

A HYBRID IOT and AI ARCHITECTURE for INTELLIGENT RIDER PROTECTION SYSTEMS

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Abstract:

Road accidents remain a major public safety challenge, particularly for two-wheeler riders, where delayed emergency response and lack of real-time safety monitoring significantly increase injury severity and fatality risk. This paper proposes an AI-enabled smart helmet-based safety and monitoring framework designed to improve rider protection through continuous assessment of critical riding conditions. The proposed system focuses on three primary safety objectives: detection of accident-like events, identification of unsafe riding behaviour such as potential intoxication, and verification of helmet compliance. To enhance reliability and reduce false alerts, the framework incorporates sensor-fusion-driven machine learning that classifies riding events more accurately than conventional threshold-based approaches. In addition, the design supports a hybrid communication strategy to ensure emergency alerts can be triggered even under limited network availability, while also enabling optional cloud/dashboard-based visualization and long-term analytics. The proposed approach further introduces rider risk scoring and anomaly detection to provide preventive warnings and decision support. Overall, this work presents a scalable and research-oriented blueprint for intelligent rider safety systems that combines edge intelligence with real-time monitoring for improved road safety outcomes.

Keywords— Smart Helmet, Rider Safety Monitoring, Edge Artificial Intelligence, Accident Detection, Sensor Fusion

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Introduction:

Two-wheeler transportation is widely adopted due to affordability and convenience. However, compared to other road users, riders face higher exposure to accidents, with critical risks arising from head injuries, delayed emergency response, and unsafe riding behaviour. Even when protective equipment is available, helmet usage and compliance are inconsistent, and conventional post-accident reporting leads to response delays.

Existing safety systems (mobile emergency apps, manual reporting, and conventional helmet usage) offer limited prevention and do not provide continuous risk monitoring. Furthermore, many IoT safety solutions

rely purely on internet connectivity, causing failure in low-network conditions. Hence, there is a need for a safety architecture that is **reliable under connectivity limitations**, and also intelligent enough to reduce false alerts from normal road conditions (e.g., potholes, sudden braking).

This work proposes a **hybrid IoT-AI smart helmet framework** that functions as a “safety co-pilot” by monitoring safety signals, detecting accident-like events, and triggering emergency alerts in offline-first mode, while also enabling optional cloud/dashboard analytics. The objective of this paper is to present a scalable framework for intelligent rider safety

monitoring, supported by a user survey evaluating acceptance and perceived usefulness.

The objectives of this paper are as follows:

- 1) To propose a hybrid smart helmet framework combining offline emergency alerting with optional online monitoring.
- 2) To present an AI-driven enhancement roadmap including crash classification, risk scoring, and anomaly detection.
- 3) To report survey-based evidence (n=52) supporting adoption potential and feature prioritization.
- 4) To outline a concise methodology and future validation plan suitable for the national conference scope.

Literature Review:

Research on smart helmet and rider safety systems has grown significantly with the rise of IoT, embedded sensing, and edge intelligence. Prior work in this domain typically focuses on accident detection, helmet compliance, intoxication monitoring, emergency alerting, and IoT-based dashboards. However, most implementations still face challenges related to false alarms, connectivity dependency, and limited preventive intelligence.

A. Accident Detection Systems

A large portion of smart helmet literature relies on inertial sensing to detect accident-like events using threshold-based rules (e.g., sharp acceleration peaks or tilt angles). While this approach is low-cost and easy to implement, it is also known to produce **false positives** due to potholes, sudden braking, and road bumps, making it unreliable under real-world road conditions [1], [4], [6]. Several IoT-based helmet systems demonstrate feasibility for crash detection and alert delivery, but often report that threshold-only detection struggles with accuracy under varied road environments [2], [3]. Hence, recent studies increasingly recommend **AI/ML-based** crash

classification to distinguish true accident events from non-critical motion patterns [9], [10].

B. Helmet Compliance Monitoring

Helmet compliance is another critical focus in smart helmet systems, where sensors are used to verify whether the rider is wearing the helmet properly. Prior designs commonly use proximity-based detection, pressure mechanisms, or strap-lock monitoring to ensure helmet usage [1], [6]. Such compliance systems are effective in principle, but practical adoption depends on robustness against bypassing and noisy readings during movement [1], [4]. This gap motivates intelligent monitoring frameworks that treat helmet compliance as a continuous behavioural signal rather than a one-time check.

