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AN EDGE-ENABLED CYBER-PHYSICAL SMART HELMET FRAMEWORK FOR REAL-TIME MOTORCYCLE ACCIDENT DETECTION AND AUTOMATED EMERGENCY RESPONSE

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A B S T R A C T

Motorcycle accidents constitute a grave public health issue in Ghana, where motorcycles constitute 37% of all accidents on the roads, with response times of 30–60 minutes leading to needless deaths. This work develops an Edge-Enabled Cyber-Physical Smart Helmet System that enables automatic accident detection and response in real time. The developed system incorporates a multi-layer framework comprising sensing, edge computing, and communication and action layers embedded within a motorcycle helmet. All computations are done locally in the absence of cloud connectivity. Empirical estimation of the detection threshold based on rigorous testing carried out on Ghana's roads showed 100% accuracy with a detection threshold of 49 ms⁻² ≈ 5g. Once an accident is detected, GPS coordinates are captured in tandem with a 20-second cancelation period, after which a GSM communication chip automatically calls emergency contacts providing recorded GPS coordinates. The time interval between when the collision occurred to when the link is established to the ambulance services was recorded at around 32 seconds, equating to a decrease of between 28 minutes to 59 minutes compared to that of the baseline system manually. Tests of the system integrated showed 100% efficiency costing GH₵ 459.15.

1. INTRODUCTION

The occurrence of road traffic crashes poses a great challenge to the current public health agenda. In 2016, there was an estimated death toll of about 1.35 million people due to road traffic crashes around the globe, and most of these occurred in underdeveloped nations (Byrne et al., 2019; World Health Organization, 2023). In Africa, the rate of mortality due to road crashes stood at 26.6 deaths per 100,000 in 2016, way above the global figure of 18.2 deaths per 100,000, and the situation continues deteriorating (Damsere-Derry et al., 2017; World Health Organization, 2023).

Ghana is one such example where the problem exists on the national scale. Road accidents are the second-highest cause of mortality in Ghana, second only to malaria, with the loss of about 1,900 lives per year (Enu, 2014). When it comes to all types of road traffic accidents in Ghana, the motorcycle category always ranks top when it comes to the severity of injury as well as mortality figures. Motorcycle accidents account for 37% of all road traffic accidents in Ghana, with the figure being higher at 3.73%

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of total deaths that occurred in the year 2018 (Luther et al., 2025). It is worth noting that the demographic makeup of motorcycle accident victims makes the situation worse, as most victims fall under the age group of 15-35 years, the most productive population section of the country. An important aspect related to the extremely high case fatality rate linked with crashes in Ghana is the delayed emergency medical response in the region (Oduro, 2022). According to research by Mahama et al. (2018) and Ghazalli et al. (2019), ambulance and EMS response times in Ghana significantly exceed international standards. The primary reason behind this delay lies in the use of manual notification of incidents, which means that injured drivers have to contact ambulance services themselves or depend on others to do so in their stead. In many cases, victims may be unconscious and unable to contact anyone, while at the same time not having any other witnesses nearby. Additionally, patients may be conveyed to medical institutions by private transport instead of ambulances, which is not good for their chances of surviving (Mahama et al., 2018). In order to overcome the challenge posed by this gap, it becomes essential for researchers and practitioners alike to move away from manually initiated notification methods towards an approach based on automated emergency response mechanisms that can function independently of any intervention by the affected rider. With the advancements being made in embedded systems, edge computing, and cyber-physical systems (CPS), it is now possible to integrate such functions into the wearable safety equipment used by riders at minimal cost. Specifically, the emergence of edge computing technology has made it possible to process the necessary information locally.

In this work, the design, development, and evaluation of an Edge-Enhanced Cyber-Physical Smart Helmet Framework for Motorcycle Accident Detection and Autonomous Emergency Notification will be discussed. The proposed solution includes the implementation of an accelerometer-based accident detection mechanism, GPS-based localization of accidents, as well as GSM-based emergency calling without any human intervention. In general, the framework is designed based on three levels, namely the physical level that detects the motorcycle accident, an edge computing level that processes the data from the sensors to detect any accident occurrence, and the communication level, which sends the alarm signals automatically. This framework can operate independently, as all its operations will be carried out locally by an embedded microcontroller. In summary the project seek to achieve the follow:

- Design an effective crash detection subsystem that is capable of detecting high-impact motorcycle crashes in less than five seconds with an accuracy of at least 75% by applying threshold-based acceleration sensing at the edge.
- Use GPS technology to detect the rider's location for the purpose of sending the coordinates to the emergency service personnel during emergencies.
- Create an alerting mechanism to alert the rider in case of any detected crash, and then provide the rider with a period during which he can manually cancel the call to the emergency services.
- Implement autonomous calling using GSM technology, such that the emergency services are alerted automatically without the rider having to do anything after crash detection.
- Evaluate the overall response time of the system from the moment of crash detection to emergency call making.

