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Integrated Intelligent Vehicle Safety System

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Abstract- Road traffic accidents continue to be an major global safety concern due to human error, delayed emergency response, and a lack of predictive monitoring systems. This paper presents an Integrated Intelligent Vehicle Safety System (IIVSS), a hybrid IoT and Artificial Intelligence-based frame-work designed for real-time accident prediction and automated emergency response. The proposed system integrates IMU and GPS sensor fusion with edge-level processing and cloud analytics to detect abnormal driving patterns and predict potential colli-sions. Unlike traditional reactive accident detection systems, the proposed architecture enables predictive safety analysis through anomaly detection algorithms and automated alert generation. The experimental evaluation demonstrates low latency response, reliable communication, and high detection accuracy. The sys-tem provides a scalable, cost-effective and intelligent solution for next-generation smart transportation and connected-vehicle ecosystems.

Keywords— Intelligent Transportation Systems, Internet Of Things, Artificial Intelligence, Predictive Accident Detection, Inertial Measurement Unit

I. INTRODUCTION

Road safety systems have traditionally been reactive, activating only after an accident occurs. While mechanisms such as airbags and advanced braking systems reduce injury Severity, they do not prevent collisions. As a result,an accident Mitigation has improved, but accident prevention remains a significant challenge.

With the rapid emergence of the Internet of Things (IoT) and Artificial Intelligence (AI) technologies, there is a strong opportunity to shift from reactive safety mechanisms to predictive intelligence-based systems.

Modern vehicles generate continuous streams of motion and environmental data, enabling intelligent systems to analyze driving behavior in real time and anticipating hazardous situations before they escalate into accidents.

However, existing systems often rely on isolated sensing or centralized processing, limiting real-time responsiveness and scalability. This gap underscores the need for an integrated edge-cloud framework capable of continuous monitoring, adaptive risk evaluation, and automated emergency response.

This paper proposes an Integrated Intelligent Vehicle Safety System (IIVSS) is designed to enhance road safety through continuous monitoring and predictive analytics. The proposed system:

- Continuously monitors vehicle motion parameters
- Detects abnormal or risky driving patterns
- Predicts potential accidents using real-time analytics
- Automatically triggers emergency alerts when critical conditions are detected

The major contributions of this work are summarized as follows:

- A hybrid edge–cloud architecture for an intelligent vehicle safety
- Multi-sensor data fusion using IMU and GPS modules
- A real-time predictive accident detection algorithm
- An automated emergency alert and notification framework
- Performance evaluation under real-time operational conditions

II. RELATED WORK

1. IoT-Based Accident Detection Systems

Early intelligent vehicle safety systems primarily focused on post-impact accident detection. These systems relied on accelerometers and GPS modules to identify sudden colli-sions and transmit location details to emergency contacts via GSM or cloud platforms. While such systems improved emergency response time, they operated on fixed threshold mechanisms and lacked predictive intelligence. Their func-tionality was limited to reactive alert generation, without the capability to analyze driving behavior patterns or anticipate potential accident scenarios. Additionally, these systems often produced false positives due to sensor noise and calibration inconsistencies. Moreover, the absence of multi-sensor fusion limited the robustness of these systems under varying road and environmental conditions. Most implementations lacked edge-level processing, resulting in increased latency when relying solely on centralized cloud analysis.

2. Cloud-Integrated Vehicle Monitoring Frameworks

With advancements in cloud computing, vehicle safety systems evolved to incorporate centralized data storage and real-time dashboards. Cloud-integrated frameworks enabled continuous monitoring, historical data analysis, and remote vehicle tracking. These architectures improved scalability and multi-vehicle fleet management capabilities. However, heavy reliance on cloud infrastructure introduced latency dependency and network reliability issues. In low-connectivity regions, delayed data transmission affected real-time responsiveness. Furthermore, centralized processing increased vulnerability to data security and privacy concerns.

