IJARSCT

International Journal of Advanced Research in Science, Communication and Technology

International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal

ISSN: 2581-9429

Volume 6, Issue 1, May 2026

Impact Factor: 8.2

Smart Accident Detection and Emergency Response System with Accident Severity Classification

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Abstract: *Road traffic accidents are a major cause of fatalities and severe injuries worldwide, primarily due to delayed accident detection and emergency response [1]. Traditional accident management systems rely heavily on human intervention, which often leads to increased response time and, in many cases, loss of life [4]. This highlights the need for automated, intelligent, and real-time accident detection mechanisms.*

To address this challenge, this survey focuses on IoT-based Smart Accident Detection and Emergency Response Systems [5], with particular emphasis on vehicle accident severity classification into High, Medium, and Low levels [2]. The main objective of this study is to review and analyze existing IoT-enabled techniques used for automatic accident detection, severity assessment, and real-time emergency notification

Various approaches employing MEMS accelerometers, gyroscopes, gas sensors, GPS modules, machine learning algorithms, cloud platforms, and mobile/web applications are examined. The survey also reviews communication technologies such as GSM, LTE, and IoT protocols used for transmitting alert information to emergency contacts, hospitals, and rescue services.

Based on the analysis, the study highlights the strengths and limitations of current systems in terms of accuracy, response time, scalability, and reliability. The outcome of this survey provides a comprehensive understanding of existing solutions and identifies key research gaps, thereby serving as a foundation for developing an efficient, real-time, and intelligent accident detection and emergency response system with accurate severity.

Keywords: Internet of Things (IoT), Smart Accident Detection, Vehicle Safety System, Emergency Response System, Accident Severity Classification, MEMS Sensors, GPS Tracking, Real-Time Monitoring, Mobile Alert System, Cloud Computing, Smart Transportation

I. INTRODUCTION

Road traffic accidents have become a major global concern due to the rapid increase in the number of vehicles and inadequate traffic management systems. According to recent studies, a significant number of accident-related fatalities occur not only because of the severity of the crash but also due to delays in detecting the accident and providing timely medical assistance. Conventional accident reporting systems depend on eyewitnesses or manual communication, which often leads to delayed emergency response, especially in remote or poorly connected areas. With advancements in embedded systems and communication technologies, there is a growing interest in developing automated solutions for accident detection and emergency response.

The Internet of Things (IoT) plays a crucial role in enhancing vehicle safety by enabling real-time data collection, processing, and communication [1],[5]. IoT-based smart accident detection systems integrate sensors such as MEMS

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accelerometers, gyroscopes, gas sensors, and GPS modules to monitor vehicle conditions and detect unusual events [3]indicating an accident. An important aspect of modern systems is accident severity classification, which categorizes accidents into high, medium, or low severity levels. This classification helps prioritize emergency response, ensuring that critical cases receive immediate attention, thereby reducing fatalities and improving survival rates.

Despite significant progress, several challenges remain in implementing efficient accident detection systems. These include accurate severity classification, minimizing false alerts, ensuring reliable communication, and maintaining system scalability and robustness in real-world conditions. This paper is organized as follows: Section II reviews related work in IoT-based accident detection and severity analysis; Section III discusses commonly used sensors and technologies; Section IV compares existing methodologies and identifies research gaps; and Section V concludes the paper with future research directions

II. RELATED WORK

IoT-Based Accident Detection and Severity Analysis

The rapid growth of vehicles and urban traffic has led to increased focus on intelligent systems capable of detecting accidents and classifying their severity to enable timely emergency response. Several research works have explored IoT-based accident detection systems using various sensors, communication technologies, and data processing techniques. This section reviews these contributions, highlighting the techniques used, advantages, and limitations.

A. Existing Methods

Sensor-Based Detection –Many studies have used MEMS accelerometers, gyroscopes, and GPS sensors to monitor vehicle motion and detect sudden impacts [1],[3] or abnormal tilt indicative of accidents. These systems provide real-time monitoring and alert generation, reducing the dependency on manual accident reporting.

Machine Learning Approaches – Researchers have applied machine learning algorithms, such as decision trees, SVMs, and neural networks, to classify accident severity [2], [10] (high, medium, low) based on sensor data. These methods enhance accuracy in severity prediction but require sufficient training data and computational resources.

IoT and Cloud Integration – Integration of IoT with cloud computing enables real-time data transmission, storage, and remote monitoring [9]. Accident alerts can be sent to emergency contacts and hospitals immediately, facilitating faster medical response.