2. LITERATURE REVIEW

Research on the use of crash detection technologies and automatic emergency notifications in motorcycles has been receiving attention for at least two decades now (Evanco, 1999). In this section, the existing literature is summarized in terms of three related domains relevant to the proposed framework, namely: (1) crash detection techniques; (2) automatic emergency notification systems; and (3) Edge Computing and Cyber-Physical Systems Architecture in the context of wearable Internet-of-Things devices.

2.1 Crash Detection Systems

The conventional process in which an emergency response will be triggered due to a road traffic collision solely depends on the use of human actions, whereby the injured, if conscious, or a third party makes a telephone call alerting the relevant emergency service. The approach has several weaknesses as far as motorcycle accidents are concerned, in that, in many cases, riders lose consciousness upon collision, and there is no third party present who would report the accident, especially in rural or peri-urban settings (Mahama et al., 2018). To overcome such challenges, automatic crash notification (ACN) systems came into existence. ACN systems refer to gadgets that can automatically detect collisions in motor vehicles and send messages to selected emergency contacts, the Emergency Medical Service provider, or other persons around (Lahausse et al., 2008). There is evidence that ACN systems reduce the duration between crash events and the time taken for sending the message to the EMS from one minute to seven minutes.

2.1.1 Accelerometer-Based Detection

The method of detecting motorcycle crashes most often used entails the use of accelerometers to detect and measure the force exerted by the rider or vehicle. The system alerts to the occurrence of a crash event when there is an abrupt change in acceleration above a set threshold that is indicative of a high-impact accident scenario. This method of detection is preferred due to its efficiency, economic value, and applicability in various crash situations (Kobayashi & Makabe, 2013; Siam et al., 2024).

Rajeswari et al. (2023) successfully demonstrated a telematic system mounted on motorcycles to perform crash detection, enhanced with a red light indicator for locating crash victims in low visibility conditions. One significant drawback observed in this research is that the crash detection unit was mounted on the motorcycle body and not the rider. As such, during a high-impact crash event, the rider can be thrown off the motorcycle, leaving the detection unit and the rider in two different locations. The placement of the detection device inside the helmet itself overcomes the above limitation. The helmet will be fixed with the head of the rider during the accident, and at the same time also acts as a protector for the electronics placed inside it. There are several cases of helmet-based accelerometer systems that have been used, with most of them having the threshold method of detection (Dhere et al., 2025; Siam et al., 2024). Although it is relatively easy to build, such methods may sometimes produce false results due to the rider's sudden stopping, bumpy roads, or violent head movements.

2.1.2. Detection Using Machine Learning Algorithms

To improve detection robustness, many scholars have studied the use of machine learning (ML) algorithms to detect crash and non-crash events from accelerometer outputs. For example, Jo et al. (2021) used LSTM networks for detecting bike accident events so as to activate the inflatable wearable airbags. This was done to show how sequence-aware models can provide improved performance in capturing the temporal characteristics of the crash events. Selmanaj et al. (2014) designed a data-driven hazard detection and classification system for motorcycles based on acceleration measurement to demonstrate that such systems would be capable of detecting and classifying hazardous events in an accurate way and would be able to learn the behavior of riders over time. However, the main drawback associated with ML-powered models involves high computing expenses. Processing requests in machine learning models results in latency that could be too lengthy to consider in emergencies, and the need for considerable memory and computational resources makes deploying such models to resource-restricted devices difficult (Deng, 2021). In addition, no datasets with Ghana-specific road accident features can be found in existing literature.

2.1.3 Smart Phone-Based Detection

The third type of crash detection system utilizes the accelerometers present in commercially available phones, usually in conjunction with a specialized mobile app (Ghazalli et al., 2019; Deng, 2021). The cost factor involved in using the phone-based approach is considerable because there is no need to invest in any special equipment other than the phone itself. Nevertheless, phone-based detection presents significant issues of accuracy due to the fact that different placements of the phone result in vastly different readings of the acceleration sensor. The variety of models produced by various brands is yet another complication, especially when it comes to the compatibility of sensors' APIs. From a safety perspective, such a lack of accuracy makes the phone-based solution undesirable.