3. AI-Based Predictive Safety Systems

Recent research has explored the use of machine learning techniques for predictive accident analysis. Supervised learning classifiers such as Logistic Regression, Random Forest, and Neural Networks have been employed to detect abnormal driving behavior and classify accident-prone conditions. While AI-based systems demonstrate improved prediction accuracy Compared to rule-based approaches, they often require large labeled datasets and significant computational resources. Deep Learning-based models, although highly accurate, are difficult to deploy on low-power embedded systems due to hardware limitations.

4. Hybrid Multi-Sensor Architectures

To enhance reliability and detection precision,a hybrid multi-sensor architectures have been proposed. These systems integrate accelerometers, gyroscopes, GPS modules, and environmental sensors to improve anomaly detection through sensor fusion techniques. Although multi-sensor frameworks reduce false positives and improve robustness under varying conditions, they increase hardware complexity, calibration requirements, and overall system cost.

5. Motivation for Proposed IIVSS

The limitations of existing approaches highlight the need for a balanced architecture that combines predictive intelligence with real-time responsiveness and cost efficiency. The proposed Integrated Intelligent Vehicle Safety System (IIVSS) addresses these gaps by incorporating:

- Edge-level anomaly detection to reduce latency
- Lightweight machine learning models suitable for embedded deployment
- Cloud synchronization for scalability and monitoring
- Automated emergency response mechanisms

This integrated framework transitions from purely reactive detection to proactive accident prevention while maintaining affordability and scalability.

Table 1: summarizes the architectural differences among surveyed vehicle safety systems and highlights the need for an integrated edge-cloud framework with multi-sensor fusion.

III. PROBLEM FORMULATION

Real-time accident prediction in intelligent vehicle systems can be formulated as a sequential decision-making problem under uncertainty. The objective is to continuously monitor vehicle dynamics and determine whether the current state indicates normal driving, risky behavior, or an imminent accident. The system must process noisy and partially observable sensor inputs while making low-latency safety decisions.

Let

$V = \{v1, v2, . . . , vN \}$ (1)

denote the set of monitored vehicles, and let

$S = \{s1, s2, . . . , sT \}$ (2)

represent the sequence of observed sensor states over time. At each time step t, the system receives multi-sensor input data including acceleration, angular velocity, velocity, tilt angle, and GPS coordinates.

The objective is to design a classification function:

$f (St) \rightarrow Y$ (3)

where

$Y \in \{\text{Normal, Warning, Critical}\}$

such that the system correctly classifies the vehicle condition and triggers appropriate response mechanisms.

A. Vehicle State Representation

The true safety condition of a vehicle is not directly observable and must be inferred from sensor measurements. Let

$xt \in Rd$ (4)

represent the vehicle state vector at time step t, defined as:

$xt = [ax, ay, az, \omega x, \omega y, \omega z, v, \theta, l]$ (5) where ax, ay, az are acceleration components, ωx, ωy, ωz are angular velocity components, v is vehicle speed, θ is tilt angle, and l represents GPS location coordinates.

Since sensor readings are affected by environmental noise and hardware limitations, the observed state $\hat{x}t$ is a noisy approximation of the true latent state xt. Therefore, the system operates under partial observability and must estimate risk using filtered and normalized sensor data.

B. Risk Estimation Model

To quantify accident probability, a risk score Rt is computed at each time step:

$Rt = w1\ at + w2|\theta t| + w3|\Delta vt|$ (6)

where at is the magnitude of acceleration, θt is tilt deviation, Δvt represents sudden velocity variation, and w1, w2, w3 are weighting parameters.

