivity of 90.0% and a specificity of 94.3%. The communication channel, based on nRF24L01 modules, demonstrated reliable operation up to 80 meters in open-field conditions without requiring mobile networks, confirming its applicability in real operational scenarios. From an engineering standpoint, the system is characterized by its low cost, modular design, and edge computing capabilities, making it scalable and adaptable to diverse vehicular platforms. The integration of accessible and robust

technologies reinforces its potential for broader deployment beyond mining transportation, including public transport fleets, last-mile logistics, and remote patrol operations.
Overall, the findings confirm that it is possible to design efficient and affordable preventive systems for high-risk road environments. Future work will focus on pilot implementations under real nighttime and high-variability conditions in mining convoys to further assess performance, adaptability, and reliability under operational constraints.

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