2.2 Emergency Notification Systems GSM-Based Notification

The main communication system used in ACN technology is the GSM network, which supports voice calls and SMS messages sent to emergency contacts or emergency medical service providers. The use of GSM communication technology is preferred because mobile networks have broad geographic coverage, even in regions where no special emergency communication infrastructure exists (Sowah et al., 2024). In the Ghanaian context, where most accidents occur outside urban centers and no central ACN system is established, GSM is the only practical means of communication.

2.2.1 Centralised and Infrastructure-Dependent Systems

As opposed to the systems based on stand-alone units such as GSM phones, centralization involves sending alerts to a centralized server via the internet, SMS, or satellite transmission. In this regard, eCall technology, which is deployed in the European Union countries, is a concrete example of centralizing the process of sending alerts through an automated platform. This system involves coordination between automotive manufacturing companies, telecommunication companies, and governments' emergency agencies to make it work properly, but unfortunately, such an effort is not possible in Ghana and many other countries in Sub-Saharan Africa. Melcher et al. (2015) suggested an eCall emergency assistance-based smart vital signs and accident monitoring system for motorcycle riders integrated into the helmets and garments, but eCall technology is not available everywhere, especially in Africa.

An internet-based system poses more reliability challenges in Ghana since there are areas in Ghana where mobile data connectivity is not reliable along roads. In such an environment, a completely autonomous system that operates using GSM voice call technology will be the most suitable option.

2.3 Edge Computing and Cyber-Physical Systems in Wearable Safety Applications

The principle of edge computing, where processing decisions are made at the edge, or point of origin of the data generation, rather than offloading to centralized cloud resources, is becoming the cornerstone concept for low-latency IoT systems (Shi et al., 2016). The use of such edge processing becomes an absolute necessity for designing the motorcycle crash detection system since its reliance on cloud systems would entail both latency and possible single points of failure.

A Cyber-Physical System (CPS) describes those systems in which computation and physical processes interact and operate with each other through continuous interaction and actuation through sensors (Lee, 2008). This means that a motorcycle crash detection system could be regarded as a typical CPS system, because there is a direct connection between computation processes, physical processes, actuations, and sensors' interactions in it. The physical subsystems in this system are the rider, the helmet, and the surrounding environment. The sensors in the system monitor the activity of those objects, and their output data triggers computational processes and actuations.

A recent study has investigated the use of CPS and edge computing technologies in the context of wearables in the realm of health and safety monitoring systems. Specifically, Siam et al. (2024) designed an accident detection system using physiological signals to ensure the safety of motorcyclists, utilizing sensors of multiple types processed on-device. In another development, Varudkar (2024) developed an accident detection mechanism using a low-cost electronic design to illustrate that a capable CPS can be realized even with strict budgetary limitations.

Even with this significant body of research work, there is one important gap identified in the literature when it comes to systems that have been created and validated on the infrastructure and roads of sub-Saharan Africa. Systems currently being used and evaluated have made some presumptions regarding connectivity and road infrastructure that simply will not apply to the situation in Ghana.

2.4 Research Inferences

Several significant inferences emerge from the analysis of relevant research that inform the design of the proposed system framework:

Regarding crash detection: The use of accelerometer-based threshold detection continues to be the best approach for this application due to its low computational burden, speed, and compatibility with embedded resource-restricted hardware. ML-based approaches have better performance in dealing with exceptional cases but suffer from latency issues and need training data specific to their operational environment, which cannot currently be supplied. The threshold level needs to be determined experimentally, considering the local road environment in Ghana.

Regarding emergency notification: The use of GSM voice calls is the sole communication method that has sufficient geographical coverage and is independent of infrastructure requirements in the case of Ghana's road network.

System architecture considerations: The helmet should be preferred to the motorcycle body since it guarantees that the detecting system will always stay collocated with the rider, despite any ejections. Everything must happen at the edge, meaning that all computing and auctioning needs to be done at the embedded device level, without any need for cloud services whatsoever. It will not only make everything faster but also more robust in terms of connectivity issues.

