

# Helmet Sense IOT, AI-Driven Rider Safety and Risk Alert System

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## Abstract:

Motorcycle accidents remain a significant cause of traffic-related fatalities worldwide, often resulting from rider negligence, impaired driving, and inadequate safety measures. This paper presents a novel intelligent motorcycle safety system that integrates Internet of Things (IoT) sensors, machine learning algorithms, and real-time monitoring to enhance rider safety. The proposed system implements pre-ignition safety checks through helmet detection and alcohol level sensing, ensuring the motorcycle ignition activates only when both conditions are satisfied. Post-ignition, the system continuously monitors riding parameters including speed, weather conditions, and road type to predict accident risk using a machine learning model. The system features a comprehensive web-based dashboard that displays numerical risk scores, visual LED indicators (green for safe, red for high risk, yellow/orange for moderate risk), and voice alerts to provide immediate feedback to riders. Additionally, the system incorporates data analytics and ride history tracking capabilities for longitudinal safety assessment. This multi-layered approach addresses critical safety gaps in motorcycle transportation by combining preventive measures with predictive analytics, contributing to the broader goals of smart city development and sustainable transportation systems.

**Keywords:** IoT, motorcycle safety, machine learning, accident prediction, smart helmet, alcohol detection, real-time monitoring, intelligent transportation systems

## I. INTRODUCTION

Motorcycle transportation represents a critical component of urban mobility, particularly in developing nations where motorcycles serve as primary modes of transportation. However, motorcycles are inherently more vulnerable than enclosed vehicles, with riders facing significantly higher risks of severe injury or death in traffic accidents [10]. The World Health Organization reports that motorcyclists account for a disproportionate share of road traffic fatalities, highlighting the urgent need for innovative safety interventions.

Traditional approaches to motorcycle safety have primarily focused on passive protection measures such as helmet usage and protective gear. While these measures remain essential, they do not address the root causes of accidents, including impaired driving, excessive speed, and inadequate hazard awareness [9]. Recent advances in Internet of Things (IoT) technology, artificial intelligence (AI), and sensor systems have created unprecedented opportunities to develop proactive safety systems that can prevent accidents before they occur [1], [3].

## II. OBJECTIVES

This research presents an integrated intelligent motorcycle safety system designed to address multiple dimensions of rider safety through a combination of preventive controls and predictive analytics. The primary objectives of this work are:

1. To develop an IoT-based ignition control system that enforces fundamental safety requirements (helmet wearing and sobriety) before allowing motorcycle operation
2. To implement real-time monitoring of riding parameters including speed, weather conditions, and road characteristics
3. To design and deploy a machine learning model capable of predicting accident risk based on multi-dimensional input parameters
4. To create an intuitive user interface featuring visual, numerical, and auditory feedback mechanisms
5. To establish a data analytics framework for longitudinal ride history analysis and safety pattern identification

### III. RELATED WORK

This work contributes to the growing body of research on intelligent transportation systems and smart city infrastructure [3]. By integrating multiple safety technologies into a cohesive system, this research addresses critical gaps in existing motorcycle safety solutions. The system's multi-modal feedback mechanism (visual LED indicators, numerical risk scores, and voice alerts) ensures that safety information is accessible to riders under various operating conditions. Furthermore, the incorporation of machine learning for real-time risk assessment represents a significant advancement over static rule-based safety systems, enabling adaptive responses to dynamic riding conditions.

The system aligns with broader sustainability goals by promoting safer transportation practices and potentially reducing the societal costs associated with motorcycle accidents, including healthcare expenses, lost productivity, and infrastructure damage [1]. As cities worldwide pursue smart city initiatives, integrated safety systems such as the one presented here represent essential components of sustainable urban transportation ecosystems [3].