C. Unsafe Behaviour and Intoxication Monitoring

Some smart helmet studies incorporate detection of unsafe riding behaviour such as intoxication indicators, fatigue, or abnormal motion patterns. Approaches using breath-level indicators for alcohol sensing are widely discussed, but they suffer from calibration needs and environmental sensitivity, limiting reliability in outdoor usage [4], [6]. Furthermore, unsafe behaviour detection cannot rely on single-sensor logic alone, and researchers highlight the need for **sensor fusion combined with learned decision models** to improve confidence in detection [9], [10].

D. Communication and Emergency Alerting

Emergency communication remains a major limitation in many smart helmet solutions. IoT-based systems frequently transmit crash alerts through network-dependent channels such as mobile applications, cloud platforms, or internet-based messaging services [2], [3], [6]. However, network reliability is inconsistent in many regions, which can cause alert delivery delays or failures. To solve this, researchers have explored offline

communication methods or hybrid alerting strategies to preserve reliability for safety-critical events [1], [6]. Therefore, an offline-first emergency layer is considered necessary for practical deployment, while cloud dashboards can be treated as optional enhancements [6].

E. IoT Dashboards and Data-Driven Safety Analytics

Several papers present web dashboards for real-time monitoring, event history, and notification delivery, but most of them only provide raw sensor logs and manual interpretation rather than intelligent analytics [2], [6]. To extract higher value, researchers propose the use of **predictive analytics** and **risk modelling**, where historical sensor patterns are analyzed to identify crash risk hotspots or unsafe riding trends [10], [11]. This direction aligns with modern road safety research that uses machine learning and large-scale driving data for crash-risk prediction [9], [10].

F. Edge AI and TinyML for Smart Safety Devices

As smart helmets are resource-constrained embedded systems, deploying ML models directly on edge devices is a growing research direction. Over-the-air (OTA) TinyML deployment has been explored to enable model updates and continuous improvement on IoT hardware while maintaining low memory and power usage [7]. Additionally, TinyML-based anomaly detection methods have been studied for monitoring irregular patterns in noisy real-world environments, enabling preventive warnings and reliability assurance [8]. These approaches provide strong support for integrating edge intelligence into rider safety frameworks.

G. Research Gap Summary: From the above literature, the major gaps identified are:

- 1) threshold-based accident detection leading to false alerts [1], [4], [6];
- 2) network-dependent alerting limiting reliability [2], [6];

- 3) limited preventive intelligence (risk scoring/anomaly detection) [8], [9];
- 4) poor long-term analytics integration [10], [11];
- 5) lack of scalable hybrid architecture combining offline reliability with optional IoT analytics [1], [6].

Thus, there is strong motivation for a proposed hybrid IoT-AI smart helmet framework that integrates offline-first emergency alerting with ML-based event classification and dashboard-driven analytics.

Existing Technologies, Limitations and Motivation:

Smart helmet solutions already exist in research and early prototype markets, primarily aiming to improve rider safety using sensing and communication modules. Several systems focus on helmet-based accident alerting, where crash-like events trigger warnings or emergency messages. Another common direction includes helmet compliance monitoring to ensure the rider is wearing the helmet properly. Many proposed solutions further support emergency messaging through mobile applications or SMS-based alerts, and some systems include web dashboards for live status tracking and basic event logging. Although these technologies demonstrate promising capability, their real-world impact remains limited due to practical deployment challenges.

A major limitation of current systems is the reliability of accident detection, as many solutions still use threshold-based rules that cannot consistently distinguish true accidents from road disturbances such as potholes, speed bumps, or sudden braking. Another significant challenge is connectivity dependence, since internet-based alerts and app-based reporting become unreliable in low-network regions, leading to delayed or failed emergency communication. Most designs also remain reactive in nature, as they primarily respond only after an accident is detected rather than providing preventive intelligence. In addition, user trust and

adoption pose challenges, as frequent false warnings reduce confidence and acceptance. Lastly, many systems provide limited research-grade analytics, as long-term datasets and predictive insights are often not integrated into the framework.

These limitations motivate the need for a scalable rider safety system that remains operational under poor connectivity conditions, reduces false alerts through intelligent event interpretation, and supports preventive decision-making. This provides a clear rationale for proposing a hybrid smart helmet framework that combines offline-first emergency communication with edge intelligence and optional dashboard-based analytics for long-term safety improvement.

Proposed System Architecture: The proposed rider safety framework follows a layered hybrid design that ensures reliability in safety-critical scenarios while enabling intelligence-driven monitoring and analytics. The first layer is the helmet-side monitoring layer, which continuously observes key rider safety signals such as accident-like motion patterns, helmet compliance behaviour, and indicators of unsafe riding. This layer supports local alerts and prepares essential event information for emergency communication.

