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# AI-Powered Smart Helmet for Two-Wheeler Rider Safety: A Review of Accident Detection, Rider-State Monitoring and Emergency Response Systems

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**Abstract—Two-wheeler riders account for a large share of road fatalities in India, and many deaths occur not at the moment of impact but during the delay before help arrives. A conventional helmet offers passive head protection but cannot recognize a crash, assess whether the rider is fit to ride or summon assistance. This paper reviews the design of AI-powered smart helmets that integrate Internet of Things (IoT) sensing, embedded intelligence and wireless communication to close this gap. The review covers alcohol detection with gas sensors, drowsiness detection from eye-blink and physiological signals, helmet-wear verification, and crash detection using inertial and impact sensors. It examines how threshold rules, classical machine learning and lightweight neural networks are used to separate real accidents from everyday shocks such as potholes or dropping the helmet, and how GPS and GSM or smartphone links deliver location-tagged alerts to emergency contacts. A layered architecture covering sensing, edge processing, connectivity, cloud services and user applications is proposed, followed by a research gap analysis, objectives, a comparison of detection approaches and a discussion of power, false-alarm, privacy and cost constraints. The review concludes that a low-cost helmet combining preventive monitoring with reliable post-crash alerting can measurably shorten emergency response times for two-wheeler riders.**

**Index Terms—Smart helmet, Internet of Things, accident detection, drowsiness detection, alcohol detection, GPS tracking, emergency alert, edge AI, road safety**

## I. INTRODUCTION

Road traffic injuries remain a leading cause of death among young adults worldwide, and the WHO global status report [1] identifies powered two- and three-wheeler users as one of the most vulnerable groups. Official Indian statistics [2] consistently show that two-wheeler riders form the largest category of road-accident victims, and a substantial share of them were not wearing a helmet. Even when a helmet is worn, a rider who crashes on an isolated road at night may remain unattended for a long time, and the delay in reaching a hospital during the so-called golden hour sharply increases the risk of death or permanent disability.

The helmet is a natural platform for intelligence because it sits on the rider's head, moves with the body and is present in every trip. Advances in low-cost microcontrollers, micro-electro-mechanical (MEMS) inertial sensors and cellular IoT modules [3] have made it feasible to embed sensing and communication inside the shell without a large increase in weight or price.

This paper reviews research on AI-powered smart helmets with three goals: (i) to classify the safety functions that have been demonstrated, (ii) to compare the detection techniques used for each function, and (iii) to propose a reference architecture and identify open problems.

## II. RELATED WORK

Early smart-helmet prototypes focused on enforcing helmet use. Rasli *et al.* [4] used sensors inside the helmet to confirm that it was worn and linked this state to the motorcycle ignition so that the engine could not be started otherwise. This established the idea of an interlock between the helmet and the vehicle, which later designs extended with alcohol sensing.

Crash detection research has drawn heavily on related work with smartphones and wearables. WreckWatch [5] used the accelerometer and microphone of a smartphone to detect car accidents and automatically notify responders with location and situational data, and it highlighted the difficulty of distinguishing a real crash from a dropped phone. Bourke *et al.* [6] evaluated threshold-based fall detection with a tri-axial accelerometer and showed that combining an impact threshold with a post-impact posture check greatly reduces false alarms, a principle directly applicable to helmets.

For rider-state monitoring, Soukupová and Čech [7] proposed the Eye Aspect Ratio (EAR), computed from facial landmarks [8], as a simple and robust indicator of eye closure; sustained low EAR values signal drowsiness. Lin *et al.* [9] demonstrated a wireless, wearable EEG system for estimating driver vigilance, indicating that physiological

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sensing integrated in headgear can reveal fatigue before visible symptoms appear.

On the computing side, edge computing [10] allows time-critical decisions such as crash confirmation to run locally, avoiding dependence on network coverage, while compact neural networks such as MobileNets [11] show how image-based drowsiness models can be executed on embedded processors. Recurrent networks such as LSTM [12] are suited to classifying short windows of inertial data. Table I summarizes these works.

