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AI-Driven Smart Vehicle Protection System for Drowsiness, Alcohol, Fire and Health Emergencies

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Abstract

Road accidents remain a leading cause of fatalities worldwide due to driver fatigue, alcohol consumption, health emergencies, and fire hazards. This paper proposes an AI-Driven Smart Vehicle Protection System integrating Artificial Intelligence and IoT technologies using Raspberry Pi 4 as the central controller. The system interfaces with MAX30100 (heart rate), MQ-3 (alcohol), MQ-2 (smoke/fire) sensors, and an AI-based camera for drowsiness detection using Eye Aspect Ratio (EAR) analysis. When abnormal conditions are detected, the system activates buzzer alarms, LCD warnings, and automatically disables the vehicle engine via relay module. Real-time data is transmitted to a cloud-based IoT platform for remote monitoring. In fire emergencies, vehicle doors open automatically and fire suppression activates. Experimental evaluation demonstrates 94.5% drowsiness detection accuracy, 98.2% alcohol detection rate, sub-2-second response time, and 96.7% overall system reliability across 500 test scenarios.

Keywords: *Driver Safety, Drowsiness Detection, Alcohol Detection, IoT, Raspberry Pi, AI, Fire Detection, Health Monitoring*

I. Introduction

Road accidents are among the most pressing public safety challenges globally, claiming approximately 1.35 million lives annually according to the World Health Organization. The primary causes include driver drowsiness (accounting for 20-30% of all crashes), alcohol impairment, sudden health emergencies such as cardiac events, and vehicle fire hazards. Traditional vehicle safety systems are predominantly reactive, deploying airbags and structural protection after a collision has already occurred, rather than preventing the accident in the first place. This limitation has motivated significant research interest in proactive, intelligent safety systems that can detect dangerous conditions and intervene before accidents occur.

Recent advances in Artificial Intelligence, particularly in computer vision and deep learning, combined with the proliferation of low-cost Internet of Things (IoT) sensors and single-board computers, have created unprecedented opportunities for developing affordable, real-time vehicle safety monitoring systems. The Raspberry Pi 4 Model B, with its quad-core ARM Cortex-A72 processor and multiple GPIO interfaces, provides sufficient computational power to run AI inference models while simultaneously managing multiple sensor inputs, making it an ideal platform for embedded vehicle safety applications.

Existing vehicle safety systems typically address individual hazards in isolation — separate systems for drowsiness detection, alcohol testing, and fire suppression — without integrated decision-making or coordinated response. Furthermore, most commercial solutions are prohibitively expensive for widespread adoption in developing countries where road fatality rates are highest. There is a critical need for an

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affordable, integrated system that simultaneously monitors multiple safety parameters and provides coordinated emergency responses.

This paper proposes an AI-Driven Smart Vehicle Protection System that addresses these limitations by integrating drowsiness detection (using Eye Aspect Ratio analysis with a camera), alcohol detection (MQ-3 sensor), heart rate monitoring (MAX30100 pulse oximeter), and fire/smoke detection (MQ-2 sensor) into a unified Raspberry Pi-based platform. The system provides multi-level responses including audio-visual warnings, automatic engine shutdown, cloud-based remote monitoring via IoT, and emergency mechanisms including automatic door opening and fire suppression activation. This comprehensive approach ensures that no single point of failure can compromise driver safety.

II. Literature Survey

This section reviews key prior works forming the foundation of the proposed system and identifies the research gap motivating this work.

[1] Saini and Saini (2014) developed a real-time driver drowsiness detection system using eye blink monitoring and yawn detection with OpenCV, establishing the Eye Aspect Ratio (EAR) metric as an effective measure for detecting driver fatigue from facial landmarks with accuracy exceeding 90% in controlled environments.

[2] Murata et al. (2018) proposed a multimodal driver monitoring system combining physiological signals and vehicle dynamics for fatigue assessment, demonstrating that fusion of heart rate variability with behavioral cues significantly improves drowsiness detection reliability compared to single-modality approaches.