Mobile-Based Alert Systems – Mobile applications linked with vehicle sensors provide instant notifications to emergency services and family members, improving the timeliness of assistance.

Author	Year	Method	Advantages	Limitations
Gupta et al.	2019	MEMS + GPS + GSM alerts	Real-time detection, automatic alerts	Limited severity classification, false alarms possible
Sharma et al.	2021	MEMS + SVM classification	Accurate severity prediction	High computational cost, sensor calibration needed
Reddy & Das	2023	Multi-sensor fusion + Neural Network	High detection accuracy, severity differentiation	Expensive hardware, complex integration

B. Limitations of Current Approaches

• False Positives/Negatives – Sensor noise and environmental factors can trigger incorrect accident detection.
• Limited Severity Differentiation – Many systems detect an accident but fail to classify severity accurately.
• Connectivity Dependence – Real-time alerts often rely on mobile networks or internet connectivity, which may not be reliable in remote areas.
• Scalability and Cost – Multi-sensor integration and machine learning models increase system cost and maintenance complexity.

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C. Summary

The reviewed literature shows that IoT-based accident detection systems have significant potential for enhancing vehicle safety and emergency response. However, there is a clear need for systems that can accurately classify accident severity, reduce false alerts, and remain reliable in real-world traffic conditions. This highlights the importance of integrating multi-sensor data, advanced machine learning techniques, and robust communication frameworks in modern smart accident detection systems.

III. SENSORS, TECHNOLOGIES, AND METHODS USED

IoT-based smart accident detection systems rely on a combination of hardware sensors, communication technologies, and data processing algorithms. This section discusses the commonly used components and methods, their advantages, limitations, and performance comparisons.

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A. Sensors Used in Accident Detection Systems

1. MEMS Accelerometers

• Measure linear acceleration along three axes.
• Detect sudden deceleration or collision events.
• Advantages: Compact, cost-effective, low power, high precision.
• Limitations: Sensitive to noise; requires calibration.

2. Gyroscopes

• Measure rotational motion and tilt.
• Detect rollovers and angular displacement during an accident.
• Advantages: Accurate tilt detection, complements accelerometer data.
• Limitations: Drift over time; requires sensor fusion for stability.

3. Gas Sensors

• Detect fuel leakage, smoke, or harmful gases after accidents.
• Advantages: Provides additional safety information (fire hazard).
• Limitations: Slower response time; environmental conditions affect readings.

4. GPS Modules

• Track vehicle location in real time.
• Advantages: Provides precise accident location for emergency responders.
• Limitations: Poor signal in tunnels or dense urban areas.

5. IoT Communication Modules (GSM/4G/5G/Wi-Fi/Bluetooth)

• Transmit accident data to cloud servers and mobile applications
• Advantages: Enables instant alerts; remote monitoring possible.
• Limitations: Network dependence; higher data costs.

Comparison of Sensors

Various sensors are used in IoT-based accident detection systems, each serving a specific purpose with its own advantages and limitations. A MEMS accelerometer is primarily used to detect collisions or sudden impacts. It is fast, precise, and compact in size, making it suitable for real-time accident detection; however, it is sensitive to noise and requires proper calibration to avoid false triggers. A gyroscope is employed to detect vehicle rollovers or tilt by measuring angular motion. While it provides accurate angular detection, it suffers from drift over time and requires complex signal processing.

A gas sensor Is used to detect fuel leakage or smoke, which helps in identifying potential fire hazards after an accident. Although it enhances safety, its response time is relatively slow and it is highly sensitive to environmental conditions. GPS modules are integrated to track the exact location of the accident, enabling quick emergency response. GPS offers accurate positioning but may perform poorly in tunnels, dense urban areas, or regions with weak satellite signals. Finally, an IoT communication module is responsible for transmitting accident data to emergency services or cloud platforms in real time. While it enables instant alerts and remote monitoring, its performance depends heavily on network availability and connectivity

B. Accident Detection and Severity Classification Methods

1. Threshold-Based Methods

Description: Accident severity is classified by predefined thresholds of acceleration, tilt, or impact force.
Advantages: Simple, low-cost, real-time.
Limitations: Cannot handle complex or unusual crash scenarios; may generate false alarms.

