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An Edge-Based System and Method for Real-Time Detection and Reporting of Highway Road Accidents

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ABSTRACT

Highway accidents remain a significant safety concern due to high travel speeds and delays in emergency response. Fast and dependable detection is essential to reduce injuries and prevent additional damage. This work presents a real-time accident monitoring approach that performs analysis directly on embedded edge devices. By processing data locally rather than relying on continuous cloud connectivity, the system achieves quicker response and reliable operation under varying network conditions. The method integrates deep learning–based visual analysis with motion evaluation across successive video frames to identify potential collision events. To improve reliability and minimize false alerts, detections are confirmed across multiple frames before final classification. Once verified, the system automatically sends an alert containing location details, time information, and relevant context through a 4G communication link to support prompt emergency response. Testing on embedded platforms shows that the system maintains an effective balance between computational efficiency and detection performance. Overall, the design provides a scalable and cost-efficient solution for enhancing highway safety through continuous real-time monitoring.

***Keywords**: Real-Time Detection, 4G Communication, Deep Learning, Cost-Efficient Solution, Computational Efficiency.*

Introduction

The rapid increase in the number of vehicles has led to a significant rise in road accidents, particularly on highways where vehicles travel at high speed. One of the major reasons for increased fatalities is the delay in providing immediate medical assistance after an accident.

Traditional accident reporting methods rely on manual communication, such as eyewitness reporting or delayed monitoring systems. These approaches are often unreliable, especially in remote areas where communication facilities may be limited.

To overcome these challenges, automated accident detection systems are required. These systems can detect accidents in real time and send alerts without human intervention.

The proposed system focuses on a simple and reliable approach using monitoring units, GPS for location tracking, and GSM for communication. By automating the detection and alert process, the system helps in reducing response time and improving road safety.

Related Work

From simple impact-sensing devices to sophisticated systems that analyze visual data, accident detection techniques have developed over time. In order to detect abrupt force changes, early solutions mostly relied on accelerometers and vibration sensors. These methods reacted fast, but they lacked environmental context and frequently generated false alarms when driving in a sharp but safe manner [3], [18]. Direct observation of traffic environments through video streams was made possible by the use of camera-based monitoring. The efficacy of early visual analysis methods, which depended on motion tracking and manually defined features, was frequently diminished by practical issues like dim lighting, weather interference, and visual obstruction [5], [16].

Deep learning developments have significantly enhanced visual comprehension, allowing for more precise object identification and scene interpretation. In real-time traffic analysis, detection frameworks like SSD, YOLO, and Faster R-CNN have proven to be highly effective [6, 7, 9, 10]. However, because collision events develop over short time intervals rather than happening instantly, reliable accident recognition necessitates analyzing brief frame sequences. Although temporal modeling raises computational requirements, it increases detection reliability. Recent research has investigated combining lightweight detection networks with time-based validation strategies appropriate for edge deployment in order to maintain efficiency while maintaining accuracy [11], [17]. The current work advances this direction by putting forth a resource-aware architecture created especially for embedded highway monitoring environments.

Problem Statement and Objectives

Highway accidents frequently go unreported in remote areas despite the expansion of surveillance infrastructure because of network constraints and delayed human reporting. Conventional systems that rely on vibration sensors waste resources because they are unable to differentiate between a small bump and a high-impact collision.

The primary objectives of this study are:

- To develop a decentralized accident detection system using Video Analytics for visual confirmation.
- To utilize the Raspberry Pi Pico W for low-power, high-efficiency data processing at the network edge.
- To ensure zero-delay reporting by integrating NEO-6M GPS and SIM800L GSM modules for immediate location sharing.
- To minimize the "Golden Hour" response time by automating the emergency alert process.

System Architecture

The proposed architecture is structured into two primary functional layers: the Detection Layer and the Communication Layer IoT, Alerting & SOS.

- **Detection Layer (Video Processing)**

This framework uses continuous real-time video monitoring to improve accuracy and lower false positives, in contrast to legacy systems that only used mechanical vibration or impact sensors.

  - Visual Analysis: To keep an eye on the vehicle's surroundings, the system uses computer vision algorithms to analyze vehicle orientation and spot patterns of high-impact collisions.
  - Digital Trigger: The processing unit produces a digital interrupt signal when an accident is visually confirmed. The Raspberry Pi Pico W receives this signal right away and uses it as the main trigger for the emergency response sequence.