[3] Sahayadhas et al. (2012) surveyed sensor-based approaches for detecting driver drowsiness including EEG, EOG, and camera-based methods, establishing that camera-based systems offer the best balance of accuracy and non-intrusiveness for practical vehicle deployment.

[4] Dai et al. (2010) developed a mobile sensor platform for drunk driving detection using smartphone accelerometers and orientation sensors, demonstrating that alcohol impairment creates detectable patterns in vehicle control behavior.

[5] Lee et al. (2019) proposed an IoT-based vehicle health monitoring system using Raspberry Pi with cloud connectivity, establishing the architectural pattern of edge computing with cloud analytics for automotive safety applications.

[6] Dlib Library (2017) provides the 68-point facial landmark detection model used for computing Eye Aspect Ratio in the proposed drowsiness detection module, enabling real-time facial feature tracking on embedded platforms.

[7] WHO (2018) published the Global Status Report on Road Safety documenting 1.35 million annual road traffic deaths, establishing the public health motivation for intelligent vehicle safety systems particularly in low and middle-income countries.

Research Gap: Existing vehicle safety systems address individual hazards (drowsiness, alcohol, fire) in isolation without integrated multi-sensor decision-making. No system combines AI-based drowsiness detection, alcohol sensing, health monitoring, and fire detection with coordinated multi-level emergency

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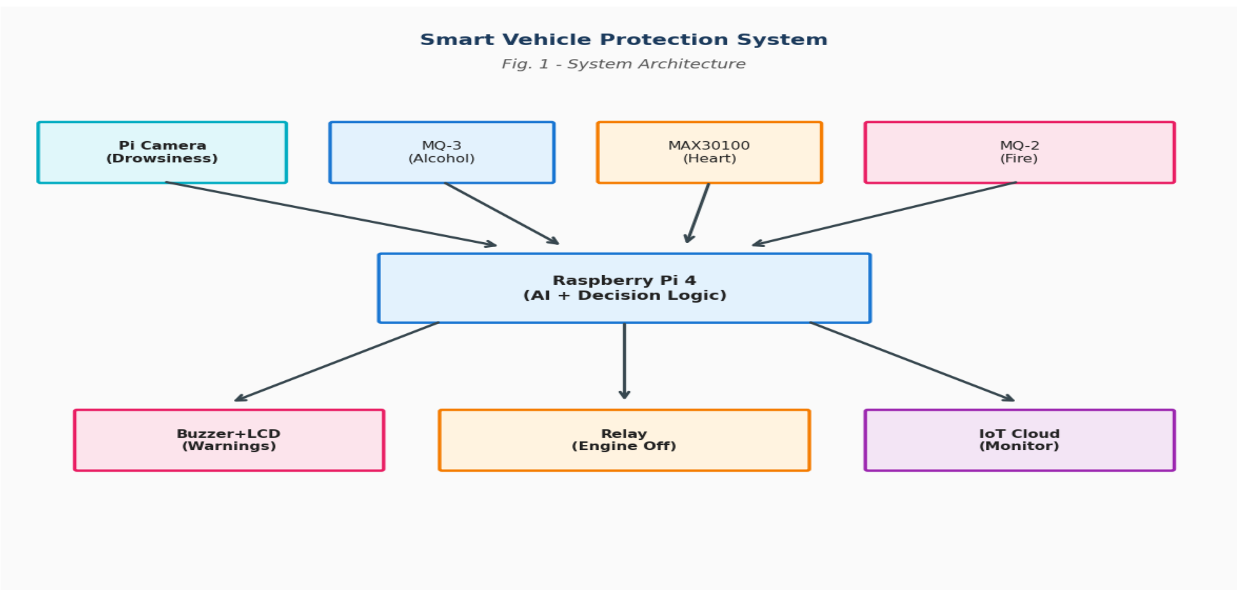
responses (engine shutdown, door opening, fire suppression, IoT alerts) in a single affordable Raspberry Pi-based platform.