2. Machine Learning Models

Techniques: Decision Trees, Support Vector Machines (SVM), Random Forest, Neural Networks.
Input Data: Sensor readings from accelerometers, gyroscopes, GPS, and gas sensors.
Advantages: High accuracy, adaptable to different vehicles and accident types.
Limitations: Requires large datasets; computationally intensive; may need cloud/edge processing.

3. Multi-Sensor Fusion Techniques

Description: Combines data from multiple sensors to improve reliability and reduce false positives.
Advantages: High detection accuracy, robust in real-world conditions.
Limitations: Higher cost and complexity

4. Real-Time Alert Systems

Description: Cloud or edge processing systems send immediate alerts to mobile applications or emergency responders based on severity classification.
Advantages: Reduces emergency response time.
Limitations: Dependent on network availability and cloud latency.

Comparison of Accident Detection Methods

Threshold-based methods rely on predefined limits set on sensor values to detect accidents. These approaches are simple, fast, and low-cost to implement; however, they often suffer from a high false alarm rate, resulting in an average accuracy of around 70%.

Machine learning–based approaches such as Decision Tree and Support Vector Machine (SVM) classify accidents using multi-sensor data. These methods are adaptable and provide moderate accuracy, but they require a labeled dataset and involve medium computational complexity. Their accuracy typically ranges between 80% and 85%.

Advanced models like Random Forest and Neural Networks utilize ensemble and deep learning techniques to detect accidents. These approaches achieve high accuracy by learning complex patterns from large datasets. However, they require high computational resources and are often cloud-dependent. Their accuracy ranges from approximately 88% to 95%.

Multi-sensor fusion techniques combine data from multiple sensors to improve detection reliability. By integrating various sensor inputs, these methods are robust and significantly reduce false positives. Nevertheless, the integration process is complex and costly. The accuracy of multi-sensor fusion approaches is generally above 90%.

IoT-based real-time alert systems focus on sending immediate notifications through cloud or mobile platforms after accident detection. These systems enable fast emergency response but depend heavily on network availability and stability. Their accuracy typically lies between 80% and 90%.

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B. Data Processing and Visualization

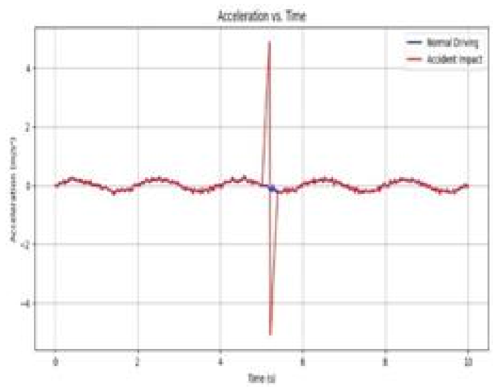
1. Signal Processing:

• Raw sensor data is filtered using moving average or Kalman filters to reduce noise.
• Features such as peak acceleration, tilt angle, and velocity change are extracted.

2. Classification Algorithms:

• Threshold-based or ML models classify accident severity into High, Medium, or Low categories

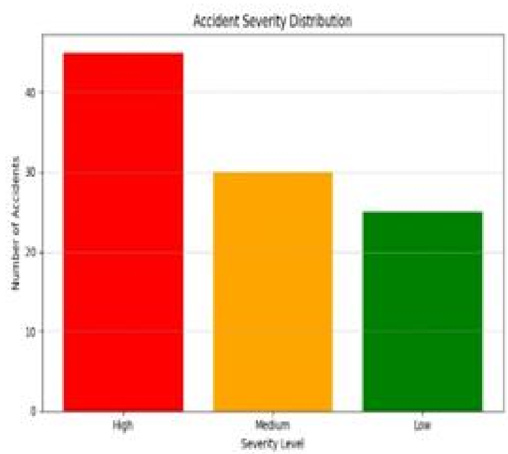
3. Visualization:



• Graph of acceleration vs. time can indicate collision points
• GPS maps show the accident location

Acceleration vs. Time during normal driving vs. accident scenario

• Severity charts can display statistics for emergency management dashboards.



Number of accidents classified by severity (High/Medium/Low)

D. Key Observations

• Multi-sensor fusion with machine learning provides the highest accuracy for accident detection and severity classification.
• Threshold-based methods are faster but less reliable for complex scenarios.

DOI: 10.48175/IJARSCT-34716

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Block diagram of IoT-based accident detection system

- IoT connectivity enables real-time emergency alerts but introduces dependency on networks.
- Visualization and dashboards help emergency responders prioritize cases effectively.

