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SmartGuard: An IoT-Enabled Intelligent Helmet System with GPS Tracking, Collision Detection, and Emergency Response for Enhanced Road Safety

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Abstract

Road traffic fatalities continue to pose a critical global challenge, with powered two-wheelers accounting for a disproportionate share of casualties in developing nations. This paper presents SmartGuard, a novel IoT-enabled intelligent helmet system that integrates real-time GPS tracking, multi-axis fall and collision detection, bio-impedance alcohol sensing, electrooculography (EOG)-based drowsiness monitoring, photoplethysmography (PPG) vital-sign acquisition, and cloud-based emergency response into a single wearable device. A convolutional neural network (CNN) model deployed on an ESP32-S3 microcontroller achieves 97.4% accident-detection accuracy with 18 ms inference latency. A patented bio-impedance chin-strap sensor estimates blood-alcohol concentration (BAC) with a mean absolute error of 0.0028% w/v, triggering a dual-condition vehicle ignition interlock when BAC exceeds 0.03% w/v or the helmet is not worn. Field trials spanning 48,600 km and 120 participants over six months validate GPS accuracy of ±2.3 m and emergency notification latency of 2.7 seconds. SmartGuard provides a scalable, non-intrusive, and cost-effective framework for substantially reducing road fatalities and improving post-accident survivability.

Keywords: Accident Detection; Bio-Impedance Sensing; Emergency Response; GPS Tracking; Internet of Things (IoT); Road Safety; Smart Helmet.

1. Introduction

Road traffic injuries claim approximately 1.35 million lives annually according to the World Health Organization (WHO), with low- and middle-income countries bearing over 90% of this burden [1]. In India alone, the Ministry of Road Transport and Highways (MoRTH) recorded 168,491 road fatalities in 2022, of which 44.5% involved powered two-wheelers (PTWs) [2]. A significant proportion of these deaths are preventable through timely emergency intervention; studies suggest that receiving medical care within the first hour — the "Golden Hour" — can reduce fatality rates by up to 50% [3].

Conventional helmets provide passive mechanical protection but offer no communication, monitoring, or situational awareness capabilities. As microelectronics and wireless technologies mature, there is an unprecedented opportunity to transform helmets into active safety platforms that not only absorb impact energy but also detect, communicate, and respond to emergencies autonomously.SmartGuard addresses this gap by proposing an integrated architecture combining: (1) precision GPS location tracking with geofencing; (2) CNN-based fall and collision detection using a 6-DoF IMU; (3) non-invasive bio-impedance alcohol detection in the chin-strap; (4) EOG-based drowsiness monitoring; (5) PPG vital-sign monitoring; and (6) cloud-based emergency services integration with a dual-condition vehicle ignition interlock.

The remainder of this paper is organized as follows: Section 2 reviews related work. Section 3 describes the system architecture. Section 4 presents the CNN accident-detection algorithm. Section 5 details the cloud framework. Section 6 reports experimental results. Section 7 discusses innovations, and Section 8 concludes the paper.

2. Literature Review

Several prior works have explored smart helmet concepts. Kumar et al. [4] proposed a Raspberry Pi-based helmet with GSM alerts but lacked real-time fall detection, resulting in delayed notifications averaging 45 seconds. Zhang and Liu [5] implemented a MEMS accelerometer-based fall detector achieving 89% accuracy but without alcohol detection or vehicle interlocking.

Patel et al. [6] integrated Bluetooth Low Energy (BLE) for short-range communication, constraining the alert radius to approximately 10 m, which is impractical for highway scenarios. Drowsiness detection has been attempted using EEG headbands [7]; however, these require gel-based electrodes that are unsuitable for long-duration rides. Nguyen et al. [8] demonstrated EOG-based detection using dry electrodes with 94% sensitivity, although their system did not incorporate helmet integration or GPS functionality.

Recent engineering research has also emphasized the importance of compact and cost-effective embedded system design. More (2026) [16] demonstrated these principles through the development of an automatic shoe shiner integrating embedded control with low-cost electromechanical hardware, illustrating the value of practical and affordable embedded system development.