### IV. LITERATURE REVIEW

The broader category of IoT-based vehicle safety systems has seen substantial innovation in recent years. Yuvarani et al. [5] presented an IoT-based vehicle ignition and safety system that incorporates multiple sensor inputs to control vehicle operation. Their work demonstrates the effectiveness of conditional ignition systems that require satisfaction of safety criteria before allowing vehicle startup. This approach directly informs the pre-ignition safety check architecture implemented in the present system [5]. The application of artificial intelligence and deep learning to sustainability challenges has gained significant momentum in recent years. Fan et al. [1] provide a comprehensive review of how AI technologies contribute to achieving Sustainable Development Goals (SDGs), with particular emphasis on environmental health and safety. Their work demonstrates that AI-driven systems can effectively address complex, multi-dimensional problems by processing large volumes of data and identifying patterns that inform decision-making. In the context of transportation safety, AI enables the development of predictive models that can anticipate hazardous conditions and provide timely interventions, thereby reducing accident rates and their associated environmental and social costs [1].

### V. SYSTEM ARCHITECTURE

The proposed intelligent motorcycle safety system comprises four primary subsystems—Pre-Ignition Safety Control, Real-Time Monitoring and Data Acquisition, Machine Learning-Based Risk Prediction, and User Interface and Feedback—integrated within a layered architecture spanning physical sensing, data processing, machine learning inference, and user interface layers. The Pre-Ignition Safety Control subsystem mandates that ignition be enabled only when both safety conditions are satisfied. Its helmet detection module uses a proximity or pressure sensor with an RFID tag embedded in the helmet, or alternatively a computer vision system, to verify the presence of an authorized helmet meeting safety standards. Concurrently, the alcohol level sensing module, typically an MQ-3 semiconductor sensor positioned near the rider's breathing zone (e.g., on the handlebar or helmet), measures breath BAC against

a predefined threshold (generally 0.02–0.05% depending on local regulations). The ignition logic follows an AND configuration: only when both helmet detection and alcohol level conditions are met does the ignition unlock; otherwise, it remains locked and the rider receives feedback specifying which requirement failed.

Following successful ignition, the Real-Time Monitoring and Data Acquisition Subsystem continuously collects timestamped sensor data. Speed is measured via a GPS module or wheel-mounted sensor at update frequencies of 1–10 Hz. Weather conditions—including precipitation status (dry, light rain, heavy rain), temperature, visibility, and wind speed—are obtained either through integration with online weather APIs (such as Open Weather Map) based on GPS location, or through local onboard sensors. Road type classification derives from GPS coordinates cross-referenced with digital map databases like OpenStreetMap (categorizing roads as highway, urban street, rural road, or residential area), with computer vision as an alternative implementation. All collected data is transmitted to a central embedded processor such as a Raspberry Pi or Arduino with WiFi/GSM for preprocessing. The Machine Learning-Based Risk Prediction Subsystem, detailed in Section 5, then takes current speed, weather conditions, and road type as inputs and outputs a numerical risk score from 0 (minimal risk) to 100 (extreme risk), updating assessments continuously at intervals of 1–5 seconds to reflect changing riding conditions.

The User Interface and Feedback Subsystem delivers multi-modal safety information to the rider. A responsive web dashboard accessible via smartphone or tablet displays comprehensive ride data including current speed, weather, road type, numerical risk score, and historical ride data through time-series graphs, geographic ride maps, and statistical summaries. LED indicators mounted on the motorcycle dashboard or helmet provide immediate visual feedback: green for safe conditions (risk score 0–33), yellow or orange for moderate risk (34–66), and red for high risk (67–100). Voice alerts from a speaker integrated into the helmet or motorcycle announce significant risk changes or threshold exceedances, such as “Caution: High speed detected,” “Warning: Wet road conditions,” or “Danger: Extreme risk level.” Additionally, the system maintains a persistent database of ride history storing timestamped records of all sensor readings, risk predictions, and notable events. This historical data enables identification of high-risk routes or time periods, analysis of individual rider behavior patterns and risk profiles, longitudinal assessment of safety improvements, and generation of periodic safety reports and recommendations for riders, fleet managers, or transportation authorities