Research gaps: To the best of my knowledge, there exists no framework dedicated to automatically helping motorcycles in emergencies within the sub-Saharan African infrastructure landscape. The solution proposed in the article would contribute by developing an effective edge-based CPS design applicable in Ghana and other countries sharing a similar environment

3. METHODOLOGY

This chapter elaborates on the design and development of the proposed Edge-Enabled Cyber Physical Smart Helmet System. This chapter follows a hierarchical order corresponding to the layers of the framework being developed. The first section explains the system architecture and is followed by the description of each layer of functionality: Physical Layer, Edge Processing Layer, and Communication and Actuation Layer, as well as the design of the power system.

3.1 Framework Architecture Overview

The proposed cyber-physical system architecture is based on three layers, where there is an integrated approach to physical sensing, edge computing, and actuation processes implemented by one helmet-integrated device. Figure 1 below shows the architecture diagram that illustrates the connections between the three layers and the flow of data among them.

Layer 1 – Physical Sensing Layer: This layer incorporates all the sensors that are used to continuously gather information about the state of the rider and the environment. In this case, the main sensor is the six-axis accelerometer and gyroscope (MPU-6050), which is used to measure the forces of inertia acting upon the helmet. The GPS module collects geographic coordinates after a crash detection event.

Layer 2 – Edge Processing Layer: This layer utilizes the embedded microcontroller exclusively (NodeMCU ESP8266). Data acquisition, signal processing, threshold checking, state handling, and decision-making processes are executed locally on the device, without any reliance on external computing resources whatsoever. The edge processing layer makes decisions on whether a crash event has taken place, controls countdown and cancel processes, coordinates the timing of GPS poll requests, and communicates with other peripheral modules. This ensures determinism in terms of responses and total operation independence from the Internet connection by relying only on on-device computations.

Layer 3 – Communication and Actuation Layer: In case of a crash, the actions that will take place in case of an emergency will be done in this layer. The functions carried out in this layer include GSM phone calls to programmed emergency contacts, voice communication of the recorded message through the SD module, voice announcements of alerts to the rider through the speaker system, and GPS coordinates and speech report to emergency contacts. The system works on the concept of a continuous feedback loop wherein the physical sensing layer supplies the inertial information to the edge processing layer at regular intervals of time; the edge processing layer processes this information against predetermined thresholds; and if there is any exceeding of the thresholds, then the communication and actuation layer performs the actions required in an emergency.

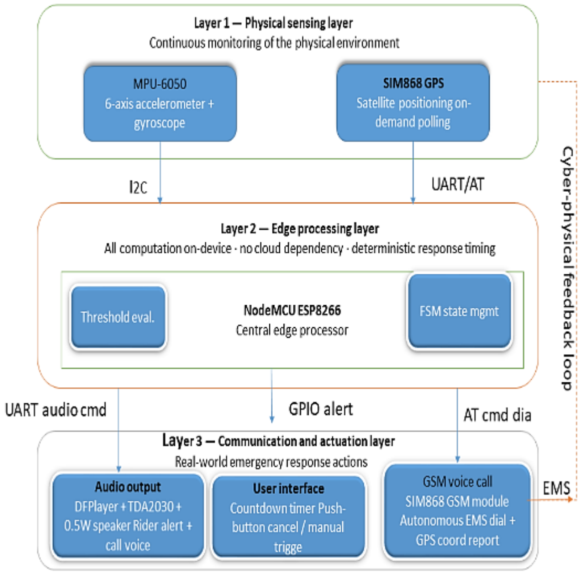


Figure 1. Three-Layer Cyber-Physical Framework Architecture and Block Diagram

The block diagram representing system-level components and their interactions in this three-layer design is given in Figure 1.

3.2 System Operation and State Machine

The working mechanism of the design can be well represented using the finite state machine (FSM), which comprises four unique states, as depicted in Figure 2.

State 1 – Idle Monitoring: This state occurs when the system is fully functional, and the microcontroller polls the MPU-6050 accelerometer at regular intervals of time. The GPS and GSM modules are put to sleep mode to save energy in battery-operated mode. The system stays in this mode under normal conditions when a motorcyclist is driving.

State 2 – Crash Event: This state is triggered when the resultant value of the accelerometer is greater than the calibrated threshold of $49 ms^{-2}$. On triggering this state, the system immediately switches ON the speaker, giving an alert sound to the rider, the GPS module, and a 20-second timer counter is started. It is to be noted that the GPS unit starts its process of triangulation from satellites as soon as the system enters crash mode, even before the 20-second counter completes.