TABLE I Summary of Literature Survey

| Sr. No. | Ref. | Year | Methodology | Findings | Research Gap |
|---|---|---|---|---|---|
| 1 | [6] | 2007 | Threshold-based tri-axial accelerometer fall detection | Impact plus posture check reduces false positives | Evaluated on falls, not vehicle crashes |
| 2 | [5] | 2011 | Smartphone accelerometer and acoustic crash detection | Automatic notification with location to responders | Designed for cars; phone drops cause false alarms |
| 3 | [4] | 2013 | Helmet-wear sensing linked to motorcycle ignition | Enforces helmet use before the engine can start | No crash detection or emergency alerting |
| 4 | [8] | 2014 | Ensemble of regression trees for face alignment | Millisecond-level landmark estimation | Accuracy drops under occlusion such as visors |
| 5 | [9] | 2014 | Wireless wearable EEG for vigilance | Detects fatigue from brain signals | Electrode comfort and cost limit mass use |
| 6 | [7] | 2016 | Eye Aspect Ratio from facial landmarks | Simple, real-time blink and eye-closure detection | Needs a camera facing the eyes; lighting sensitive |
| 7 | [10] | 2016 | Edge computing paradigm | Low-latency local decisions without cloud | General framework, not helmet-specific |
| 8 | [11] | 2017 | Depthwise separable CNNs (MobileNets) | Efficient vision models for embedded devices | Still heavy for low-end microcontrollers |

## 1. Preliminaries

### 1. Safety Functions Of A Smart Helmet

The functions of a smart helmet can be divided into preventive and reactive groups, as shown in Fig. 1. Preventive functions stop a risky trip before it starts or warn the rider during the ride; reactive functions detect a crash and trigger help. A third group, assistive functions, includes navigation prompts and hands-free calling.

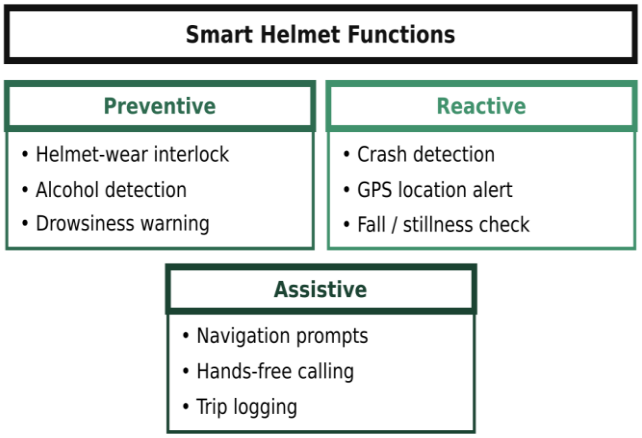



Fig. 1. Classification of smart-helmet safety functions.

### 2. Enabling Technologies

A typical helmet contains a three-axis accelerometer and gyroscope (inertial measurement unit, IMU), an MQ-3 type alcohol sensor near the chin guard, a force-sensitive resistor or limit switch to verify that the helmet is worn, and optionally an infrared eye-blink sensor or small camera. A microcontroller such as an ESP32 performs local processing, a GPS receiver provides position, and a GSM

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module or a Bluetooth link to the rider's phone delivers alerts. These components follow the general IoT architecture of perception, network and application layers described by Atzori *et al.* [13] and Gubbi *et al.* [14].

### 2.3 Problem Statement And Objectives

### 1. Identified Research Gaps

The following gaps are identified from the literature:

- **G1:** Many prototypes rely on a single fixed acceleration threshold, which produces false alarms on rough Indian roads and misses low-speed falls.
- **G2:** Few studies report field trials with real riders over long periods; most validation uses simulated drops or bench tests.
- **G3:** Alcohol and drowsiness modules are often evaluated separately rather than as a combined rider-fitness score.
- **G4:** Power consumption and battery life of always-on sensing are rarely quantified.
- **G5:** Privacy of continuous location and biometric data has received little attention.

### 4. Objectives Of The Review

The objectives of this study are:

- To review the safety functions and sensors used in AI-powered smart helmets.
- To compare threshold, machine learning and deep learning approaches for crash and drowsiness detection.
- To propose a layered architecture combining edge inference with cloud-based alerting.
- To define a crash-confirmation workflow that minimizes false alarms while keeping alert latency low.
- To identify practical challenges and future research directions for low-cost deployment in India.

### 5. Proposed Framework

The proposed architecture, shown in Fig. 2, organizes the helmet into five layers so that safety-critical functions continue to work even when network connectivity is unavailable.

