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TOWARDS EFFICIENT EMERGENCY RESPONSE: A MULTI-SENSOR APPROACH TO ACCIDENT DETECTION

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Keywords: Automatic accident detection; Sensor network; Emergency response; Accident severity detection.

The emergence of sensor technologies and embedded devices has created significant potential for autonomous accident-detection systems that will enhance emergency response and road safety. In this paper, an automated accident detection system is proposed that rapidly notifies the emergency center of the accident's location and severity. Five sensors, such as a gyroscope, an IR flame sensor, a glass-break sensor, a smoke sensor, and a vibration sensor, are integrated with the STM32 microcontroller board. An algorithm is proposed with three severity levels based on the activation of a sensor or group of sensors. Emergency responders can prioritize their interventions by categorizing accidents into severity levels, thereby allocating resources more efficiently and effectively. The proposed method offers significant potential to strengthen road safety and enhance emergency response to road accidents.

1. INTRODUCTION

The increasing number of fatal crashes has made modern technologies necessary to improve emergency response and road safety. According to statistics, road accidents are the primary cause of injury-related deaths. Road accidents claim the lives of around 1.2 million people, and as many as 50 million people are injured each year. They are the leading killer of young people aged 5-29 years, according to a World Health Organization (WHO) report [1]. Road accidents can occur for a variety of reasons, some of which include driver negligence brought on by sleepiness, drunken driving, speeding, *etc*. The amount of time it takes an ambulance to arrive at the scene of the accident and transport the patient to the hospital has a significant impact on the victim's chance of survival. Most car accidents result in minor injuries that allow the person to be saved; however, when rescue teams arrive later than expected, the injuries become fatal. Therefore, the primary objective is to locate the scene of the accident and promptly provide the rescue teams with the information they need to preserve the victim's life. Therefore, automatic accident detection systems are desperately needed. They can expedite rescue efforts, reduce the number of casualties following an incident, and save a great many lives.

Accident detection systems are fundamentally embedded electronics platforms that rely on sensor fusion, threshold computation, and real-time signal monitoring, aligning directly with contemporary developments in electrical and electronic engineering. Vehicles with sensor capabilities come with sensors that track variables including impact force, global positioning system (GPS), speed, and acceleration. Algorithms are used to collect and interpret real-time data, differentiating possible accidents from typical driving activity. Automatic emergency notifications are delivered to designated contacts and emergency services upon detection, initiating actions such as airbag deployment or SOS signals. Post-accident data analysis aids in reconstruction and cause identification, while ongoing vehicle monitoring finds issues before they lead to accidents. All things considered, an automated accident detection system improves road safety, speeds up emergency responses, and makes them easier to carry out, thus saving lives and increasing total vehicle trustworthiness.

Recent works published in *Revue Roumaine des Sciences Techniques — Série Électrotechnique et Énergétique* emphasize the relevance of sensor-based monitoring, embedded/IoT platforms, real-time signal processing, and optimization/control approaches in engineering applications. In particular, studies on IoT-enabled voltage control and real-time monitoring frameworks [2], advanced DFT-based signal estimation techniques for damped vibrations [3], hybrid optimisation methods for predictive control [4], sliding-mode learning controllers for stability in microgrids [5], and applications of lightweight deep-learning for real-time classification [6] demonstrate methodological approaches that are directly relevant to the design choices in this paper. Inspired by these developments, the proposed multi-sensor STM32 framework integrates vibration and event sensors with low-latency signal processing and a severity classification algorithm to provide robust and fast accident detection and prioritization. These studies collectively highlight the growing significance of intelligent sensing and embedded decision systems in modern engineering solutions. The methodological parallels also reinforce the practicality of employing microcontroller-based architectures for real-time critical-event monitoring. [7] proposed an intelligent and efficient IoT system solution that instantly alerts the family member whenever an accident occurs and sends the accident's location on a map. In this system, the ESP32 microcontroller is considered the core of the overall system. The sensors considered in this system are an IR sensor, an ultrasonic sensor, an accelerometer, and an MQ-3 gas sensor to detect the various aspects of the vehicle's functioning and the driver's condition. The development of intelligent accident detection systems has gained significant momentum with the integration of Internet of Things (IoT), machine learning, and cloud-based technologies. Several studies have proposed innovative approaches to reduce accident response time and improve detection accuracy. Bhakat *et al.* [8] developed an AI-enabled system using IoT and deep learning that analyzes camera and audio data on fog nodes to generate real-time alerts. Similarly, [9] presented an IoT-based accident detection and rescue framework employing GPS, accelerometers, and vibration sensors integrated on a Raspberry Pi platform, achieving reliable detection within 40 seconds. [10] introduced a smart helmet system that monitors physiological parameters such as heart rate and SpO_2 alongside motion data, providing real-time accident detection with 93% accuracy. [11] utilized force sensors and video analytics in combination with cloud processing to detect accident types and assess severity using AI models.