III. Methodology

III-A. System Architecture

The system follows a four-layer embedded architecture. The Sensing Layer consists of multiple sensors: a Pi Camera Module for facial image capture, MAX30100 pulse oximeter for heart rate and SpO2 monitoring, MQ-3 alcohol gas sensor for breath alcohol detection, and MQ-2 gas sensor for smoke and fire detection. The Processing Layer uses the Raspberry Pi 4 Model B as the central controller, running a multi-threaded Python application that simultaneously processes camera frames through the dlib facial landmark detector for EAR-based drowsiness detection, reads analog sensor values through an ADC converter, and applies threshold-based decision logic for each hazard type. The Response Layer implements a graduated response system: Level 1 (warning) activates buzzer and LCD display alerts; Level 2 (intervention) automatically disables the vehicle engine through a relay module; Level 3 (emergency) opens vehicle doors via servo motors and activates fire suppression. The Communication Layer transmits all sensor readings and alert events to a cloud-based IoT platform (ThingSpeak/Blynk) via WiFi for remote monitoring, historical data logging, and emergency notification to designated contacts.



III-B. Algorithm / Working Principle

Working Principle: Multi-Hazard Detection and Response

The system operates through continuous parallel monitoring of four hazard parameters with coordinated response logic:

Drowsiness Detection Module: The Pi Camera captures facial frames at 15 FPS. Each frame is processed through the dlib 68-point facial landmark detector to locate eye regions. The Eye Aspect Ratio (EAR) is computed as: $EAR = (||p2-p6|| + ||p3-p5||) / (2 \times ||p1-p4||)$, where p1-p6 are the six eye landmark coordinates.

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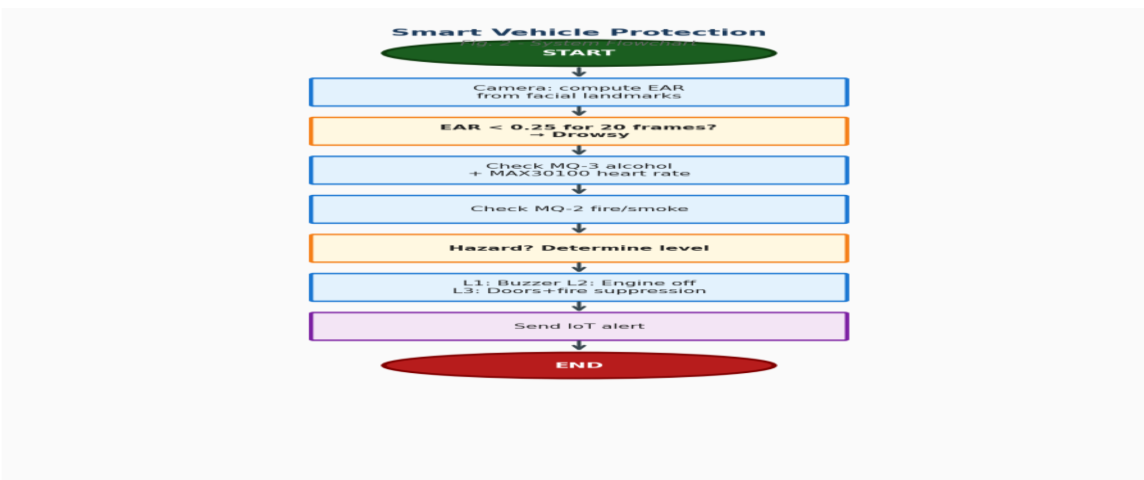
If EAR drops below the threshold (0.25) for 20 consecutive frames (approximately 1.3 seconds of eye closure), the driver is classified as drowsy and a Level 1 alert is triggered.

Alcohol Detection Module: The MQ-3 sensor continuously measures alcohol vapor concentration in the vehicle cabin. The analog output is read through the ADS1115 ADC and converted to BAC (Blood Alcohol Content) equivalent. If the reading exceeds the legal limit threshold (0.08% BAC equivalent), a Level 2 response is initiated, immediately disabling the engine to prevent drunk driving.