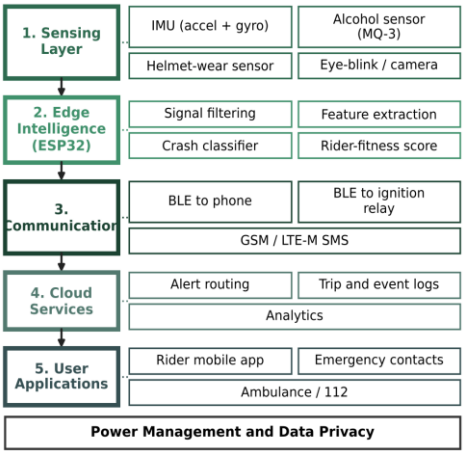



Fig. 2. Proposed layered architecture of the AI-powered smart helmet.

### 6 Sensing Layer

The IMU samples acceleration and angular velocity at 50 to 100 Hz. The alcohol sensor is read before ignition, the wear sensor confirms that the strap is fastened, and an optional eye-blink sensor or camera monitors alertness.

### 7 Edge Intelligence Layer

The microcontroller filters raw signals, extracts features such as peak acceleration, jerk and orientation change, and runs a compact classifier. A rider fitness module combines alcohol level and drowsiness indicators into a single decision that can block ignition or trigger a vibration and buzzer warning.

### 8 Communication Layer

Bluetooth Low Energy links the helmet to the rider's smartphone and to a receiver on the motorcycle that controls the ignition relay. A GSM or LTE-M module provides an independent path for SMS alerts when the phone is unavailable.

### 9 Cloud And Application Layers

A cloud service stores trip logs, forwards alerts to registered contacts and nearby emergency services, and supports a mobile application that shows the rider's live location after a crash. Fleet operators and insurers may receive aggregated, consented safety statistics.

## III. WORKING METHODOLOGY

Fig. 3 illustrates the crash-detection and alert workflow. The resultant acceleration is computed from the three axes as

$$|a| = \sqrt{(ax^2 + ay^2 + az^2)} \quad (1)$$

A candidate impact is flagged when |a| exceeds a threshold, typically several times gravitational acceleration. Because

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potholes and dropped helmets can also produce spikes, the candidate event is passed to a classifier that examines the surrounding time window for features such as sudden orientation change, absence of normal riding vibration and prolonged stillness.

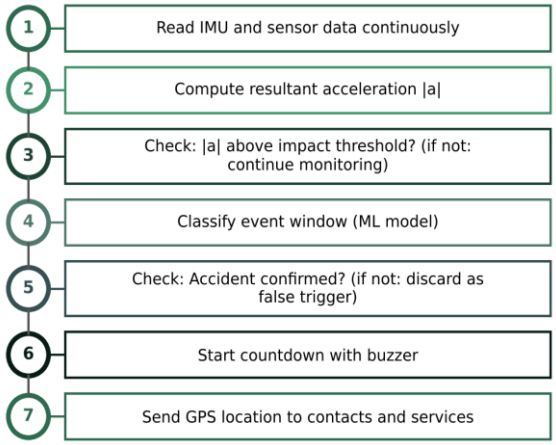



Fig. 3. Crash detection and emergency alert workflow.

If the classifier confirms an accident, the helmet starts a short countdown with an audible alarm, during which a conscious rider can cancel a false alarm by pressing a button. If the countdown expires, the system sends the GPS coordinates and a map link to emergency contacts and, where integrated, to a local ambulance service. Drowsiness is evaluated continuously using the eye aspect ratio

$$EAR = (\|p_2 - p_6\| + \|p_3 - p_5\|) / (2\|p_1 - p_4\|) \quad (2)$$

where $p_1$ to $p_6$ are eye landmarks; an EAR below a calibrated value for consecutive frames triggers a warning.

## IV. DISCUSSION

### 1. Comparison Of Approaches

Table II compares common detection techniques used in smart helmets. Threshold methods are cheap and transparent but brittle; classical machine learning offers a good balance on microcontrollers; and deep models give the best accuracy at the cost of memory and power.