Further, [12] implemented a GSM- and GPS-based ESP32 system to automate rescue alerts upon accident detection. A similar GSM-GPS approach was taken by [13], focusing on location-based alerting using a microcontroller. This approach, by including alcohol detection to enhance

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preemptive safety measures, demonstrates the utility of IoT platforms in accident prevention and was extended in [14]. [15] presents an efficient vehicle collision alert system using crash sensors and cellular communication, while [16] proposed a system integrating GNSS with IoT to improve vehicle localization and accident tracking accuracy.

Recent advancements include deep learning and generative models. [17] proposed a deep learning and IoT-based system for accident detection in smart city environments, integrating LSTM and ResNet to achieve high detection accuracy and reliability. 18] explored accident anticipation through real-time video analysis using feature reuse in CNNs, enabling early warning of potential accidents. [19] employed a hybrid GAN-CNN model to enhance detection and reduce false positives using traffic surveillance imagery.

Recent advancements in accident detection have explored a wide range of approaches, including cloud-based systems and machine learning algorithms, to enhance accuracy and responsiveness. Several researchers have utilized cloud platforms to store, analyze, and transmit accident data in real time [20–22]. Several limitations exist in the literature despite the significant progress in accident detection systems. The primary focus in many systems is on accident detection without implementing the severity classification, which would help to prioritize emergency response. IoT and cloud-based systems need continuous internet supply and high computational resources, which impose a threat to real-time deployment in low-resource environments. Computer vision and deep learning approaches are accurate but impose latency and complexity, and require huge datasets. Many works are done with a limited number of sensors, which can lead to false alarm rates due to environmental noise or isolated events. The above-discussed gaps drive the need for a real-time, lightweight, multi-sensor embedded system capable of accident detection and severity classification, and motivate the proposed system.

This paper features an automated system for detecting vehicle accidents that promptly alerts the emergency center with the location information and with the severity level of the accident. The proposed system works by integrating five distinct sensors on the STM32 platform and categorizing accidents into three severity levels for more effective emergency response [23]. The significant contributions of this paper are as follows:

1) An algorithm is proposed for the automatic detection of the severity level of the accident based on the activation of the sensors.
2) The proposed system automatically sends the location information along with the severity level of the accident to the emergency center.
3) The proposed system can be deployed in any kind of vehicle, and it would be a cheap aftermarket solution available, allowing owners of older vehicles to retrofit certain capabilities.

This paper is henceforth organized as follows. Section 2 discusses the proposed system, and Section 3 discusses the results and discussion. Finally, the paper is concluded in Section 4.

2. METHODOLOGY

The prime motive of our work is to automatically detect the occurrence of an accident and to notify the nearby healthcare emergency center instantly. The STM32 microcontroller is the backbone of the proposed system, and five sensors, such as a gyroscope, an IR flame, a glass break, a smoke sensor, and a vibration sensor, are incorporated in this work. Based on the activation of a sensor or group of sensors, the severity of the accident is classified as low, mid, or high. GSM and GPS modules are used here to send an accident alert to the emergency center, including the severity level and the precise location of the accident. The hardware components utilized for the proposed system are given in Table 1.