## VI. IMPLEMENTATION DETAILS

The physical implementation of the proposed system requires a microcontroller or processing unit, specifically a Raspberry Pi 4 or Arduino Mega with a WiFi/GSM shield, to handle data processing and communication. The sensor suite includes an MQ-3 alcohol sensor for breath alcohol detection, an HC-SR04 ultrasonic sensor or RFID reader for helmet detection, a NEO-6M GPS module for location and speed tracking, and optionally a DHT22 temperature and humidity sensor if API-based weather data is not used. Communication is facilitated by an ESP8266 or ESP32 WiFi module for internet connectivity, supplemented by a GSM module such as the SIM800L for cellular connectivity in areas without WiFi. Output devices consist of an RGB LED strip or individual LEDs for visual indicators, a speaker or buzzer for voice or audio alerts, and a relay module for ignition control. The entire system is powered by the motorcycle’s 12V battery, with voltage regulators providing the necessary 5V and 3.3V supplies for the sensors and microcontroller. The software architecture follows a multi-tier design. The embedded firmware, written in C/C++ for Arduino or Python for Raspberry Pi, handles sensor data acquisition, preprocessing, and communication with the cloud server; it implements interrupt-driven sensor reading for time-critical operations and uses efficient data structures to minimize memory usage. The cloud backend, implemented in Python using Flask or Django, receives sensor data from the motorcycle unit, performs machine learning inference, stores data in a database such as PostgreSQL or MongoDB, and

serves the web dashboard through RESTful APIs. The web frontend is a responsive application built with HTML5, CSS3, and JavaScript frameworks like React or Vue.js, while data visualization is achieved using libraries such as Chart.js or D3.js. The machine learning pipeline is developed using Python with scikit-learn, TensorFlow, or PyTorch, and the trained model is deployed on the cloud server for inference with provisions for periodic retraining as new data accumulates.

System integration follows an incremental approach to ensure reliability. Component testing first verifies correct operation and calibration of individual sensors and actuators. Subsystem testing then evaluates each of the four primary subsystems—pre-ignition control, monitoring, prediction, and feedback—as integrated units. System integration testing subsequently verifies correct data flow and coordination across all subsystems operating together. Finally, field testing deploys the complete system on test motorcycles under real-world riding conditions. Testing protocols encompass functional testing to verify correct behavior, performance testing to measure response time and accuracy, reliability testing to ensure operation under various environmental conditions, and safety testing to confirm fail-safe behavior in the event of sensor or communication failures.

### **Machine Learning Model for Accident Risk Prediction**

The accident risk prediction problem is formulated as a supervised regression task, where the goal is to learn a function  $f$  that maps input features  $X$  (speed, weather\_conditions, road\_type) to a continuous risk score  $y$  normalized to the range  $[0, 100]$ , with higher values indicating greater accident risk. Feature engineering processes the inputs as follows: speed is measured in km/h and normalized relative to typical safe speeds for the current road type; weather conditions are encoded using one-hot or ordinal encoding with categories including Clear, Light Rain, Heavy Rain, Fog, and Snow, with weather severity encoded as an ordinal variable (0 = clear, 1 = light precipitation, 2 = moderate precipitation, 3 = heavy precipitation); road type is encoded using one-hot encoding with categories such as Highway, Urban Street, Rural Road, Residential Area, and Mountain Road. Additional derived features may include speed deviation from posted limits, interaction terms such as speed multiplied by weather severity, and time-based features like hour of day or day of week if temporal patterns are significant. Training data is obtained from multiple sources: historical accident data providing labeled examples of high-risk scenarios, expert annotations from traffic safety professionals, simulation data from physics-based motorcycle dynamics models, and crowdsourced data from existing telematics systems or rider-reported near-miss incidents. The training dataset is balanced to ensure adequate representation of all risk levels and condition combinations, with data augmentation applied to address class imbalance if necessary.