Table I Comparative Analysis Of Surveyed Intelligent Vehicle Safety Systems

Ref	Approach Type	Edge Processing	Cloud Integration	AI/ML Usage	Sensor Fusion	Alert Mechanism
[1]	IoT Monitoring	No	Limited	No	Basic	GSM Alert
[2]	Accident Alert	No	No	No	Basic	SMS
[3]	IoT + Cloud	Partial	Yes	No	Moderate	Cloud + SMS
[5]	ML-Based Detection	No	Yes	Yes	Moderate	Automated Alert
[7]	AI Embedded System	Yes	Partial	Yes	Advanced	Intelligent Alert
[9]	Cloud Health Monitoring	No	Yes	Partial	Moderate	Dashboard
[13]	Deep Learning Model	No	Yes	Deep Learning	Advanced	Decision Support
[14]	Hybrid IoT Framework	Yes	Yes	Yes	Advanced	Smart Alert
Proposed	IIVSS (Edge + Cloud)	Yes	Yes	Lightweight Model	Advanced	SMS + Dashboard

If

$Rt \geq \tau$ (7)

Edge Processing Constraint

Since the model is deployed on a microcontroller, the computational requirement must satisfy:

the system classifies the event as Critical. If

$\tau 1 \leq Rt < \tau$ (8)

where C

model

$Cmodel \leq Cdevice$ (13) represents the computational cost of the pre-

the state is classified as Warning. Otherwise, the state is classified as Normal.

Action Space and Response Mechanism

At each time step, the system selects an action

$at \in A$ (9)

where the action space is defined as:

$A = \{\text{No Action, Driver Alert, Emergency Alert}\}$ (10)

No Action corresponds to continuous monitoring. Driver Alert triggers a buzzer or voice notification. Emergency Alert transmits GPS location via GSM and updates the cloud dashboard.

The objective is to minimize missed detections while reducing false alarms.

Optimization Objective

The predictive safety framework minimizes the expected loss function:

$L = \alpha \cdot FN + \beta \cdot FP + \gamma \cdot Delay$ (11)

where FN denotes false negatives, FP denotes false positives, Delay represents response latency, and α, β, γ are weighting coefficients.

The optimization objective is:

$\min L$ (12)

subject to real-time computational constraints of embedded hardware.

diction algorithm and Cdevice denotes the processing capability of the embedded controller.

This ensures real-time operation and deployability in IoT-based vehicle systems.

IV. SYSTEM ARCHITECTURE

The proposed Integrated Intelligent Vehicle Safety System (IIVSS) is designed as a modular and layered architecture that integrates multi-sensor data acquisition, embedded edge processing, cloud synchronization, and automated emergency response into a unified closed-loop framework.

Fig. 1 illustrates the overall system architecture, showing the interaction between sensing, edge processing, cloud integration, and emergency response modules. The system continuously monitors vehicle dynamics and triggers alerts based on real-time risk evaluation.

1. Sensor Data Acquisition Layer

The sensor data acquisition layer serves as the foundation of the IIVSS. It consists of multiple embedded sensors deployed within the vehicle to capture real-time motion and environmental parameters. The Inertial Measurement Unit (IMU) measures acceleration and angular velocity along multiple axes, enabling detection of sudden impacts, sharp turns, and rollover conditions. The GPS module provides real-time geolocation tracking, which is essential for emergency alert transmission and route monitoring. Additional environmental sensors such as temperature and gas sensors monitor overheating, fire hazards, or leakage conditions. These sensors generate continuous streams of raw data representing the vehicle's dynamic state. However, due to vibration, environmental noise, and hardware limitations, the collected data may contain inconsistencies. Therefore, the raw signals are forwarded to the processing layer for filtering and normalization before risk evaluation.