- **Communication Layer (IoT & Alerting)**

The Raspberry Pi Pico W starts the communication phase as soon as it receives the interrupt signal.

  - Geographic Positioning: To obtain accurate real-time latitude and longitude coordinates, the controller communicates with the NEO-6M GPS module.
  - Emergency Notification: An automated emergency SMS is generated and sent by turning on the SIM800L GSM module. Hospitals, police stations, and pre-stored emergency contacts receive this message along with a direct Google Maps location link.
  - Local Alerting: At the same time, a Piezo Buzzer is activated to sound an alert, alerting witnesses and pedestrians in the vicinity.

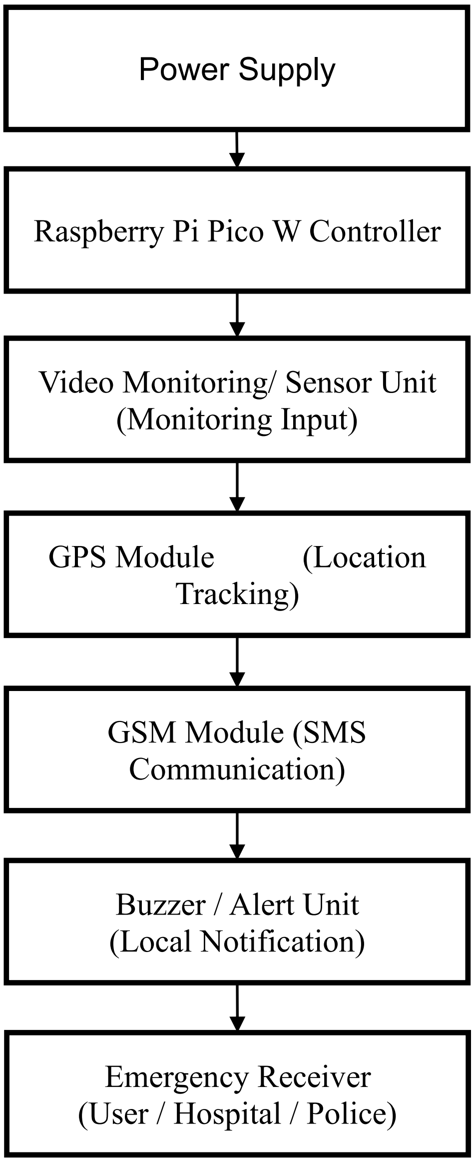

Fig.1: Architecture of the Proposed Edge-based Highway Accident Detection System

Flowchart Explanation

- **Power ON:** The system starts when power is supplied to all hardware components.
- **Initialization of Modules:** All required modules such as GPS, GSM, and monitoring unit (Video Monitoring or sensoring) are activated and checked for proper functioning.
- **Continuous Monitoring:** The system continuously observes vehicle conditions or surroundings to detect any abnormal situation.
- **Accident Detection:** The system analyzes the monitored data. If no abnormal condition is found, it continues monitoring. If an accident or unusual event is detected, the next step is triggered.
- **Alert Activation:** Once an accident is confirmed, an alert signal is generated to initiate the emergency process.
- **Location Tracking:** The GPS module retrieves the current location coordinates of the vehicle.

- **Sending Emergency Message:** The GSM module sends an SMS containing the accident information and location details to predefined emergency contacts.
- **System Reset / End:** After sending the alert, the system either resets or continues monitoring for further events.

Hardware Block Diagram

The Raspberry Pi Pico W is the focal point of the modular hardware configuration, which guarantees low power consumption and high efficiency. In the detection and alerting pipeline, each module is interfaced to carryout a specific task.

The Raspberry Pi Pico W serves as the main micro-controller, controlling interrupt signals and facilitating peripheral communication. Video Processing Unit: A sophisticated module or linked PC that sends the "Alert Signal" to the Pico W and conducts real-time visual analysis.