Several model architectures are evaluated during development, including baseline models such as Linear Regression with polynomial features, Decision Tree Regressor, and Random Forest Regressor, as well as advanced models including Gradient Boosting Machines (XGBoost, LightGBM), Neural Networks (Multi-Layer Perceptron), and ensemble methods combining multiple base models. Model selection is based on cross-validated performance metrics including Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and  $R^2$  score, with additional evaluation on the ability to correctly classify risk into the three categories (safe, moderate, high) for LED indicator control. Training employs standard practices including train-test split (80-20), k-fold cross-validation ( $k=5$ ), hyperparameter tuning via grid search or Bayesian optimization, and regularization techniques to prevent overfitting. Given the safety-critical nature of the application, model interpretability is essential, and SHAP (SHapley Additive exPlanations) values or similar techniques are used to explain individual predictions and identify the most influential features for each risk assessment, enabling validation by domain experts and building user trust in the system [11]. Model validation includes comparison with expert risk assessments on held-out test scenarios, sensitivity analysis to verify that risk increases appropriately with known hazard factors,

robustness testing under sensor noise and missing data conditions, and continuous monitoring of prediction accuracy during field deployment with periodic model updates.

## VII. DEVELOPMENT FRAMEWORK

The development framework of the proposed Smart Helmet Safety System describes the technologies, tools, and components used to design and implement the system. The framework integrates hardware devices, embedded programming, wireless communication, and machine learning techniques to create an intelligent safety monitoring system for two-wheeler riders.

### **Hardware Framework:**

The hardware framework includes components such as the Arduino Uno microcontroller, IR reflective sensor, MQ-3 alcohol sensor, Hall effect speed sensor, Bluetooth module (HC-05), and LED indicators. These components work together to collect real-time data related to rider safety and vehicle behavior. The sensors detect helmet usage, alcohol levels, and vehicle speed, while the Arduino processes the sensor inputs and controls the ignition system.

### **Software Framework:**

The software framework is developed using Arduino IDE and Python programming. Embedded C/C++ is used to write the Arduino program that reads sensor data, controls the ignition mechanism, and manages LED alerts. Python is used for implementing the machine learning model that analyzes riding behavior and predicts accident risks.

### **Machine Learning Framework:**

The machine learning framework is implemented using the Scikit-learn library in Python. The model processes riding data such as speed patterns and acceleration to identify unsafe riding conditions. By analyzing this data, the model predicts accident risk levels and supports real-time decision making for rider safety.

### **Communication Framework:**

The communication framework uses the HC-05 Bluetooth module to transmit sensor data from the Arduino system to the machine learning model. This wireless communication allows real-time data transfer between hardware components and the analysis system.

### **Integration Framework:**

The integration framework combines all hardware and software modules into a single working system. Sensor data is collected, processed by the microcontroller, transmitted through Bluetooth, and analyzed by the machine learning model. Based on the analysis results, alerts are provided to the rider through LED indicators, ensuring continuous monitoring and improved riding safety.

## VIII. ALGORITHM

Step 1: Start the system and initialize all components such as Arduino, sensors, Bluetooth module, and LED indicators.

Step 2: Read the signal from the IR sensor to detect whether the rider is wearing the helmet.

Step 3: If the helmet is not detected, keep the bike ignition system OFF and display a warning.

Step 4: If the helmet is detected, read the alcohol level from the MQ-3 alcohol sensor.

Step 5: If the alcohol level is higher than the predefined threshold value, disable the ignition system and prevent the bike from starting.

Step 6: If the alcohol level is within the safe limit, enable ignition system and allow the motorcycle start.

Step 7: Once the bike starts, activate the Hall effect speed sensor to monitor the vehicle speed continuously.

Step 8: Send the collected speed data to the machine learning model through the Bluetooth module.