Table 1

Hardware components of the proposed system.

S. No	Component Name	Model
1.	Microcontroller	STM 32
2.	Transformer	(230 - 12V) Step Down
3.	Rectifier	Bridge rectifier
4.	LCD	16×2 display
5.	Gyroscope sensor	ADXL335
6.	IR Flame/Fire sensor	-
7.	Glass break sensor	KY- 037
8.	Smoke sensor	Mq-2
9.	Vibration sensor	SW-420
10.	GSM Module	SIM900C
11.	GPS Module	NEO-6M

An algorithm is proposed for the automatic detection of the severity level of the accident based on the activation of each sensor or group of sensors. The emergency center is informed of the location and severity level of the accident. The vibration sensor is activated when the vehicle encounters a collision since the collision would create vibration. The smoke and fire sensors are activated when the vehicle encounters any smoke emissions or fire.

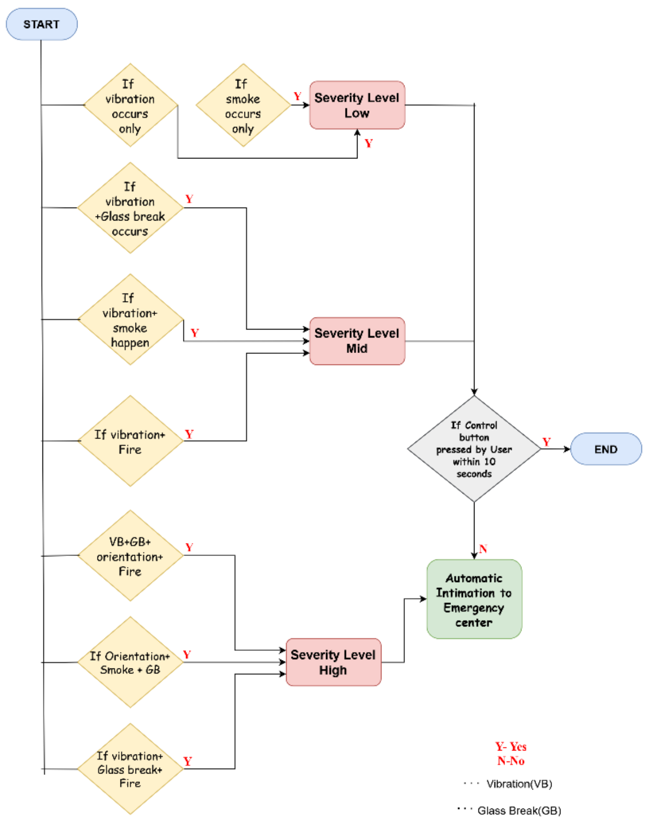


Fig. 1 – Flow diagram of the proposed algorithm for severity level detection.

The glass break sensor is activated while detecting glass breaks using the frequency of sounds when the vehicle's glass is broken after an accident. The gyroscope sensor is activated when the vehicle orientation is changed after a collision (*i.e.*, the vehicle could have rolled or fallen upside down after a collision). The flow diagram of the proposed algorithm is shown in Fig. 1. The decision-making logic follows a structured combination of logical conditions. Individual sensor activations are first evaluated independently, and subsequent decisions are made using clearly defined logical operators. Specifically, low severity corresponds to single-sensor activation (logical OR condition), while mid and high severity levels are determined using combinations of multiple sensors (logical AND conditions). Each decision node in the flowchart has a "No" branch to the END node, indicating that no accident has occurred.