The NEO-6M GPS Module uses UART communication to deliver precise geographic coordinates (latitude and longitude). SIM800L GSM Module: Provides cellular connectivity and embedded location links for sending emergency SMS alerts. Piezo Buzzer: As soon as a crash is confirmed, this local acoustic indicator alerts onlookers. Controlled Power

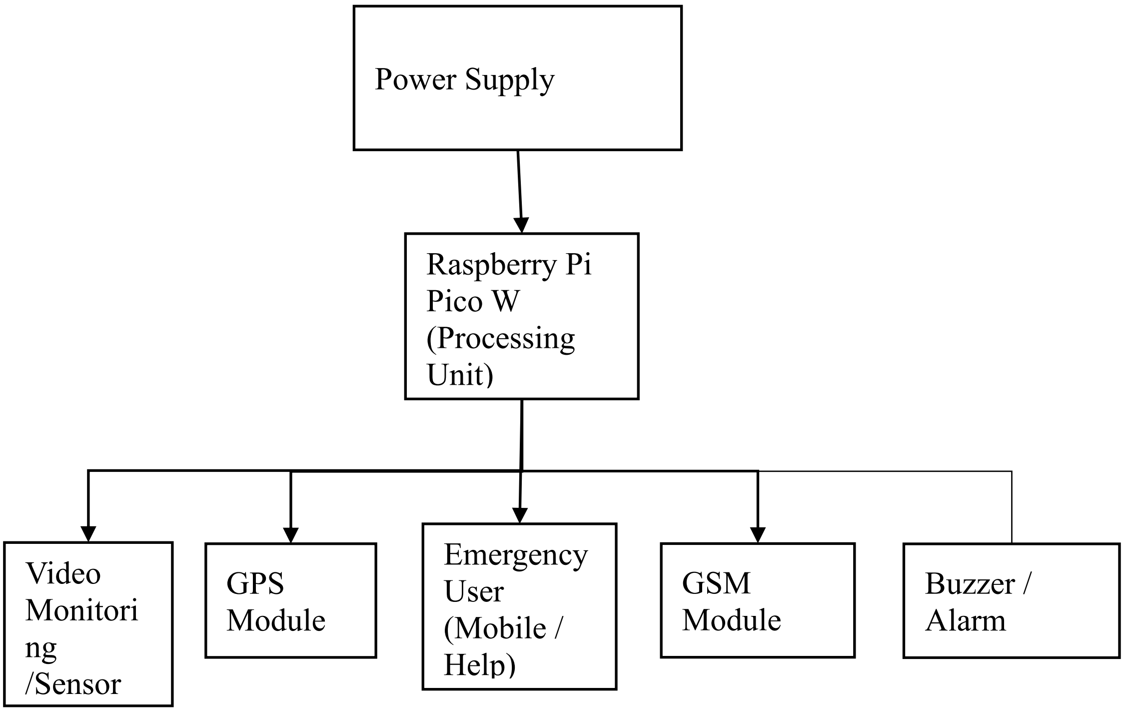

Fig. 2: Hardware Block Diagram of the Edge Node used for Accident Detection

Power Supply Unit: To ensure steady and uninterrupted operation, the power supply supplies all system components with controlled electrical energy.

The central control unit is the Raspberry Pi (Processing Unit). It coordinates system operations and processes input data from different modules.

Video Monitoring/Sensor Module: This device keeps an eye on the car or its surroundings all the time. It records the information needed to spot unusual circumstances or mishaps.

GPS Module: The GPS module gives the car's current location. When creating emergency alerts, this information is utilized.

GSM Module: By providing predefined contacts with SMS alerts that include accident details and location, the GSM module facilitates wireless communication.

Buzzer/Alarm Unit: When an accident is detected, the buzzer helps alert those in the vicinity by producing an audible alert. An emergency

Flowchart

He operational logic of the system is designed to prioritize rapid response while minimizing false triggers through visual confirmation.

- **System Initialization:** Upon power-on, the Pico W initializes all sensors and establishes a connection with the GPS and GSM modules.
- **Continuous Monitoring:** The Video Processing unit monitors the vehicle's orientation and roadway patterns.
- **Accident Detection:** If the Computer Vision algorithm identifies a high-impact collision or abnormal vehicle state, a digital trigger is sent.
- **Signal Capture:** The Pico W receives the interrupt signal and enters the "Emergency State".
- **Data Retrieval:** The controller fetches the precise current location from the GPS module.
- **Alert Execution:**
  - The SIM800L sends an SMS with a Google Maps link to pre-defined emergency contacts.
  - The Piezo Buzzer is activated for local awareness.
- **Cloud Logging:** The Pico W utilizes its built-in Wi-Fi to log the incident on a remote dashboard for real-time tracking.