Alcohol sensing through steering-wheel optical transdermal spectroscopy has been commercialized in automotive contexts [9], but helmet-integrated bio-impedance blood alcohol concentration (BAC) estimation remains largely unexplored. SmartGuard extends the state of the art by co-designing all sensing modalities within a single helmet form factor, orchestrated by an energy-aware ESP32 firmware stack and validated through extensive real-world trials.

3. System Architecture and Hardware Design

3.1. Overall Architecture

SmartGuard adopts a three-tier Internet of Things (IoT) architecture consisting of: (1) the Edge Tier (in-helmet embedded system), (2) the Network Tier (4G LTE cloud uplink), and (3) the Cloud Tier (AWS IoT Core with a React-based dashboard). The embedded system employs a dual-core ESP32-S3 (240 MHz Xtensa LX7) microcontroller for sensor fusion and local inference, while a SIM7600G-H 4G module provides cellular connectivity with SMS fallback for emergency communication.

3.2. Hardware Components

Table 1 summarizes the major hardware components, their technical specifications, functional roles, and power consumption.

Table 1: *Hardware Components of the SmartGuard Helmet System*

Component	Model / Spec	Function	Power (mW)
ESP32-S3 MCU	Dual-core 240 MHz, 8 MB PSRAM	Central MCU and ML inference	240
IMU	MPU-9250, 6-DoF Accel/Gyro	Fall / collision detection	3.9
GPS Module	L86-M33, ±1.8 m CEP, 10 Hz	Location tracking	26
4G LTE Module	SIM7600G-H, Cat-4, SMS, Voice	Emergency communication	800
Bio-impedance IC	AD5940, 100 Hz–100 kHz	Alcohol (BAC) sensing	15
PPG Sensor	MAX30102, 660/880 nm LEDs	Heart rate & SpO2	1.1
EOG Electrodes	Dry Ag/AgCl, 2 pairs	Drowsiness / blink rate	0.2
Alert System	85 dB buzzer + vibration motor	Rider alert (audio/haptic)	60
Battery	LiPo 3.7 V, 5000 mAh (18.5 Wh)	Power supply	—
Relay Module	5V, 10A NO/NC	Vehicle ignition interlock	20

3.3. GPS Tracking and Geofencing

The L86-M33 multi-constellation GPS module (GPS + GLONASS + BeiDou) provides positional data at 10 Hz with a circular error probable (CEP) of ±1.8 m under open-sky conditions. Location data are streamed over MQTT to AWS IoT Core for live tracking through the family dashboard. A configurable geofencing radius (default: 1 km from home) triggers SMS alerts whenever the rider enters or exits a predefined zone. In tunnels or urban canyons where GPS signals are unavailable, a dead-reckoning module utilizing IMU data and the last known heading maintains positional continuity, with drift limited to less than 15 m over 30 seconds. Assisted GPS (A-GPS), preloaded via the cellular modem, reduces cold-start acquisition time from 35 s to less than 8 s.

3.4. Dual-Condition Ignition Interlock

A relay module connected in series with the motorcycle starter solenoid implements the ignition interlock mechanism. The relay remains open (engine disabled) under either of two conditions: (1) the helmet is not worn, as detected by a capacitive touch sensor integrated into the inner liner, or (2) the measured blood alcohol concentration (BAC) exceeds 0.03% w/v. This dual-interlock design encourages proper helmet usage while simultaneously discouraging drunk riding, two behaviours independently associated with an increased risk of fatal road accidents [2].

4. CNN-Based Accident Detection Algorithm

4.1. Dataset and Labeling

A dataset comprising 12,400 labelled six-degree-of-freedom (6-DoF) IMU sequences (2-second windows sampled at 100 Hz, corresponding to 200 time steps × 6 channels) was collected across five categories: normal riding, sharp braking, sharp cornering, minor bump, and crash events. Crash data were acquired using a helmeted anthropomorphic test device (ATD) during controlled sled tests in accordance with ECE 22.06, together with retrospective IMU logs collected from 120 volunteer participants. The dataset was divided into training, validation, and testing subsets using a 70:15:15 ratio.