The second layer is the offline-first emergency alert layer, introduced to address connectivity limitations that commonly affect IoT-based safety systems. In this layer, emergency alerts are transmitted through an offline communication path to a nearby receiver or gateway, allowing the system to trigger safety escalation even when internet connectivity is unavailable. This design ensures that critical accident alerts remain dependable and are not blocked by network failure.

The third layer is the IoT dashboard and analytics layer, which becomes active when connectivity is available. This layer enables real-time visualization, event-history logging, notification delivery, and long-term safety analytics. By combining offline-first alerting

with optional online monitoring, the architecture supports both immediate rider protection and data-driven safety improvement. This hybrid design is intended to function as a practical blueprint for an intelligent rider safety ecosystem.

Methodology: The proposed methodology is designed as a pipeline that converts continuously collected safety signals into meaningful safety decisions and alerts. As illustrated in Fig. 1, the process begins with data acquisition, where rider-related safety indicators are collected through the helmet-side monitoring layer. This is followed by preprocessing, where raw inputs are filtered, normalized, and prepared for analysis to reduce noise and improve stability under real road conditions. Next, feature extraction is performed to derive informative indicators such as motion dynamics, compliance stability patterns, and behaviour-related variations that improve the interpretability of the data.

Proposed Methodology Pipeline

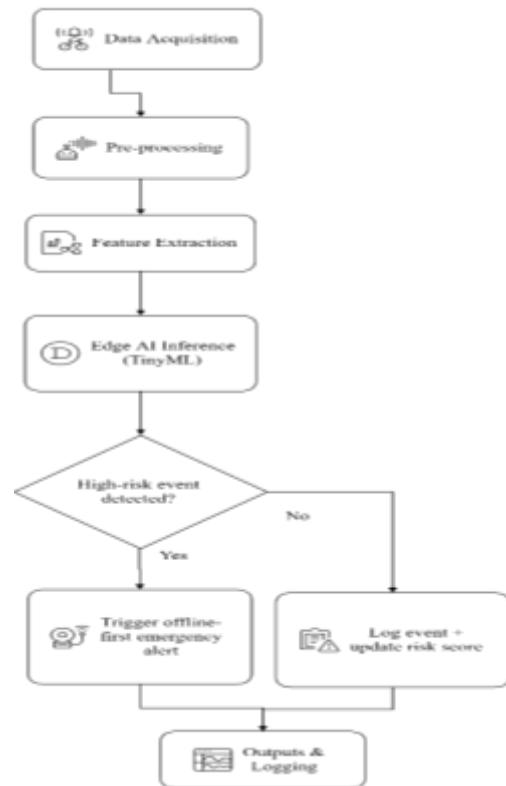


Fig. 1 Proposed methodology pipeline for the AI-enabled rider safety framework

The extracted feature set is then passed to the AI inference stage, where a lightweight machine learning model performs classification of riding events into appropriate categories, such as normal movement, road disturbance, abnormal motion, or crash-like events. Based on the decision flow shown in Fig. 1, the decision layer evaluates risk severity and produces outputs such as rider risk score and anomaly flags. If a high-risk condition is identified, the emergency protocol is triggered through the offline-first alert path, ensuring safety escalation even when network services are limited. Otherwise, the event is logged for monitoring and the risk score is updated. In parallel, the dashboard layer receives the event updates whenever connectivity is available, enabling live monitoring, notifications, and long-term analytics.

AI Based Enhancements:

Artificial Intelligence enhances the proposed framework by improving decision reliability, reducing false alarms, and enabling preventive safety monitoring. In conventional smart helmet designs, accident detection often relies on fixed threshold rules that fail to separate harmless road disturbances from genuine crash events. To address this, the framework incorporates AI-driven event classification where machine learning models learn motion patterns and classify riding events more accurately. By analyzing inertial patterns and derived features such as jerk, RMS, variance, and stability metrics, the model can distinguish between normal riding, potholes/speed bumps, sudden braking, falls, and high-confidence crash events. This directly reduces false alerts and improves user trust.

Beyond accident detection, AI supports a rider risk scoring mechanism that estimates risk continuously instead of reacting only after events occur. The risk score is computed by combining multiple signals such as abnormal riding patterns, compliance instability, and unsafe behaviour indicators. This transforms the

system into a preventive safety assistant capable of issuing early warnings and recommendations. The framework also proposes anomaly detection to identify unusual behaviour patterns, repeated safety violations, or potential sensor malfunction and drift, improving system robustness over time. Finally, once sufficient event history is accumulated, the analytics layer supports predictive insights such as trend analysis, risk behaviour patterns, and safety recommendation generation, enabling research-grade outcomes and long-term safety improvement.