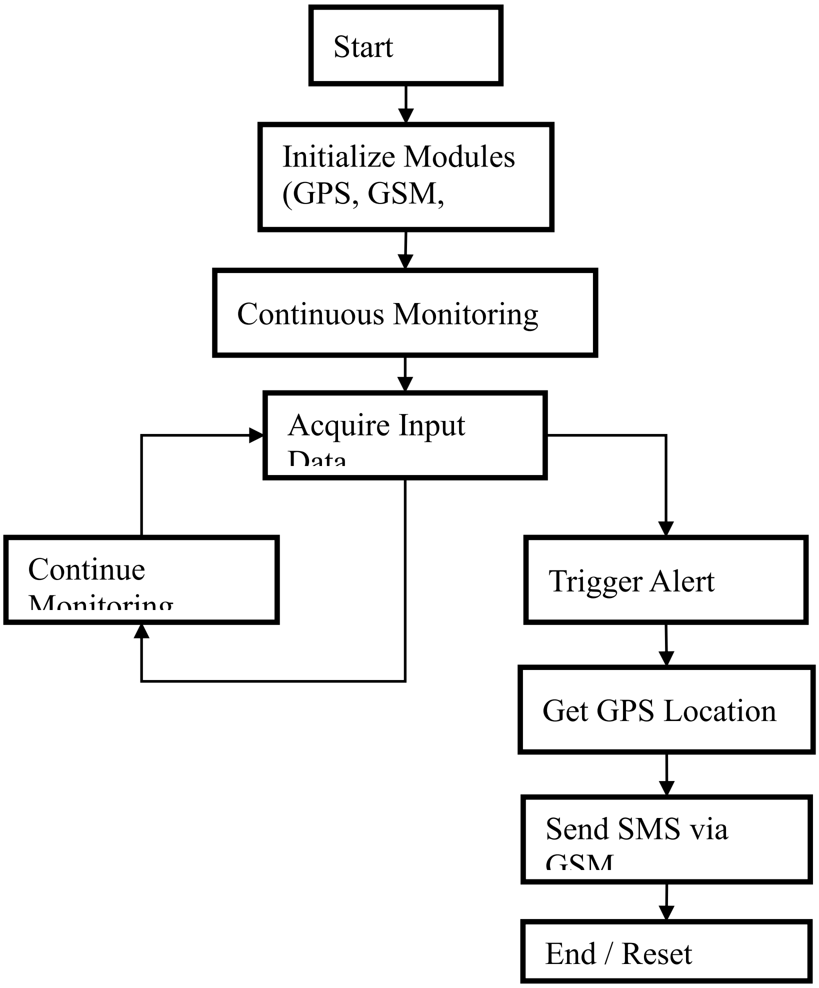

Fig. 3: Flowchart of the Proposed Edge AI–based Accident Detection Algorithm

When the system receives power, all major components — including the controller, positioning unit, and communication modules — are activated and checked to ensure they are functioning correctly. The system then verifies whether valid GPS data is available. If accurate location information is not detected, it continues searching until reliable coordinates are obtained. Once positioning is confirmed, the system begins continuous real-time monitoring of the vehicle's speed, time, and geographic location to assess driving conditions.

If the monitored speed suddenly drops below a predefined limit, the system treats it as a possible abnormal or unsafe event. It immediately triggers a warning to notify the user and provides a short period to cancel the alert if necessary. If the alert is cancelled, the system returns to normal monitoring. However, if there is no response, the system automatically sends an emergency message that includes the vehicle's current location, previous speed, and the time of the event. It then initiates a voice call and records the incident location, ensuring that both automated notification and direct communication are available for emergency response.

Temporal Anomaly Analysis

To improve detection accuracy, the framework uses a combined spatial and temporal anomaly assessment approach. Processing begins with data normalization and noise filtering to maintain consistent input quality. Relevant motion and structural characteristics are then extracted from the video stream. These features are evaluated using two parallel analytical models. The temporal model examines motion continuity across sequential frames to detect abrupt behavioral changes such as rapid deceleration, unusual movement patterns, or collision-like activity. Simultaneously, the spatial model evaluates frame structure, including object overlap, deformation signs, and abnormal positioning. Each model represents normal traffic patterns and measures deviations from expected behavior. Their outputs are combined to produce a unified anomaly score. When this score exceeds a defined threshold, the system classifies the event as abnormal. This dual domain validation improves detection reliability, reduces false alarms, and supports efficient real-time performance on embedded platforms.