The activation of either a vibration sensor or a smoke sensor is classified as severity level low since the vehicle could have encountered a minor collision or a minor smoke emission due to the high temperature. The activation of the vibration sensor followed by the glass break sensor, the vibration sensor followed by the smoke sensor, and the vibration sensor followed by the fire sensor are classified as severity level mid. These cases are chosen in particular order because, after the vehicle collision, the vehicle's glass may break, smoke emissions may happen, or even fire may happen. For severity low and mid, there is a control button near the driver, which, if pressed within ten seconds, the proposed system doesn't send any intimation to the ambulance service. If not pressed, the location information will be shared with the ambulance service, along with the severity of the accident information, based on the activation of the sensors. The activation of vibration sensor followed by glass break and gyroscope sensors, gyroscope sensor followed by smoke and glass break sensors, vibration sensor followed by glass break and fire sensors are classified as severity level high. Severity high is denoted as a severe accident, and in this case, the proposed system automatically sends the location information to the ambulance service along with the severity information as 'major accident'. These cases are chosen in a particular order because, after a vehicle collision, the glasses may break, the vehicle's orientation may change, and the vehicle may even catch fire.

3. RESULTS AND DISCUSSION

The hardware setup of the proposed system is shown in Fig. 2.

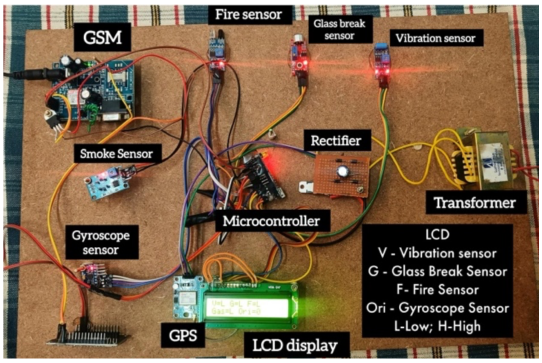
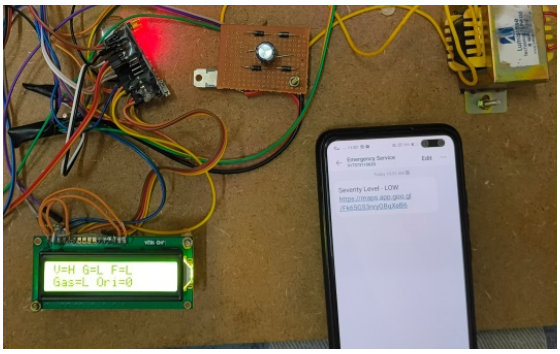
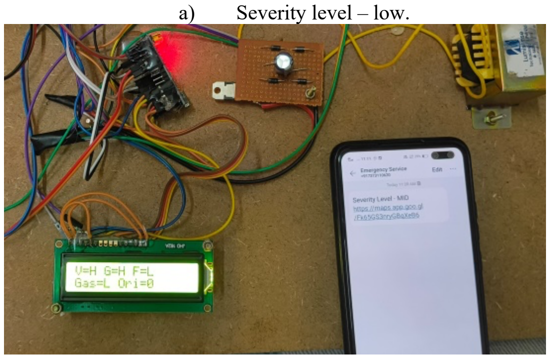


Fig. 2 - The hardware setup of the proposed system

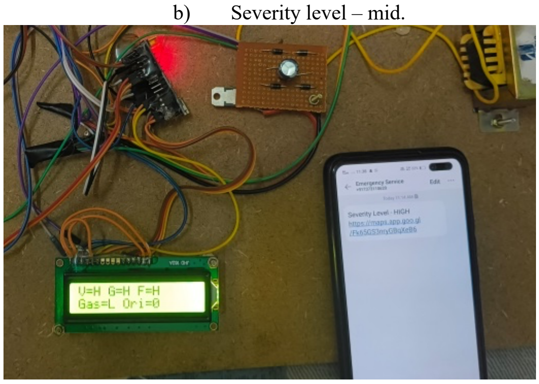
To test sensor activation, an LCD module is interfaced with the developed model. If any sensor is activated, the status is displayed "H" (high) for the corresponding sensor in the LCD module.



a) Severity level – low.



b) Severity level – mid.



c) Severity level – high.

Fig. 3 – Sample output snaps for each severity level.