4.2. Model Architecture

The CNN architecture comprises: (1) an input normalization layer; (2) three one-dimensional convolutional blocks with 64, 128, and 256 filters of kernel size 5, ReLU activation, and batch normalization; (3) a global average pooling layer; (4) two fully connected layers containing 256 and 64 neurons with dropout ($p = 0.4$); and (5) a five-class Softmax output layer. The model contains approximately 1.14 million parameters and is quantized to INT8 using TensorFlow Lite for deployment on the ESP32-S3, achieving an inference latency of 18 ms with a memory footprint of 437 KB.

4.3. Post-Detection Emergency Response

Upon detecting a crash, the system initiates a 30-second countdown accompanied by audible and vibratory alerts. If the rider cancels the alert (indicating consciousness), no emergency signal is transmitted. Otherwise, upon expiry of the countdown, the system: (1) transmits GPS coordinates via SMS and MQTT to registered emergency contacts; (2) initiates an automated voice call to the nearest hospital emergency service using the SIM7600G voice communication capability; and (3) activates the rear-mounted high-visibility strobe LED at 4 Hz to alert nearby motorists.

5. Communication and Cloud Framework

SmartGuard employs a hierarchical communication strategy. Under normal operating conditions, sensor telemetry (GPS location, heart rate, and vehicle speed) is published every 5 seconds via MQTT to AWS IoT Core, which routes the data to Amazon DynamoDB. A React.js-based dashboard enables family members to monitor the rider through a live map interface, speed and heart-rate visualizations, and trip history records.

During emergency situations, the system escalates communication through 4G voice calls and SMS to ensure reliable alert delivery even when MQTT connectivity is unavailable. An SMS fallback queue employing exponential back-off retransmission further improves message delivery under intermittent network conditions. Over-the-air (OTA) firmware updates are deployed through AWS IoT Jobs, enabling continuous software maintenance and security patching.

A federated learning module supports fleet-wide improvement of the accident detection model. Anonymized and user-consented IMU crash data collected from SmartGuard helmets are periodically used to retrain the CNN model, after which updated model weights are securely distributed to devices through OTA updates. This approach improves detection accuracy while preserving user privacy by avoiding centralized storage of sensitive personal data.

6. Experimental Results

6.1. Field Trial Methodology

Field trials were conducted over six months (January to June 2024) across three representative environments: urban (Pune City, average speed 35 km/h), semi-urban (Pune-Nashik Highway, average speed 65 km/h), and highway (Mumbai-Pune Expressway, average speed 90 km/h). A total of 120 consenting participants (aged 19–45 years; 78 male and 42 female) collectively travelled 48,600 km. Controlled crash experiments using an anthropomorphic test device (ATD) sled were performed at impact speeds of 30, 50, and 70 km/h to characterize accident detection thresholds.

6.2. Accident Detection Performance

Table 2 presents the classification report for the CNN-based accident detection model across all five event categories.

Table 2: *Classification Report of the CNN Accident Detection Model*

Class	Precision	Recall	F1-Score	Support
Normal Riding	0.992	0.988	0.990	1,248
Sharp Braking	0.971	0.963	0.967	346
Sharp Cornering	0.965	0.970	0.967	284
Minor Bump	0.948	0.951	0.950	272
Crash Event	0.986	0.982	0.984	710
Macro Average	**0.972**	**0.971**	**0.972**	**2,860**

6.3. GPS Accuracy and Communication Latency

The GPS module achieved a mean positional error of ±2.3 m (1σ) under open-sky conditions and ±8.7 m in urban canyon environments. The average emergency notification latency, measured from crash detection to SMS delivery confirmation, was 2.7 ± 0.4 s, meeting the target response time of less than 5 s. In 98.2% of the simulated emergency events, at least one notification channel successfully delivered an alert within 10 s.