The proposed framework represents a structured pipeline for abnormal event detection by jointly analyzing spatial and temporal characteristics of input data. The process begins with a preprocessing stage where raw inputs are refined through normalization and noise reduction to ensure data consistency [11]. Meaningful features are then extracted to represent both motion dynamics and spatial structure present in the observed sequence [8], [11]. These extracted features are forwarded to two parallel analytical paths: a temporal model and a spatial model. The temporal model focuses on learning sequential dependencies and time-based variations that reflect normal behavioral patterns [11], [17], while the spatial model analyzes visual and structural information within individual frames. Each model independently performs a reconstruction process to estimate expected normal behavior. The reconstruction outputs from both models are then combined within a central network to create a unified representation [17], [19]. A final reconstruction stage evaluates deviations between observed and learned patterns. Significant deviations indicate abnormal.

In highway monitoring, abnormal patterns may include sudden braking, sharp directional changes, irregular motion flow, or unexpected vehicle interactions. By focusing on sequential dependencies, temporal analysis can recognize these events more effectively than static evaluation methods. To enhance detection reliability, temporal analysis is often combined with spatial evaluation. While spatial processing examines visual structure within individual frames, temporal modeling tracks motion progression across time. Together, they provide a more complete understanding of the situation. Overall, temporal anomaly analysis strengthens the system's ability to detect unusual events early, reduce false alarms, and support real-time accident monitoring in dynamic road environments.