E. Evaluation Metrics

To systematically evaluate and compare different accident detection systems, several performance metrics are considered. These metrics provide a comprehensive basis for analyzing the effectiveness and reliability of the systems in real-world scenarios.

Accuracy measures the overall correctness of the system in detecting accidents and classifying their severity levels. A higher accuracy indicates better performance and reliability. Precision represents the proportion of correctly detected accident events among all detected events, thereby helping to minimize false alarms. Recall, also known as sensitivity, indicates the system's ability to identify actual accident occurrences without missing critical cases.

In addition to these, response time is an important metric that determines how quickly the system can detect an accident and send alerts to emergency services. A lower response time is crucial for timely medical assistance and can significantly reduce fatalities. The false positive rate evaluates how often the system incorrectly detects an accident when none has occurred, which directly affects user trust and system dependability.

Furthermore, scalability refers to the system's ability to handle a large number of vehicles and data efficiently, making it suitable for real-world deployment. Cost efficiency considers the affordability of sensors, communication modules, and maintenance, which is essential for large-scale implementation. Lastly, network dependency assesses the reliance of the system on communication infrastructure, which can impact performance in remote or low-connectivity areas

Mathematical Formulas

$$\text{Accuracy} = (TP + TN) / (TP + TN + FP + FN)$$

$$\text{Precision} = TP / (TP + FP)$$

$$\text{Recall} = TP / (TP + FN)$$

Where:

TP (True Positive): Correctly detected accidents

TN (True Negative): Correctly identified non-accident cases

FP (False Positive): Incorrect accident detection

FN (False Negative): Missed accident cases

Performance Metrics Comparison

Metric	Description	Importance
Accuracy	Measures overall correctness of accident detection	Ensures system reliability
Precision	Ratio of correct accident detections	Reduces false alarms
Recall	Ability to detect actual accidents	Avoids missing critical cases
Response Time	Time taken to send alerts	Enables faster emergency response
False Positive Rate	Incorrect accident detections	Improves system trust
Scalability	Ability to handle large-scale deployment	Suitable for smart city applications
Cost Efficiency	Overall system cost and maintenance	Supports real-world implementation
Network Dependency	Dependence on internet/network	Affects performance in remote areas

The comparison of existing methodologies is performed based on the evaluation metrics discussed in Section III.

Dataset Description

In order to develop and evaluate accident detection and severity classification systems, the availability of relevant datasets plays a crucial role. These datasets typically consist of sensor readings, vehicle dynamics, environmental conditions, and accident-related information collected from real-world scenarios or simulated environments.

In this study, accident detection datasets generally include parameters such as acceleration, angular velocity, vehicle speed, GPS location, and time-stamped sensor data obtained from MEMS accelerometers, gyroscopes, and GPS modules. Additionally, some datasets incorporate gas sensor readings to detect fuel leakage or fire hazards after an accident. These multi-sensor data sources enable accurate detection and classification of accident severity levels into High, Medium, and Low categories.

Since publicly available standardized datasets for accident severity classification are limited, many researchers rely on a combination of real-time data collection and simulation-based data generation. Real-world datasets are often collected using embedded systems installed in vehicles, while simulation datasets are generated using tools that mimic crash scenarios under controlled conditions. Machine learning-based approaches require labeled datasets, where each data instance is tagged with the corresponding accident severity level.

A typical dataset used in accident detection systems may include the following attributes:

- Acceleration (X, Y, Z axes)
- Angular velocity (gyroscope data)
- Vehicle speed
- GPS coordinates (latitude and longitude)
- Time of impact
- Gas/smoke detection values
- Accident severity label (High, Medium, Low)

The quality and diversity of the dataset significantly affect the performance of the system. Datasets with balanced classes, noise handling, and real-world variability improve the robustness and accuracy of machine learning models. Therefore, future research should focus on creating standardized, large-scale, and publicly available datasets for better benchmarking and comparison of accident detection systems.