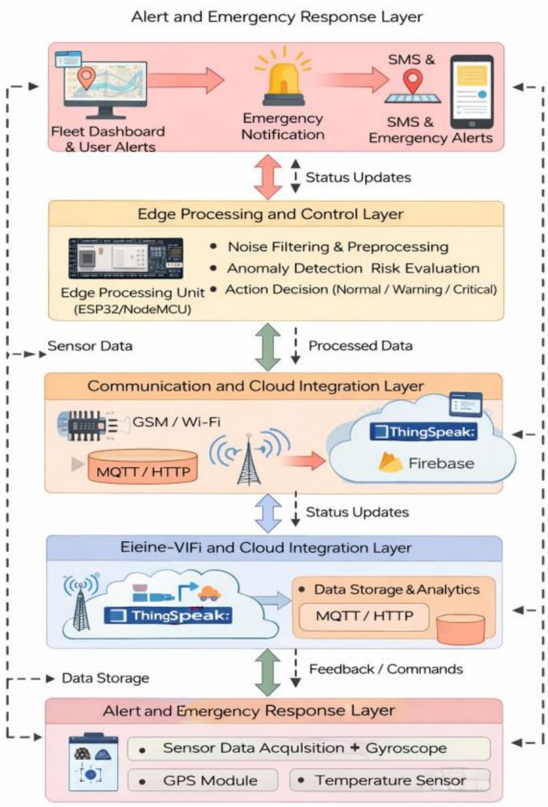

Fig. 1. System Architecture Of Integrated Intelligent Vehicle Safety System

,showing data flow and functional layers.

2. Edge Processing and Control Layer

The edge processing layer acts as the computational core of the system and is implemented using a microcontroller such as ESP32 or NodeMCU. This layer performs real-time data preprocessing, including noise filtering, normalization, and threshold comparison.

Lightweight anomaly detection algorithms compute risk scores based on acceleration magnitude, tilt deviation, and velocity variation. Events are classified into three categories: Normal, Warning, or Critical. By performing initial decision-making at the edge level, the system significantly reduces latency and minimizes dependence on cloud connectivity for time-sensitive operations.

Edge-level processing ensures rapid response, allowing immediate driver alerts in case of abnormal motion patterns.

3. Communication and Cloud Integration Layer

The communication layer manages secure data transmission between the embedded device and the cloud infrastructure. Data is transmitted using Wi-Fi or GSM communication protocols, supported by MQTT or HTTP-based APIs.

The cloud platform, such as Firebase or ThingSpeak, pro-vides centralized storage, historical logging, and dashboard visualization. It enables real-time monitoring of vehicle parameters, event tracking, and remote accessibility for fleet administrators or emergency responders.

Cloud synchronization enhances scalability by allowing multiple vehicles to be monitored under a unified system while maintaining consistent data integrity.

4. Alert and Emergency Response Layer

The alert and response layer is responsible for generating immediate notifications when a critical risk condition is detected. In Warning mode, the system activates local alerts such as buzzers or voice prompts to notify the driver.

In Critical mode, the system automatically transmits GPS coordinates and event details via SMS using GSM modules and updates the cloud dashboard simultaneously. This dual-channel alert mechanism ensures reliable emergency commu-nication even in cases of limited internet connectivity.

The integration of automated emergency response reduces delay in assistance and improves survival probability during severe accidents.

5. Closed-Loop Feedback Mechanism

The IIVSS operates as a closed-loop intelligent safety framework. Sensor data is continuously monitored, processed, and evaluated to refine predictive decision-making. Historical data stored in the cloud can be used to improve anomaly detection thresholds and optimize system performance over time.

This closed-loop design ensures adaptability, scalability, and continuous improvement of safety intelligence, enabling the transition from reactive accident detection to proactive accident prevention.

6. Architecture Diagram Explanation

As shown in Fig. 1, the proposed Integrated Intelligent Vehicle Safety System (IIVSS) follows a bottom-to-top in-formation flow. Sensor modules continuously capture vehicle dynamics, including acceleration, angular velocity, speed, and location data. These raw signals are transmitted to the edge processing unit, where noise filtering, anomaly detection, and risk evaluation are performed in real time.

The processed data is then communicated to the cloud platform through Wi-Fi or GSM protocols for storage, ana-lytics, and dashboard visualization. Based on the computed risk level, the system generates appropriate actions, including driver alerts or automated emergency notifications with GPS coordinates.