State 3 – Cancellation: In case the rider is awake and the event was just not an actual crash, the push button can be pressed during the countdown process, and thus the system enters the Cancellation state. The countdown will stop, the GPS module will be turned off, and the system will return to state 1. An audio message confirming the cancellation of the EMS contact will be played.

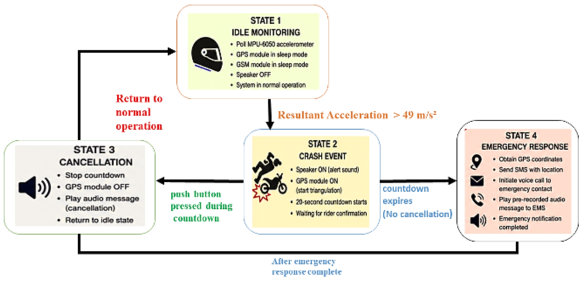


Figure 2. System Finite State Machine Diagram

State 4 – Emergency Response: In case the countdown ends without a cancelling message from the rider, the system switches to Emergency Response state. First, the GPS module will be asked about coordinates, and the GSM module will receive an AT command to call the programmed number by using an SMS message. Once the call has been established, the SD card module will play a prepared audio message to inform EMS providers about the crash and provide its coordinates.

3.3 Electronic Components and Circuits

The chosen electronic components for our design are stated in Table 1 below. The choice of the electronic components followed three factors: suitability to the task, availability locally in the Ghanaian market, and economic costs.

Table 1. System Component List

Component	Specification	Notes
Microcontroller	NodeMCU ESP8266	Central edge processing unit
Accelerometer/Gyroscope	MPU-6050	6-axis IMU; I²C
GSM/GPS Module	SIMCom SIM868	Integrated GSM/GPS module
SD Card Audio Module	DFPlayer MP3-TF-16P	MP3 playback with built-in amplifier
Audio Amplifier	TDA2030	Additional gain for the helmet speaker
Speaker	0.5 W, 8 Ω	Helmet-integrated audio output

The NodeMCU ESP8266 board acts as the central processing unit of the edge node. The sensing interface for the MPU-6050 accelerometer uses the I²C communication protocol, in which the SCL and SDA signals are connected to pins D1 and D2, respectively. The MPU-6050 is supplied at 3.3 volts through the microcontroller's on-board power regulator since its maximum allowed input

voltage is 3.46 volts (TDK InvenSense, 2024). The MPU-6050 sensor operates in the continuous mode, with measurements being periodically taken at a predetermined sampling interval by the microcontroller.
The resultant acceleration magnitude is computed from the three-axis readings as:

$$a_{\{resultant\}} = \sqrt{\{a_x^2 + a_y^2 + a_z^2\}} \quad (1)$$

This value is then tested against the calibration-based threshold level for the crash. Using resultant magnitude, instead of any particular axis, is important because it makes crash detection orientation-insensitive, which is essential considering the variable orientations of the helmet with respect to the direction of impact in practical collisions.
Push-button input is provided on the RX pin of the microcontroller, and it acts in two ways: either it cancels an ongoing EMS countdown timer or initiates the emergency response procedure.
SIM868 development module incorporates both GSM and GPS capabilities in one module. The module is interfaced with the microcontroller using a UART connected to D5 and D6 pins. All functionalities of the GSM and GPS modules can be accessed by sending AT commands through the serial communication interface.
The DFPlayer MP3-TF-16P audio module is also connected to the microcontroller using another UART communication interface connected to D7 and D8 pins, where D8 is connected with a 1kΩ series resistor.

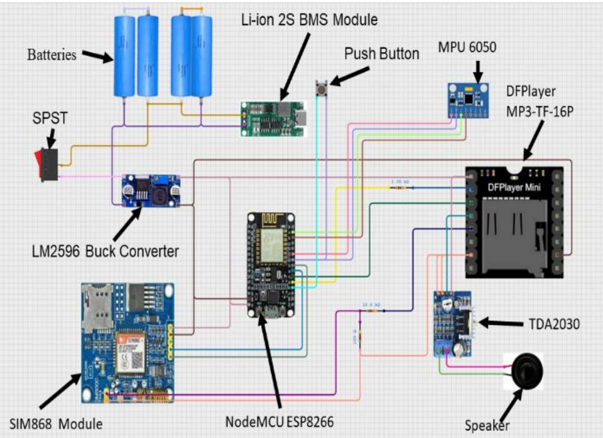


Figure 3. Circuit Schematic Diagram

The module has two outputs, of which one connects directly to the TDA2030 audio amplifier, outputting to the helmet speaker while the other is connected to the receive pin of the SIM868 module using a voltage divider consisting of 10kΩ and 100Ω resistors to limit the voltage from the module to between 0.1 and 1V, suitable for input to the GSM module for transmitting audio signals. The configuration allows the device to transmit pre-recorded voice messages during emergencies, independent of rider consciousness and ability to talk.