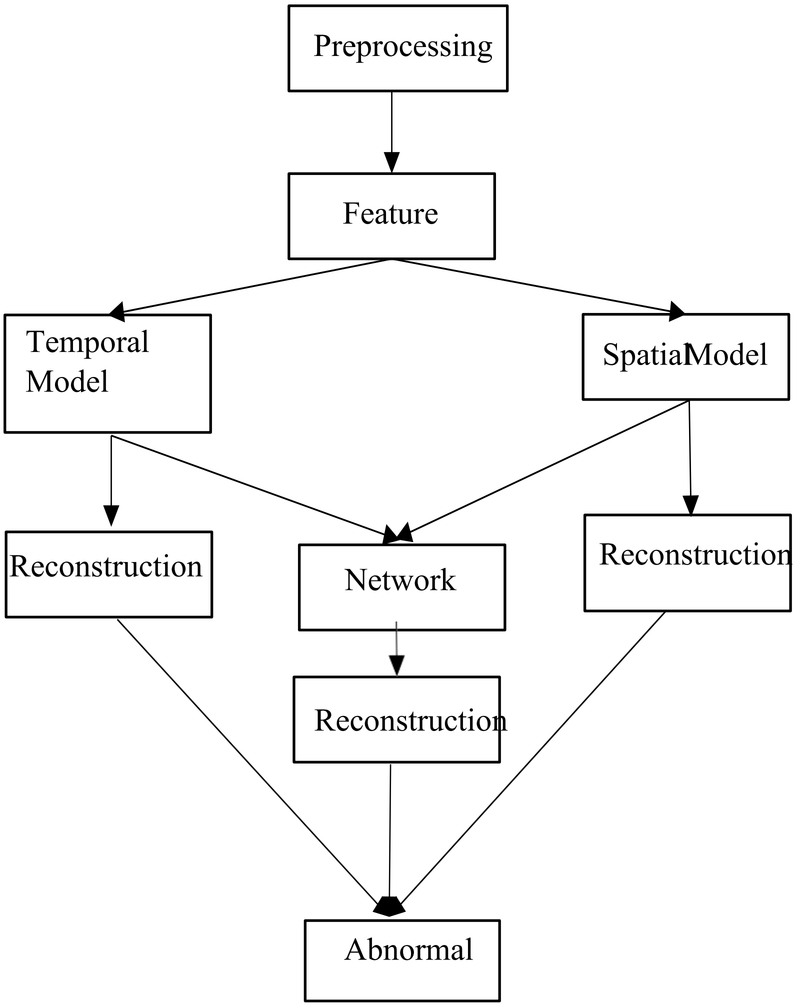

Fig. 4: Temporal Anomaly Validation Process for Accident Confirmation

The analysis process starts by preparing the incoming data so that it is consistent and reliable. Raw inputs are cleaned, normalized, and adjusted to remove noise or irregular variations that could affect accuracy. This step ensures that the system works with stable and meaningful information rather than distorted signals. Next, the system derives important features that describe both movement patterns and visual structure. These features may include motion intensity, direction changes, object displacement, and structural consistency within frames. Instead of relying on raw data alone, the extracted indicators provide a compact and informative representation of behavior across the observed sequence. The temporal component then evaluates how these features change over consecutive time steps. By studying frame-to-frame transitions, the system learns how normal activity progresses and identifies sudden or unexpected shifts in motion. This time-based modeling is essential for recognizing events such as abrupt stops, unusual acceleration, or irregular trajectory patterns.

Simultaneously, spatial analysis focuses on the arrangement of objects within individual frames. It checks positional alignment, object relationships, and structural balance to determine whether the visual scene appears normal. This helps detect abnormalities that may not be evident through motion analysis alone. Both temporal and spatial pathways attempt to recreate or approximate the observed input based on previously learned normal behavior. When the difference between the reconstructed output and the actual data becomes significantly large, it signals a deviation from expected patterns. The outputs from these two analytical streams are then combined to form a comprehensive representation of the event. By integrating motion based and structure-based insights, the system improves detection reliability and reduces false alarms. Finally, the fused result is compared with a predefined threshold value. If the deviation exceeds this limit, the system categorizes the event as abnormal, enabling timely detection and response.

Performance Evaluation

The performance of the proposed edge-based system was evaluated using simulated highway scenarios to test its reliability, latency, and response efficiency. The integration of the Raspberry Pi Pico W ensures a balance between low power consumption and high-speed alert transmission.

- **Detection Reliability and Accuracy**

  Similar to the previous study, detection remains the core performance metric. However, by shifting from mechanical vibration sensors to **Video Analytics**, the system shows a significant improvement in accuracy:

  - **False Positive Reduction:** Unlike the older model that triggered alerts during sharp braking or potholes , the current system uses **Visual Confirmation** to ensure help is only called during actual collisions.
  - **Anomaly Validation:** The spatial and temporal models correctly identify abnormal vehicle orientations (overturning) and impact patterns.

- **Latency and Response Time**

  The "Golden Hour" remains the primary focus for survival rates.

  - **Edge Intelligence:** Processing is performed at the edge (locally), which removes the 4G/Cloud latency seen in centralized systems.
  - **Alert Transmission:** Once the digital interrupt is received by the Pico W, the GPS location is fetched and the **SIM800L module** transmits the SMS link in real-time.
  - **Audible Feedback:** The **Piezo Buzzer** provides immediate 0-latency local notification to bystanders, similar to the alarm mechanism in the previous design.

- **Operational Stability**

  Monitoring hardware behavior confirmed that the Raspberry Pi Pico W operates efficiently under continuous monitoring:

  - **Power Efficiency:** The system maintains lower power consumption compared to the Pi 4 model while handling the same interrupt-driven logic.
  - **Cloud Integration:** Using the Pico W’s built-in Wi-Fi, the system maintains a stable connection for remote dashboard updates without additional hardware.

Conclusion

The development of the AI-Based Smart Accident Detection and Real-Time Emergency Alert System marks a significant advancement in highway safety technology. By transitioning from traditional vibration-based sensors to an intelligent Video Analytics framework, the system effectively addresses the critical challenge of false positives while ensuring high detection reliability. The integration of the Raspberry Pi Pico W as a centralized edge controller proves to be both cost-effective and highly efficient, successfully bridging the gap between digital incident detection and physical emergency response.

This framework effectively automates the reporting process and eliminates the dependency on the victim’s or witnesses' ability to report a crash manually. By reducing response times through the instantaneous transmission of precise GPS coordinates via the SIM800L GSM module, the system optimizes the critical "Golden Hour" for medical intervention. Furthermore, the use of a Piezo Buzzer enhances local awareness by alerting nearby pedestrians for immediate first-aid, while the built-in Wi-Fi on the Pico W opens new avenues for real-time cloud logging and remote monitoring. Ultimately, this scalable and robust architecture offers a practical solution for diverse transportation sectors, ensuring that emergency services reach accident sites without unnecessary delay to save lives.

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