The sensor calibration and threshold selection details are given in Table 2. The sample output for the three severity cases is given below in Fig. 3. If any sensor is non-activated, the status is displayed 'L' (low) in the LCD module. The LCD module is configured with the following letters for denoting each sensor: V – Vibration sensor, G – Glass break sensor, F – Fire sensor, Ori – Gyroscope Sensor, and Gas – Smoke sensor. The GSM module is loaded with a default SIM card and is used for sending information to the emergency center.

In Fig. 3(a), the vibration sensor is only activated, and as per the proposed algorithm, the system considers this scenario as a low-level accident. In Fig. 3(b), both vibration and glass break sensors are activated, and the system considers this scenario as a medium-level accident. The switch button in the microcontroller board is used as the control button; if pressed within ten seconds, the proposed system doesn't send any intimation to the emergency center. In Fig. 3(c), both vibration and glass break and fire sensors are activated, and the system considers this scenario as a high-level severe accident, and it automatically sends the intimation to the emergency center as a high-severity-level accident along with the location of the incident.

Table 2

Sensor calibration and threshold selection parameters.

S.No	Sensor (Name & Model)	Calibration Method	Threshold / Condition Defined
1	Vibration Sensor (SW-420)	Adjusted using onboard potentiometer under controlled vibration conditions	Triggered for high-frequency shock signals above normal vehicular vibration levels
2	Smoke Sensor (MQ-2)	Calibrated using controlled smoke exposure	Threshold set at approximately 300–400 ppm to detect hazardous smoke levels
3	Flame Sensor (IR Flame)	Tested under controlled flame exposure and varying light conditions	Triggered based on IR intensity corresponding to flame presence, immune to ambient light
4	Glass Break Sensor (KY-037)	Tuned using acoustic signal testing for glass shattering sounds	Detects high-frequency sound signals (> 3 kHz) typical of glass break events
5	Gyroscope Sensor (ADXL335)	Calibrated for angular displacement and orientation changes	Triggered for tilt beyond ±45° or sudden angular changes indicating rollover or severe impact
6	Data Synchronization	Time-based sampling and fusion approach	Sensors sampled every 100 ms; events grouped within ≤ 2 seconds considered a single incident

The experimental validation involved 15 distinct test scenarios designed to simulate different accident conditions, including minor collisions, moderate impacts, and severe crash events. These scenarios were created using controlled mechanical impacts, simulated smoke generation, controlled flame exposure, and induced vibration patterns to replicate real-world accident conditions. Each scenario was repeated multiple times to ensure consistency in observations. While these controlled experiments provide initial validation, large-scale testing in real traffic environments is part of future work.

To further evaluate system performance, statistical analysis was conducted on the experimental results. The proposed system achieved an average detection accuracy of 92% with a standard deviation of ±2.1%, indicating consistent performance across different scenarios. The false-positive rate remained at 3%, demonstrating robustness to environmental disturbances. The response time showed low variability, with a mean of 30 seconds and a variance of 4.5 seconds^2. These results confirm the reliability and stability of the multi-sensor fusion approach.

It is essential to ensure the proper placement of these sensors in the vehicle and to make sure that these sensors are properly calibrated to minimize false alarms and maximize their effectiveness in detecting accidents. The gyroscope sensor could be placed in a central location within the vehicle, ideally mounted near the vehicle's center of gravity. The flame and smoke sensors could be mounted near potential ignition sources such as the engine compartment, near fuel lines, or electrical systems. Placing the glass-break sensor near the vehicle's windows or the windshield is essential. The vibration sensor could be placed in key structural points of the vehicle, such as the front and rear bumpers, doors, and frame, to provide comprehensive accident detection coverage.

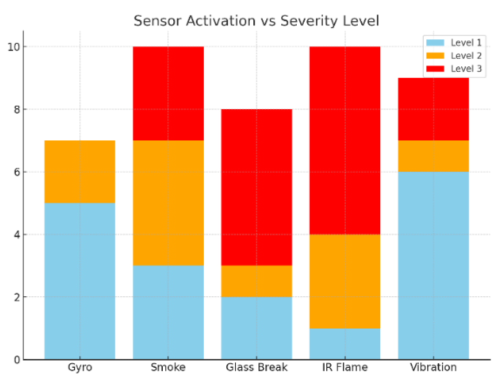


Fig. 4 – Sensor activation vs severity level.