TABLE II Comparison of Detection Techniques

| Technique | Accuracy | Compute Cost | Remarks |
|---|---|---|---|
| Fixed threshold on \|a\| | Low–Medium | Very low | Many false alarms on rough roads |
| Threshold + posture check | Medium | Low | Fewer false alarms; simple to explain |
| SVM / Random Forest on features | High | Low–Medium | Good fit for ESP32-class devices |
| LSTM / 1-D CNN on raw IMU | High | Medium | Needs labelled crash data |
| CNN on eye images | High | High | Camera adds cost and privacy concerns |

### 2. Open Challenges And Future Work

Table III lists the main challenges. Future work should create open datasets of real two-wheeler crashes and near-misses, explore helmet-to-vehicle and vehicle-to-infrastructure communication for automatic ambulance dispatch, harvest energy from solar cells on the shell, and integrate with the national 112 emergency response system. Regulatory acceptance will require that added electronics do not weaken the shell's certified impact protection.

TABLE III Challenges and Possible Solutions

| Challenge | Possible Solution |
|---|---|
| False crash alarms | Multi-stage confirmation and user cancel window |
| Battery life | Duty-cycled sensing, BLE, solar assistance |
| Network dead zones | Edge decisions and SMS fallback; store-and-forward |
| Rider acceptance | Light weight, low cost, comfortable fit |
| Location privacy | Consent-based sharing; encrypted logs |

## V. CONCLUSION AND FUTURE WORK

The smart helmet transforms a passive protective device into an active safety system that can prevent unsafe riding and summon help after a crash. The reviewed literature shows that reliable crash detection depends less on a single sensor than on combining impact detection with context-aware confirmation, and that edge processing is essential where mobile coverage is weak. A low-cost design that integrates alcohol and drowsiness checks, machine-learning-based crash confirmation and dual-path alerting can make a meaningful contribution to reducing two-wheeler fatalities,

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provided that false alarms, battery life and data privacy are addressed through field-tested engineering.

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## REFERENCES

1. World Health Organization, Global Status Report on Road Safety 2023. Geneva, Switzerland: WHO, 2023.
2. Ministry of Road Transport and Highways, Road Accidents in India 2022. New Delhi: Government of India, 2023.
3. A. Al-Fuqaha, M. Guizani, M. Mohammadi, M. Aledhari, and M. Ayyash, "Internet of Things: A survey on enabling technologies, protocols, and applications," IEEE Commun. Surveys Tuts., vol. 17, no. 4, pp. 2347–2376, 2015.
4. M. K. A. Mohd Rasli, N. K. Madzhi, and J. Johari, "Smart helmet with sensors for accident prevention," in Proc. Int. Conf. Electr., Electron. Syst. Eng. (ICEESE), 2013, pp. 21–26.
5. J. White, C. Thompson, H. Turner, B. Dougherty, and D. C. Schmidt, "WreckWatch: Automatic traffic accident detection and notification with smartphones," Mobile Netw. Appl., vol. 16, no. 3, pp. 285–303, 2011.
6. A. K. Bourke, J. V. O'Brien, and G. M. Lyons, "Evaluation of a threshold-based tri-axial accelerometer fall detection algorithm," Gait Posture, vol. 26, no. 2, pp. 194–199, 2007.
7. T. Soukupová and J. Čech, "Real-time eye blink detection using facial landmarks," in Proc. 21st Comput. Vis. Winter Workshop, 2016.
8. V. Kazemi and J. Sullivan, "One millisecond face alignment with an ensemble of regression trees," in Proc. IEEE CVPR, 2014, pp. 1867–1874.
9. C.-T. Lin et al., "Wireless and wearable EEG system for evaluating driver vigilance," IEEE Trans. Biomed. Circuits Syst., vol. 8, no. 2, pp. 165–176, 2014.
10. W. Shi, J. Cao, Q. Zhang, Y. Li, and L. Xu, "Edge computing: Vision and challenges," IEEE Internet Things J., vol. 3, no. 5, pp. 637–646, 2016.
11. A. G. Howard et al., "MobileNets: Efficient convolutional neural networks for mobile vision applications," arXiv:1704.04861, 2017.
12. S. Hochreiter and J. Schmidhuber, "Long short-term memory," Neural Comput., vol. 9, no. 8, pp. 1735–1780, 1997.
13. L. Atzori, A. Iera, and G. Morabito, "The Internet of Things: A survey," Comput. Netw., vol. 54, no. 15, pp. 2787–2805, 2010.
14. J. Gubbi, R. Buyya, S. Marusic, and M. Palaniswami, "Internet of Things (IoT): A vision, architectural elements, and future directions," Future Gener. Comput. Syst., vol. 29, no. 7, pp. 1645–1660, 2013.

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