Survey-Based User Feedback:

To evaluate perceived usefulness, acceptance, and adoption potential of an AI-enabled smart helmet safety framework, a survey was conducted using Google Forms and received a total of 52 responses. The results highlight significant safety gaps and strong relevance of the proposed approach. Helmet usage behaviour indicates clear compliance inconsistency, as only 25% of respondents reported always wearing a helmet, while 32.7% wear it sometimes and 11.5% reported never wearing a helmet. This suggests that technology-based compliance support can play a meaningful role in improving rider safety.

Accident exposure among respondents was also notably high, with 48.1% stating they have witnessed a road accident and 23.1% reporting that they have personally experienced an accident. When asked about major reasons for two-wheeler accidents, over speeding (51.9%) and poor road conditions (48.1%) emerged as the most common perceived causes, supporting the need for both risk prediction and intelligent road-noise classification. Regarding technology acceptance, 51.9% of participants rated 4/5 or 5/5 that technology can significantly reduce accidents. Respondents also expressed moderate-to-high comfort toward AI monitoring rider behaviour, with responses concentrated mainly around 3/5 and 4/5 levels. Additionally, accident risk prediction (32.7%)

and automatic emergency alerts (30.8%) were identified as the most preferred AI features, indicating alignment with the proposed framework's focus areas. Adoption potential was encouraging, as 58.8% respondents indicated they would use a smart helmet with AI safety features, while 50% reported willingness to pay extra if safety benefits are ensured. Overall, the survey results support the practical relevance of the proposed framework and highlight that user interest is strongest for systems that offer both risk prediction and reliable emergency alerting.

Expected Outcomes:

Since this work is presented as a proposed framework with prototype-level validation, outcomes are reported in terms of expected behavioural improvements and evaluation objectives rather than large-scale deployment metrics. The integration of AI-based event classification is expected to reduce false accident alerts compared to threshold-only detection by learning to separate road disturbances from crash-like events. The offline-first emergency alerting layer is expected to improve reliability by ensuring that safety-critical alerts remain functional even when internet connectivity is unavailable. The addition of rider risk scoring and anomaly detection further enhances the system by enabling preventive safety warnings rather than purely reactive accident reporting.

Survey findings provide strong user-backed justification for these expected outcomes, as respondents demonstrated inconsistent helmet compliance, high accident exposure, and meaningful acceptance of AI-based monitoring. The framework is also expected to provide a scalable foundation for long-term analytics, enabling trend identification, risk behaviour analysis, and safety recommendations as more data is collected. These expected outcomes reflect the framework's goal of combining reliability, intelligence, and adoption feasibility in a unified rider safety ecosystem.

Discussion:

The proposed framework addresses key limitations in existing rider safety solutions by combining reliability and intelligence. Offline-first alerting ensures emergency communication remains functional under network limitations, which is essential for realistic road conditions. AI-based event classification improves trust by reducing false warnings caused by normal road disturbances, while rider risk scoring shifts the focus from reactive safety to preventive monitoring.

Survey outcomes further highlight real-world relevance: helmet compliance is inconsistent, accident exposure is common, and users show strong interest in AI risk prediction and automatic emergency alerts. However, adoption success will depend on system transparency, low false-alarm rates, comfort, and cost feasibility.

Conclusion:

This paper proposed an AI-enabled smart helmet framework for rider safety that integrates continuous monitoring, AI-based event classification, and offline-first emergency alerting with optional IoT dashboard analytics. The proposed approach aims to reduce false accident alerts, provide preventive safety warnings through risk scoring, and generate long-term insights using historical data. Survey-based feedback (n=52) indicates significant rider safety gaps, strong interest in risk prediction and emergency alerts, and high adoption potential.

Future work will focus on controlled dataset development, pilot testing under real road conditions, and deployment evaluation of lightweight edge-AI models for practical implementation.

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Cite This Article:

Jha S.T., Kalmani V.K., Jadhav A.J. & Maurya S.S.P. (2026). A Hybrid IoT And AI Architecture for Intelligent Rider Protection Systems. In Aarhat Multidisciplinary International Education Research Journal: Vol. XV (Number I, pp. 221 – 227). Doi: <https://doi.org/10.5281/zenodo.18610909>