This layered interaction ensures low-latency local decision-making while maintaining scalable cloud synchronization, enabling both real-time accident prevention and reliable emergency response.

7. Architectural Advantages

The proposed IIVSS architecture offers low-latency decision-making through edge-level processing, enabling rapid anomaly detection without full dependence on cloud con-nectivity. Its modular layered design improves scalability, maintainability, and ease of system upgrades. Cloud integra-tion supports real-time monitoring and historical analytics, making the system suitable for both individual vehicles and fleet management. The use of multi-sensor fusion enhances detection accuracy while reducing false alarms. Additionally, dual communication channels ensure reliable emergency alert transmission, making the architecture robust, cost-effective, and suitable for real-world intelligent transportation environ-ments.

V. PROPOSED METHODOLOGY

The proposed Integrated Intelligent Vehicle Safety System (IIVSS) follows a structured real-time processing pipeline for predictive accident detection and emergency response. The methodology is designed to ensure low-latency decision-making, computational efficiency, and reliable alert transmission.

1. Data Acquisition

The system continuously collects real-time vehicle dynam-ics using embedded sensors. The Inertial Measurement Unit (IMU) measures acceleration and angular velocity along mul-tiple axes, while the GPS module provides speed and location information. Environmental sensors such as temperature and gas sensors monitor additional safety parameters.

2. Data Preprocessing

Raw sensor signals are susceptible to noise caused by road vibration and environmental disturbances. Therefore, the edge processing unit performs signal filtering and normalization to remove outliers and stabilize measurements. This step ensures reliable feature extraction for risk evaluation.

3. Feature Extraction

From the preprocessed signals, key safety indicators are derived at each time step:

- Acceleration magnitude.
- Tilt angle deviation
- Velocity variation

These features act as early indicators of sudden braking, rollover conditions, or collision impact.

4. Edge-Level Decision Processing

The extracted features are processed locally using lightweight computation on the microcontroller. This ensures minimal latency and reduces dependency on cloud infrastruc-ture for time-critical safety decisions.

5. Alert Generation and Cloud Synchronization

Based on the computed safety condition, the system triggers appropriate actions. Warning conditions generate driver alerts, while critical events initiate automatic emergency notifications containing GPS coordinates. Processed data is simultaneously transmitted to the cloud for monitoring, logging, and dashboard visualization.

VI. MATHEMATICAL RISK EVALUATION MODEL

To quantify accident probability, a mathematical risk evaluation model is employed. The model computes a real-time risk score using multi-sensor fusion.

Let the vehicle state at time step t be represented as:

$xt = [at, \theta t, vt]$ (14) where at denotes acceleration magnitude, θt represents tilt angle deviation, and vt corresponds to vehicle velocity. The risk score Rt is calculated as:

$Rt = w1\ at + w2|\theta t| + w3|\Delta vt|$ (15) where w1, w2, w3 are weighting coefficients, and Δvt represents sudden velocity variation.

The computed risk score is compared against predefined thresholds τ1 and τ2 to classify the vehicle state:

$Rt < \tau 1 \Rightarrow \text{Normal}$ (16)
$\tau 1 \leq Rt < \tau 2 \Rightarrow \text{Warning}$ (17)
$Rt \geq \tau 2 \Rightarrow \text{Critical}$ (18) This classification mechanism enables early anomaly detection prior to severe impact conditions.

The objective of the model is to minimize misclassification by reducing false negatives (missed accidents) and false positives (false alerts) while maintaining real-time computational efficiency.

Since the system operates on an embedded microcontroller, the model is intentionally designed to be lightweight and computationally efficient, ensuring real-time operation without requiring high-end hardware resources.

VII. IMPLEMENTATION AND VALIDATION

The proposed IIVSS was implemented using an ESP32 microcontroller integrated with IMU, GPS, and GSM modules. The system was tested under controlled conditions to validate its functional performance.