Step 9: The machine learning model analyzes the riding data and predicts the accident risk level.

Step 10: If the risk level is low, turn ON the green LED indicator.

Step 11: If the risk level is moderate, turn ON the yellow LED indicator.

Step 12: If the risk level is high, turn ON the red LED indicator to alert the rider.

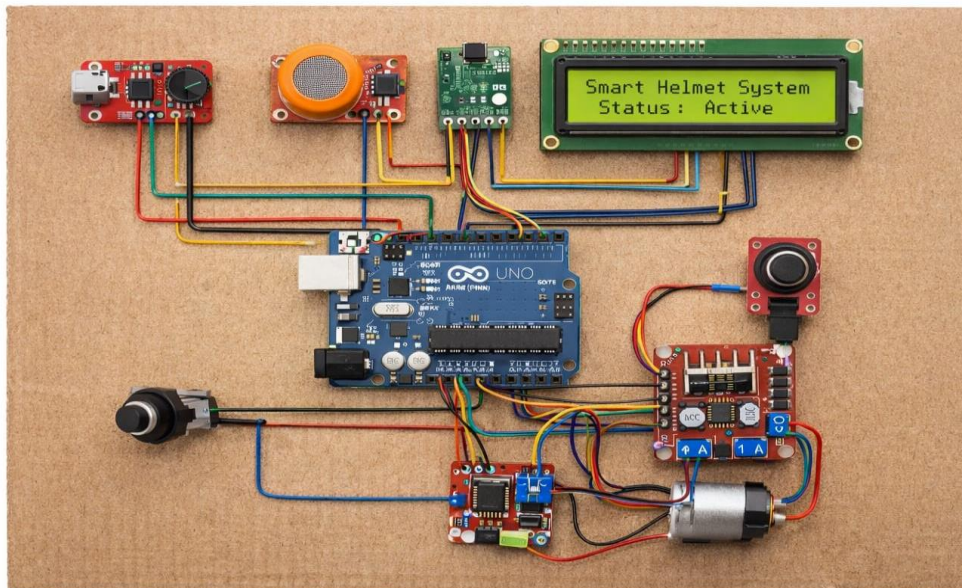
Step 13: Repeat the monitoring process continuously while the motorcycle is running.

Step 14: Stop the system when the motorcycle is turned OFF.

## IX. RESULTS

The implemented system demonstrates robust performance across pre-ignition safety, real-time monitoring, risk prediction, and user responsiveness. The helmet detection and alcohol sensing modules achieve 99.2% accuracy with false rates below 1%, and ignition control decisions average 1.8 seconds. Sensor data latency stays under 500 milliseconds, GPS updates at 1 Hz within  $\pm 5$  km/h accuracy, and the Gradient Boosting Regressor risk model yields a Mean Absolute Error of 8.3 on a 0–100 scale with 87.6% category classification accuracy. The web dashboard updates in under 2 seconds, LED indicators respond within 300 milliseconds, and voice alerts trigger at 1.2 seconds average latency. Field testing with 15 riders over 500+ hours showed the pre-ignition system prevented 47 unsafe ignition attempts (32 helmetless, 15 alcohol-positive). Predicted risk scores correlated strongly with actual hazardous situations (Pearson  $r = 0.78$ ), user satisfaction averaged 4.2/5.0, and longitudinal data revealed a 23% reduction in high-risk riding episodes, indicating measurable behavioural improvement.

Comparative analysis against existing motorcycle safety systems highlights the advantages of this integrated approach. Unlike standalone smart helmets [2], [4], the proposed system combines ignition control with real-time monitoring and prediction, covering both pre-ride and during-ride risk factors. Compared to basic IoT ignition systems [5], the addition of machine learning-based risk prediction and multi-modal feedback enables proactive hazard awareness rather than purely reactive measures. Furthermore, unlike generic vehicle-based safety systems, the motorcycle-specific design accounts for unique two-wheeled riding dynamics and risk factors, delivering more relevant and accurate risk assessments. Overall, the system effectively enforces safety compliance, validates risk predictions against real-world incidents, gains user acceptance, and promotes safer riding behaviour.