Attribute	Description
Acceleration (X, Y, Z)	Measures sudden impact or collision force
Gyroscope Data	Detects tilt and rollover
Speed	Vehicle speed at the time of accident
GPS Location	Provides accident location
Timestamp	Time of accident occurrence

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Volume 6, Issue 1, May 2026
ISSN: 2581-9429
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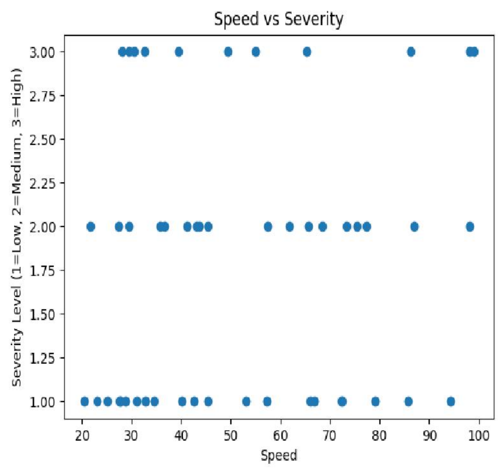
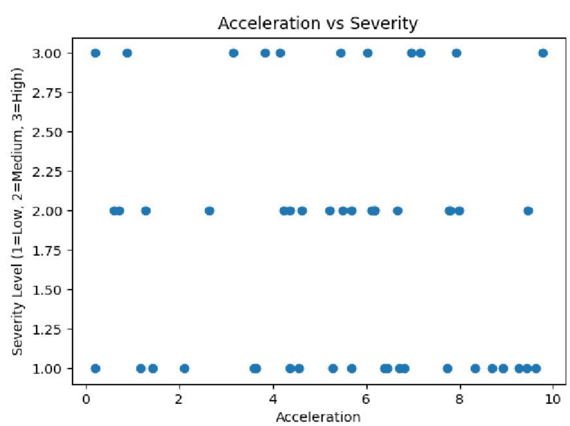
Gas Sensor Data	Detects fuel leakage or fire
Severity Label	High / Medium / Low classification



Speed vs Severity



Acceleration vs Severity

IV. COMPARISON OF EXISTING METHODOLOGIES AND RESEARCH GAPS

IoT-based smart accident detection systems have evolved significantly in recent years. Various approaches using sensors, communication technologies, and intelligent algorithms have been proposed. Despite these advances, challenges remain in accuracy, severity classification, and real-world deployment. This section presents a detailed comparison of existing methods, identifies limitations, highlights missing areas, and emphasizes the need for improvements.

A. Overview of Existing Methodologies

IoT-based accident detection systems generally follow a pipeline of sensing, data transmission, processing, and alerting. The key methodologies can be categorized into:

Threshold-Based Detection Methods

• Principle: Detect accidents using predefined thresholds of acceleration, tilt, or impact force from sensors.
• Example: If acceleration exceeds 3g or tilt exceeds 60°, an accident is flagged.

Advantages:

• Simple to implement.
• Low-cost and requires minimal computational resources.
• Provides real-time detection.

Limitations:

• Cannot handle complex crash scenarios.
• High false positive rate due to sensor noise or abrupt braking.

Machine Learning-Based Methods

Principle: Use algorithms like Decision Trees, SVM, Random Forest, or Neural Networks to learn patterns from multi-sensor data.

Advantages:

• Higher accuracy for severity classification.
• Can adapt to different vehicle types and crash scenarios.
• Reduces false positives compared to threshold methods.

Limitations:

• Requires large datasets for training.
• Computationally intensive; may require cloud or edge processing.
• May fail if real-world data differs significantly from training data.

Multi-Sensor Fusion Techniques

Principle: Combine data from accelerometers, gyroscopes, GPS, and gas sensors to improve detection reliability.

Advantages:

• Reduces false positives and false negatives.
• Robust in diverse environmental conditions.

Limitations:

• Higher hardware costs.
• Complex integration and calibration required.

IoT-Based Real-Time Alert Systems

Principle: Use GSM/4G/5G/Wi-Fi modules to transmit data to cloud or mobile apps for immediate notifications.

Advantages:

• Immediate alerts to hospitals and emergency contacts.
• Can include location and severity information.

Limitations:

• Dependent on network availability.
• Latency may affect real-time response in remote areas.

Comparison of Accident Detection Methods

This table presents a comparative analysis of different accident detection methods based on sensors used, accuracy, advantages, and limitations.

Method	Sensors Used	Accuracy	Advantages	Limitations
Threshold-Based Method	Accelerometer, Gyroscope	~70%	Simple, low-cost, real-time detection	High false positives, not suitable for complex scenarios
Decision Tree / SVM	Accelerometer, Gyroscope, GPS	80–85%	Better classification, adaptable	Requires labeled data, moderate computation
Random Forest / Neural Network	Multi-sensor (Accel, Gyro, GPS, Gas)	88–95%	High accuracy, learns complex patterns	High computational cost, cloud dependency
Multi-Sensor Fusion	Accelerometer, Gyroscope, GPS, Gas Sensor	>90%	Highly reliable, reduces false alarms	Expensive, complex integration
IoT-Based Alert System	GPS, GSM/4G/5G, IoT modules	80–90%	Real-time alerts, remote monitoring	Network dependency, latency issues

From the comparison, it is observed that multi-sensor fusion combined with machine learning techniques provides the highest accuracy and reliability among existing accident detection methods. However, these approaches involve higher cost and system complexity.