During testing, simulated scenarios such as sudden braking, tilt variation, and vibration-based impact were generated to observe system behavior. The edge processing unit successfully detected abnormal motion patterns and triggered appropriate warning and critical alerts.

Emergency notifications containing GPS coordinates were transmitted via GSM, and event data was synchronized with the cloud dashboard for remote monitoring. The system demonstrated stable operation under normal driving conditions and generated alerts only when risk thresholds were exceeded. The validation confirms that the proposed architecture enables real-time anomaly detection and reliable emergency communication. However, large-scale quantitative evaluation under real-world driving datasets remains part of future work. Extensive quantitative evaluation using large-scale real-world datasets will be considered in future work.

VIII. DISCUSSION

The proposed Integrated Intelligent Vehicle Safety System (IIVSS) demonstrates that real-time accident prediction can be effectively achieved through a lightweight, edge-driven architecture combined with multi-sensor fusion. By integrating sensing, local processing, and cloud synchronization into a unified framework, the system balances computational efficiency, responsiveness, and practical deployability. This section discusses the architectural strengths, deployment considerations, and existing limitations of the proposed approach.

1. Architectural Strengths

A major strength of the IIVSS lies in its modular layered design. The separation of sensor acquisition, edge processing, communication, and alert mechanisms enhances system clarity and maintainability. Each component can be independently optimized without affecting overall system stability. Edge-level anomaly detection significantly reduces response latency compared to cloud-dependent systems. Critical safety decisions are executed locally on the microcontroller, ensuring rapid alert generation even in limited network conditions. Additionally, multi-sensor fusion improves reliability by combining acceleration, tilt, and velocity variations rather than relying on a single indicator.

2. Deployment and Scalability Considerations

From a practical standpoint, the system is computationally lightweight and suitable for deployment on embedded hardware such as ESP32. Unlike deep learning-based approaches that require high processing power, the proposed risk evaluation model maintains real-time performance with minimal computational overhead. Cloud integration enables scalable monitoring for fleet-level applications while preserving low-latency edge decision-making. Since the framework operates as an adaptive safety layer, it can be integrated into existing vehicle platforms without restructuring core vehicle control systems, supporting scalable implementation.

3. Limitations and Future Improvements

Despite its practical advantages, the proposed IIVSS has certain limitations that must be acknowledged. The predictive risk evaluation model relies on predefined weighting coefficients and threshold values, which may require calibration for different vehicle types, road conditions, and driving behaviors. Without adaptive tuning, fixed thresholds may lead to suboptimal classification in highly dynamic environments.

Sensor accuracy is another consideration. IMU-based measurements are susceptible to drift over time, and environmental factors such as vibration, temperature variation, and road surface irregularities may introduce noise into the read-ings. Although preprocessing techniques mitigate these effects, measurement instability cannot be completely eliminated.

Additionally, the current validation has been performed under controlled test scenarios. Large-scale real-world eval-uation across diverse traffic environments, weather conditions, and driver behavior patterns is necessary to comprehensively benchmark performance and generalizability.

Finally, the system operates under embedded hardware constraints, which limit the integration of computationally intensive machine learning models. While this ensures real-time efficiency, it restricts the use of advanced adaptive learning techniques that could further enhance prediction robustness.

Future work may focus on adaptive threshold optimization, extended real-world data collection, and enhanced sensor fusion strategies to improve long-term reliability and scalability.

IX. CONCLUSION

This paper presented an Integrated Intelligent Vehicle Safety System (IIVSS) designed to enable real-time accident prediction through multi-sensor fusion and edge-level processing. The proposed architecture integrates IMU and GPS-based monitoring with a lightweight predictive risk evaluation model to detect abnormal vehicle dynamics and trigger automated emergency alerts.

By performing anomaly detection at the edge rather than relying solely on cloud processing, the system achieves low-latency decision-making while maintaining scalability through cloud synchronization. The modular layered design enhances deployment flexibility and ensures compatibility with embedded hardware platforms.