Figure 4 illustrates the frequency of individual sensor activations mapped to the three predefined severity levels. Notably, the vibration and gyroscope sensors are frequently triggered in low-severity incidents (Level 1), indicating their sensitivity to minor collisions or impact. Conversely, the IR flame and glass break sensors are more often associated with higher severity levels (Level 3), signifying serious events such as fire or window shattering. The data support the idea that different sensors carry varied significance in classifying accident severity and emphasize the necessity of a multi-sensor strategy for reliable incident classification.

Figure 5 compares the time required to alert emergency services between the traditional manual method and the proposed automated system. The proposed system achieves an average response time of approximately 30 seconds, comparable to that of existing accident detection systems. Rather than focusing solely on response speed, the key advantage of the proposed approach lies in its ability to combine multi-sensor fusion with severity-based classification, enabling more efficient prioritization of emergency response and improved decision-making.

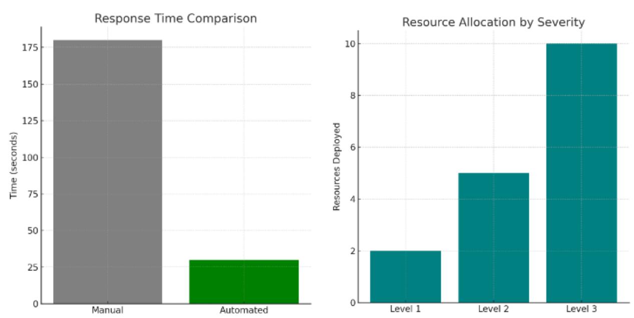


Fig. 5 – Response time comparison and resource allocation by severity.

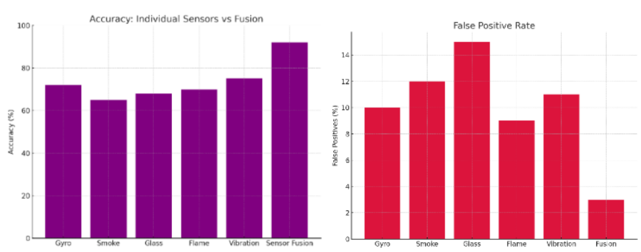


Fig. 6 – Accuracy of detection: individual sensors vs sensor fusion and false positive rate.

Figure 5 also shows that more resources are allocated to incidents classified under higher severity levels. Level 1 accidents are generally managed with minimal intervention, while Level 3 incidents, involving fire or major structural damage, require a comprehensive response including fire services, ambulances, and police support. This pattern demonstrates how the proposed system enables smart allocation of emergency resources based on real-time classification, potentially reducing operational strain and improving response outcomes.

As shown in Fig. 6, the detection accuracy of individual sensors is shown to range between 65% and 75%, depending on the type of sensor. However, when data from all sensors is fused and processed collectively, the accuracy rises sharply to 92%. This enhancement can be attributed to the complementary nature of the sensors, where weaknesses in one sensor are compensated for by the strengths of others. Sensor fusion thus offers a more holistic understanding of the event, minimizing the chances of both false negatives and false positives.

Figure 6 also compares the false positive rates of individual sensors and the fused sensor system. Individual sensors show a higher rate of false alarms, ranging from 9% to 15%, mainly due to their sensitivity to environmental factors and isolated events. In contrast, the fused system exhibits a significantly reduced false positive rate of only 3%. This result further validates the robustness of the multi-sensor approach, which minimizes erroneous alerts by evaluating multiple sensor inputs before triggering an emergency response.