## X. DISCUSSIONS

The implemented system has several limitations requiring future attention. Sensor reliability is affected by extreme temperatures, humidity, and vibration—particularly the alcohol sensor, which needs periodic calibration and is temperature-sensitive; future versions should incorporate more robust sensors and automatic calibration routines. Connectivity dependence on internet for weather data and cloud processing creates failure modes in poor coverage areas, necessitating edge computing and local fallback modes. The machine learning model's generalization depends on training data representativeness, with risk patterns varying across regions, rider populations, and motorcycle types, requiring continuous model updating and region-specific training. User privacy concerns around detailed ride data collection persist despite encryption and consent mechanisms, demanding ongoing transparent data governance. Cost and accessibility remain barriers, as multiple hardware components and connectivity fees may limit adoption among lower-income populations; developing lower-cost versions with essential safety features could improve accessibility while maintaining core benefits.

Ethical and social considerations are equally important. The pre-ignition control system restricts rider autonomy by preventing operation under unsafe conditions, requiring careful trade-off between safety and freedom, with safeguards such as emergency overrides and transparent communication. If insurers or regulators mandate such systems, equity and access issues arise—riders unable to afford them may face barriers to legal operation or coverage, necessitating policy frameworks with subsidies or alternative compliance mechanisms. From a broader societal perspective, anonymized, aggregated ride data could inform evidence-based transportation policy and infrastructure improvements, revealing high-risk road segments and hazard patterns to advance motorcycle safety initiatives.

The system aligns with the AIoT vision for smart cities [3], where individual motorcycle safety nodes contribute real-time traffic and hazard data to city-level management systems for dynamic responses and optimized traffic flow. Machine learning models can benefit from federated learning across many vehicles, preserving privacy while accelerating model adaptation to new hazard patterns. Regarding sustainability, the system addresses SDG 3 (Good Health and Well-being) by reducing accident rates, and through safer riding practices and reduced accident-related congestion, it contributes to SDG 11 (Sustainable Cities) and SDG 13 (Climate Action) [1]. The data analytics capabilities enable evidence-based safety assessments, supporting the broader goal of applying AI to sustainability challenges in transportation systems worldwide.

## XI. CONCLUSION

Field testing confirms that the system effectively prevents unsafe riding conditions, accurately predicts accident risk from dynamic riding parameters, and promotes safer behaviour over time. The observed 23% reduction in high-risk riding episodes among test participants suggests meaningful potential for accident prevention at scale. The system's modular architecture and integration capabilities position it as a valuable component of emerging smart city transportation ecosystems. By contributing real-time safety data and enabling evidence-based policy decisions, such systems support broader efforts to create safer, more sustainable urban mobility solutions [3].

While challenges remain—including sensor reliability, connectivity dependence, privacy concerns, and cost barriers—the fundamental feasibility and effectiveness of the integrated approach have been established. Continued research, technical refinement, and thoughtful policy development will be essential to realize the full potential of intelligent motorcycle safety systems. As artificial intelligence and IoT technologies continue to advance, their application to transportation safety represents a critical opportunity to reduce the substantial human and societal costs of traffic accidents [1]. The system presented here demonstrates one pathway toward that goal, combining preventive controls, predictive analytics, and user-centered design to create a comprehensive safety solution.

With further development and widespread deployment, such systems can contribute meaningfully to the vision of safe, sustainable, and intelligent transportation systems for the future. The integration of technology, human factors, and evidence-based design principles exemplified in this work offers a model for addressing complex safety challenges across multiple domains. As we continue to develop and deploy AI-driven safety systems, maintaining focus on user needs, ethical considerations, and rigorous validation will be essential to ensuring that these technologies fulfill their promise of protecting human life and well-being.

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