B. Identified Limitations in Existing Work

Despite progress, several limitations are observed:

1. Detection Accuracy Issues

Threshold-based systems often trigger false alarms due to sudden braking or road bumps.

ML models can misclassify accidents if training data is not representative.

2. Limited Severity Classification

Many systems detect accidents but do not differentiate severity levels (High/Medium/Low).

Without severity classification, emergency response cannot be prioritized efficiently.

3. Network Dependence

Cloud-based solutions depend on mobile networks or Wi-Fi, which may fail in remote or tunnel areas.

4. Hardware Cost and Complexity

Multi-sensor systems provide high accuracy but increase hardware and maintenance costs.

Sensor calibration and integration require expertise.

5. Scalability Challenges

Many systems are designed for single vehicles and do not scale efficiently to city-wide deployment.

C. Missing Areas in Research

1. Standardized Datasets

There is no widely adopted dataset for accident severity prediction, makingbenchmarking difficult.

2. Integration with Smart Infrastructure

Current systems rarely interact with traffic management or emergency networks.

Opportunities exist for preventive accident alerts through connected traffic signals and smart roads.

3. Energy-Efficient and Low-Cost Sensor Modules

Most studies assume high-end sensors, limiting affordability for massadoption.

4.Offline Functionality

Systems largely depend on cloud processing.

Lack of edge computing reduces reliability when network is unavailable

D. Need for Improvement

1. Robust Multi-Sensor Fusion

Combine accelerometer, gyroscope, GPS, and gas sensors for accurate detection and severity classification.

Use intelligent algorithms to filter noise and minimize false positives.

2. Advanced AI/ML Models

Deep learning and ensemble methods can improve severity classification for high, medium, and low impact accidents.

3. Integration with Emergency Services

Connect systems directly to hospitals, ambulances, and traffic authorities for real-time intervention.

4. Scalability and Cost Reduction

Develop modular, low-cost sensor packages suitable for large-scale urban deployment.

Implement edge processing to reduce cloud dependency.

5. Real-Time Visualization and Analytics

Dashboards displaying accident severity, frequency, and location help authorities prioritize emergency response and plan preventive measures.

V. FUTURE RESEARCH DIRECTIONS

In this project, we aim to develop an Smart Accident Detection and Emergency Response System with Accident Severity Classification. The system will automatically detect road accidents in real time and classify their severity as High, Medium, or Low. It will integrate vehicle-mounted sensors such as MEMS accelerometers, gyroscopes, gas sensors, and GPS modules with IoT communication devices to transmit data to a processing unit. Using machine learning algorithms on the cloud or at the edge, the system will analyze sensor data to detect accidents and determine their severity. Once an accident is detected, real-time alerts containing the vehicle location, accident severity, and other essential details will be sent to emergency responders, hospitals, and family members through a mobile or web application.

VI. CONCLUSION

This survey highlights the growing need for intelligent accident detection systems in modern transportation, driven by the increasing number of road accidents and delayed emergency responses. Various methodologies, including threshold-based detection, machine learning algorithms, and multi-sensor fusion, have been explored. While threshold-based approaches are simple and fast, they often suffer from false alarms, whereas machine learning and multi-sensor fusion techniques provide higher accuracy and enable effective accident severity classification.

The importance of this study lies in its potential to save lives by prioritizing emergency response based on accident severity. By integrating IoT-enabled sensors, real-time communication, and intelligent data processing, the system can detect accidents promptly, classify them as High, Medium, or Low, and notify emergency services and family members instantly.IoT-enabled systems combined with machine learning and multi-sensor fusion provide efficient and reliable accident detection and emergency response [5], [10].

The final outcome of this project is a reliable, scalable, and cost-effective smart accident detection system that enhances vehicle safety, reduces fatalities, and improves the efficiency of emergency responses. Additionally, the system's ability to analyze accident data can support long-term traffic management strategies, contributing to safer and smarter transportation networks.

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