Table 3 provides a comparative overview of the proposed system alongside several recent accident detection frameworks. Most prior works rely on a combination of accelerometers, GPS, and vibration sensors, achieving high accuracy but lacking accident severity classification. Systems that use physiological data or camera feeds demonstrate good responsiveness but are either complex to deploy or computationally expensive. Recent deep learning approaches offer excellent detection accuracy (~96%) yet depend heavily on cloud infrastructure and omit risk-level differentiation. In contrast, the proposed system integrates five complementary sensors with the STM32F407VG board and GSM/GPS modules, achieving 92% accuracy, a 30s response time, and a low false positive rate of 3%.

Table 3

Comparative analysis of the proposed accident detection system with existing state-of-the-art approaches.

Work	Sensors / Modalities	Platform	Response Time	Accuracy / F1-score	False Positive Rate	Severity Classification
[8]	Dash-cam video + audio (fog computing)	IoT/fog	~15 s	98 %	–	No
[9]	Accelerometer + vibration + GPS	Raspberry Pi + GSM	~40 s	91 %	4 %	No
[10]	Accelerometer + GPS + HR + SpO_2	Helmet MCU + Wi-Fi	~25 s	93 %	2–5 %	No
[11]	Force sensor + camera + ESP8266 + GSM + GPS	Raspberry Pi + Cloud	30–45 s	–	–	Deep-learning severity detection
[12]	Accelerometer + GSM + GPS	ESP32 / Raspberry Pi	~35 s	–	–	No
[13]	GPS + GSM	Arduino-based	~40 s	–	–	No
[14]	Accelerometer + alcohol sensor + GPS + GSM	AVR/MCU	~30 s	–	–	No
[15]	Crash sensor + GPS + GSM	NodeMCU / SIM900A	~30 s	–	–	No
[16]	GNSS (GPS) + IoT sensors	Edge Cloud	~20 s	–	–	No
[17]	IoT Sensors + CCTV video + Deep Learning	STM32 + Cloud + LSTM + ResNet	~20 s (real-time)	96.7% accuracy using ResNet-101 and LSTM	No	No
[18]	Video frames from dash-cams	Deep CNN + Feature reuse	~18 s (video-based anticipation)	91.5% F1-score	No	No
[19]	Traffic camera images	GAN + CNN + Feature fusion model	Near real-time	94.2% detection rate	No	No
Proposed System, 2025	Gyro, IR flame, glass-break, smoke, vibration	STM32F407VG + GSM/GPS	30 sec	92%	3%	Yes (3 levels)

The experimental validation presented in this work is based on controlled laboratory scenarios designed to ensure repeatability and safety. While this approach enables systematic evaluation, it may not fully capture the complexity of real-world traffic environments. Factors such as unpredictable driver behavior, varying road conditions, and environmental disturbances could influence system performance. While sensor fusion helps reduce false positives, occasional erroneous triggers due to non-critical vibrations or external disturbances cannot be eliminated. The system also depends on GSM communication, and network availability may influence alert transmission time, particularly in remote areas. Additionally, issues related to data security during transmission and system performance in multiple simultaneous accident scenarios require further attention. The absence of large-scale real-world validation limits the generalizability of the results. Future work will focus on real-time deployment, enhanced reliability, and integration with large-scale real-time testing in live traffic conditions.

4. CONCLUSION

The proposed system demonstrates a practical and efficient solution for real-time accident detection and severity classification using a multi-sensor embedded framework. By integrating sensor fusion with severity-based decision-making, the system enables faster and more effective emergency response. While the response time is comparable to existing systems, the integration of severity classification and reduced false positive rate provides a practical advantage in real-world emergency management scenarios.

CREDIT AUTHORSHIP CONTRIBUTION STATEMENT

EMERSON NITHIYARAJ ELWOOD: Conceived the study, designed the system architecture, and supervised the overall research process. Developed the accident detection algorithm, analyzed the results, and contributed significantly to writing and refining the manuscript.

SHENBAGARAJAN ANANTHARAJAN: Assisted in hardware integration, sensor interfacing, and experimental validation. Contributed to data analysis, result interpretation, and manuscript proofreading to ensure technical accuracy and coherence.

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