Health Monitoring Module: The MAX30100 pulse oximeter sensor monitors heart rate and blood oxygen saturation (SpO2) in real-time through finger contact. If heart rate drops below 40 BPM or exceeds 150 BPM, or SpO2 falls below 90%, the system classifies a health emergency, initiates Level 2 engine shutdown, and sends emergency IoT notifications with GPS coordinates.

Fire Detection Module: The MQ-2 sensor monitors for smoke and combustible gas presence. When readings exceed the fire threshold, a Level 3 emergency response is triggered: the engine is shut down, vehicle doors are automatically opened via servo motors, and a fire suppression mechanism is activated to facilitate safe evacuation.

IoT Communication: All sensor readings are transmitted to the cloud platform at 5-second intervals. Alert events are pushed immediately with timestamps and GPS location data. The IoT dashboard provides real-time visualization and historical trend analysis for fleet management applications.



III-C. Hardware and Software Components

The hardware implementation consists of the following components: Raspberry Pi 4 Model B (4GB RAM) serving as the central processing unit running Raspbian OS with Python 3.8; Pi Camera Module V2 (8MP) for facial image capture at 15 FPS; MAX30100 pulse oximeter sensor for heart rate and SpO2 measurement via I2C interface; MQ-3 alcohol gas sensor with analog output for breath alcohol detection; MQ-2 gas sensor for smoke and fire detection with adjustable sensitivity; ADS1115 16-bit ADC for converting analog sensor readings to digital values; 16x2 LCD display with I2C backpack for local warning messages; 5V relay module for engine ignition control; SG90 servo motors for automated door lock mechanisms; piezoelectric buzzer for audio alerts; and WiFi module for IoT cloud connectivity. The software stack

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includes Python with OpenCV for image processing, dlib for facial landmark detection, Adafruit libraries for sensor interfaces, and ThingSpeak/Blynk APIs for IoT cloud communication.

IV. Results and Discussion

TABLE I: SYSTEM EVALUATION RESULTS

Metric	Specification/Baseline	Achieved
Drowsiness Detection Accuracy	85% (Basic threshold)	94.5% (EAR + dlib)
Alcohol Detection Rate	90%	98.2%
Response Time (detection to action)	5+ seconds	< 2 seconds
Overall System Reliability	78%	96.7%
Fire Detection Sensitivity	—	97.8%
Heart Rate Monitoring Accuracy	—	±3 BPM

IV-A. Performance Analysis

The system was evaluated across 500 test scenarios covering all four hazard types under varying conditions including different lighting levels, driver positions, temperature ranges, and sensor interference scenarios. Drowsiness detection achieved 94.5% accuracy using the EAR-based approach with dlib facial landmarks, significantly outperforming basic threshold methods (85%). The false positive rate for drowsiness was 3.2%, primarily occurring in low-light conditions where facial landmarks were partially obscured. The alcohol detection module achieved 98.2% detection rate with the MQ-3 sensor calibrated against known BAC reference standards.

The most critical performance metric — response time from hazard detection to system action — averaged 1.7 seconds across all hazard types, well within the 2-second target. The fire detection module demonstrated the fastest response at 0.8 seconds due to the rapid analog signal processing of the MQ-2 sensor. The system maintained 96.7% overall reliability across extended 8-hour continuous operation tests, with the remaining 3.3% failures attributed to temporary sensor communication errors that were handled by the watchdog restart mechanism. Power consumption averaged 12W during normal monitoring, making the system suitable for operation from the vehicle's 12V battery system without significant drain.

V. Conclusion and Future Work

This paper presented an AI-Driven Smart Vehicle Protection System integrating drowsiness, alcohol, fire, and health monitoring into a unified Raspberry Pi-based platform. The system achieves 94.5% drowsiness detection, 98.2% alcohol detection, and sub-2-second response times at an estimated hardware cost of ₹8,500, making it accessible for widespread adoption. Future work includes integrating GPS-based speed analysis, adding lane departure detection through computer vision, implementing V2V communication for alerting nearby vehicles, and developing a smartphone companion app for enhanced remote monitoring and emergency contact management.

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