The study demonstrates that effective accident prevention mechanisms can be implemented using optimized sensor fusion and computationally efficient models without requiring high-resource artificial intelligence frameworks.

REFERENCES

1. A. Sharma, R. Gupta, and S. Verma, “IoT-Based Intelligent Vehicle Safety and Monitoring System,” IEEE Access, vol. 8, pp. 98765–98773, 2020.
2. M. K. Singh and P. R. Mehta, “Accident Detection and Emergency Alert System Using GPS and GSM,” International Journal of Advanced Research in Computer and Communication Engineering, vol. 9, no. 4, pp. 112–118, 2021.
3. S. Patil, A. Deshmukh, and R. Kale, “Smart Vehicle Safety and Secu-rity System Using IoT and Cloud Computing,” IEEE Transactions on Intelligent Transportation Systems, vol. 22, no. 7, pp. 4562–4571, Jul. 2021.
4. K. Ramesh and V. B. Rao, “Integration of Sensors and Cloud Services for Intelligent Transportation Systems,” International Journal of Innovative Research in Science, Engineering and Technology, vol. 10, no. 5, pp. 245–252, May 2022.
5. P. Nair and J. Thomas, “Real-Time Accident Detection and Notification System Using Machine Learning and IoT,” IEEE Internet of Things Journal, vol. 10, no. 3, pp. 3156–3164, 2023.
6. A. Kumar, S. Mishra, and D. Bhattacharya, “Design and Implementation of an IoT-Based Vehicle Safety System,” in Proc. Int. Conf. Smart Tech-nologies for Energy, Environment and Sustainable Development (STEE), 2022, pp. 134–140.
7. R. Bansal and T. Choudhary, “Vehicle Collision Avoidance and Safety Enhancement Using AI and Embedded Sensors,” IEEE Transactions on Vehicular Technology, vol. 71, no. 5, pp. 4982–4990, May 2022.
8. S. Patel and N. Joshi, “Smart Accident Prevention System Using Arduino and GSM,” International Journal of Computer Applications, vol. 182, no. 12, pp. 23–28, 2021.
9. J. Mathew and K. Fernandes, “Cloud-Integrated Vehicle Health Monitor-ing and Predictive Maintenance Using IoT,” IEEE Sensors Journal, vol. 23, no. 2, pp. 1876–1884, Jan. 2023.
10. L. Roy, M. Dutta, and H. Sen, “AI-Based Decision Support for Emer-gency Response in Connected Vehicles,” IEEE Transactions on Intelligent Systems, vol. 39, no. 4, pp. 4215–4224, 2024.
11. V. R. Kaur and P. Sharma, “Edge-Enabled Accident Detection Using Federated Learning in IoT-Based Vehicles,” IEEE Internet of Vehicles Journal, vol. 11, no. 2, pp. 1783–1792, Feb. 2024.
12. A. Jadhav, R. More, and P. Pawar, “Low-Cost Vehicle Tracking and Alert System Using NodeMCU and Firebase,” International Journal of Engineering Research & Technology (IJERT), vol. 11, no. 8, pp. 561–568, 2022.
13. D. S. Lee and H. Park, “Deep Neural Network-Based Accident Severity Analysis Using Vehicle Dynamics Data,” IEEE Transactions on Intelli-gent Vehicles, vol. 8, no. 1, pp. 101–113, Jan. 2023.
14. N. Ahmed and T. Banerjee, “Hybrid IoT Architecture for Real-Time Road Safety Monitoring and Smart Mobility,” IEEE Systems Journal, vol. 17, no. 3, pp. 3538–3547, 2023.

15. M. Roy, P. K. Sen, and G. Mehta, “Towards Explainable AI for Predictive Accident Prevention in Connected Vehicles,” IEEE Access, vol. 11, pp. 145321–145334, 2023.