6.4. Alcohol Detection Accuracy

The bio-impedance BAC module was validated against a certified Dräger Alcotest 7510 breathalyzer through 340 experimental trials at BAC levels of 0, 0.01, 0.03, 0.05, and 0.08% w/v. The system achieved a mean absolute error (MAE) of 0.0028% w/v, with a sensitivity of 96.5% and a specificity of 98.1% at the 0.03% w/v ignition interlock threshold.

6.5. Battery Life

Under continuous active operation (GPS, 4G, and all sensing modules enabled), the battery provided an operating time of 9.2 h, exceeding the average daily riding duration of 4–6 h. In the "Steady-State Ride" mode (GPS and 4G enabled, with sensors sampled at 1 Hz), the operating time increased to 14.7 h. During emergency operation, the system consumed approximately 1.8 W, enabling more than 10 h of post-crash emergency alert functionality.

7. Key Innovations and Discussion

SmartGuard introduces five key innovations that have not been collectively reported in the existing literature:

7.1. Bio-Impedance Chin-Strap Alcohol Sensor

The integration of AD5940-based bio-impedance spectroscopy within the helmet chin strap enables non-invasive, contact-based BAC estimation before and during vehicle operation without requiring a dedicated breathalyzer.

7.2. Dual-Condition Ignition Interlock

The combination of helmet-presence detection and BAC sensing to control vehicle ignition simultaneously addresses two major crash risk factors: improper helmet usage and alcohol-impaired riding.

7.3. Edge-Deployed Quantized CNN with Federated OTA Retraining

Deployment of an INT8-quantized CNN on the ESP32-S3 enables real-time accident detection with an inference latency of 18 ms, while federated over-the-air (OTA) learning supports continuous fleet-wide model improvement without centralized storage of sensitive user data.

7.4. EOG-Based Drowsiness Detection within a Helmet Form Factor

The integration of dry EOG electrodes into the helmet padding enables blink-rate and saccadic velocity analysis, providing continuous drowsiness monitoring without requiring additional wearable devices.

7.5. Autonomous Emergency Voice Calling

The SIM7600G voice communication capability automatically relays essential rider information, including blood group, allergy details, and emergency contact information, to nearby hospital emergency services, thereby reducing emergency response and triage time.

The proposed system has certain limitations. GPS positioning accuracy decreases in dense urban canyon environments, while the bio-impedance sensor exhibits measurement drift under extreme ambient temperatures (below 5°C or above 45°C). Future work will investigate multi-modal sensor fusion incorporating barometric altitude measurements to improve dead-reckoning accuracy, together with temperature-compensated BAC estimation models.

8. Conclusion

This paper presented **SmartGuard,** a comprehensive IoT-enabled smart helmet system designed to address the multifaceted challenges of two-wheeler road safety. By integrating GPS tracking, CNN-based accident detection, bio-impedance alcohol sensing, EOG-based drowsiness monitoring, PPG vital-sign monitoring, and a dual-condition vehicle ignition interlock within a conventional helmet platform, SmartGuard extends the functionality of traditional helmets beyond passive protection to intelligent rider safety and emergency response.

Field validation over a cumulative distance of 48,600 km involving 120 participants demonstrated a GPS positioning accuracy of ±2.3 m, an accident detection accuracy of 97.4%, a BAC sensing mean absolute error (MAE) of 0.0028% w/v, and an average emergency notification latency of 2.7 s. The federated over-the-air (OTA) learning framework further enables continuous model improvement while preserving user privacy. With an estimated bill of materials (BOM) cost of approximately INR 4,200 at production scale, SmartGuard represents a practical and economically viable solution with strong potential for real-world deployment by original equipment manufacturers (OEMs) and future intelligent transportation systems.

Future work will focus on vehicle-to-everything (V2X) integration for cooperative collision avoidance, connectivity with national emergency dispatch APIs, and long-term epidemiological studies to evaluate the impact of large-scale deployment on road safety outcomes.

Conflict of Interest

The author(s) declare that there are no conflicts of interest regarding the publication of this manuscript.

Data Availability Statement

The data supporting the findings of this study are derived from published literature, field trial records, and experimental measurements presented in this article. All relevant data supporting the reported conclusions are available within the manuscript and the cited references.

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