When making emergency calls, audio filtering is turned on, and gain is added to the microphone inputs of the SIM868 module through AT commands.
The full circuit schematic showing all component interconnections is presented in Figure 3.

3.3.1 Calibration of Crash Detection Threshold

An important feature of the edge processing layer is the acceleration threshold that separates the actual crashes from other movements on the bike. Instead of setting the crash threshold at a level suggested in the literature, based on studies performed under varying circumstances, the crash threshold was calibrated using an empirical set of physical experiments performed locally using the helmet and the accelerometer mounted therein.
At the beginning, the threshold was set at 29.415 ms^{-2} (equivalent to 3g), which coincided with the thresholds set in other works reported previously. The test results obtained during the empirical crash simulations are presented in detail in Section 4 below and show that this threshold was not suitable for the Ghanaian environment since normal riding activities such as braking and head movements caused acceleration beyond 3g, thereby leading to an unacceptably high rate of false positives. After conducting a calibration process, the crash threshold was adjusted to 49 ms^{-2} (equal to 5g). This process of empirical calibration is a significant contribution by this model; it provides a means of threshold determination based on empirical data.

3.4 Power Subsystem Design

Consistent and reliable power is critical in safety-critical wearable devices. The power subsystem is constructed to facilitate the sustained operation of the system throughout the duration of the usage period corresponding to the use of motorcycles in Ghana.
The power supply is constituted by four lithium-ion batteries of the 18650 variety (2000 mAh and 3.7 V). They have been connected in a 2S2P format, resulting in 7.4 volts' nominal pack voltage with a total capacity of 4000 mAh. The BMS module for 2S lithium-ion batteries regulates charging up to 2 amps via USB-C charging port while providing protection from over-discharging of the batteries. A SPST switch is used for powering the other parts of the circuit, and an LM2596 buck converter reduces 7.4 volts to 5 volts (Table 2).
The maximum current consumption by the entire system (where the GSM module is sending data, the GPS module is getting a signal lock, and the audio module is playing audio) is around 3 A, which implies that the minimum time of operation in the worst-case scenario will be around 1.33 hours. However, while under riding conditions, only the microcontroller and the accelerometer continuously consume power, whereas all other modules are either in idle or low power modes. The nominal current consumption in such cases is around 207.6 mA, implying an operation time greater than 19 hours – plenty of hours to ride a motorcycle on one charging session.

Table 2. Current and Power Ratings of the Main System Components

Component	Power State	Current Rating	Power Rating
Accelerometer	Always active	3.9 mA	0.01 W
Microcontroller	Always active	170.0 mA	0.85W
SIM868 Module	Active	223.0 mA – 2.0 A	1.12 W – 10.00 W
	Idle	13.7 mA	0.07 W
SD Card Reader	Active	50 mA	0.25 W
	Idle	20 mA	0.10 W

3.5 Physical Integration

Integrating the electronics into the helmet body has the dual purpose of protecting the circuitry in case of crashes and maintaining close contact between the detection and communication system and the rider even in situations where there is rider separation due to the crash with the motorcycle.

Since the operation of the GSM and GPS antennas depends on having an unimpeded line of sight, the two antennas were placed externally to the helmet body. The other electronic units were all mounted internally within the helmet body through mechanical mounting.

The audio circuitry, specifically the speaker connection and audio interconnection circuitry among the DFPlayer, TDA2030, and SIM868 microphone input, was specially targeted in this phase due to the detection of this loose connection as a potential failure mode during the first testing of the integrated system.

4. RESULTS AND DISCUSSION

The proposed framework was assessed using an experiment consisting of four stages. These include: accelerometer threshold assessment, GPS accuracy test, system integration test, and cost evaluation. All tests were done by mounting all sensors in the helmet in typical Ghanaian operating conditions.

4.1 Accelerometer Threshold Calibrated Value

4.1.1 Baseline Sensor Calibration

Prior to any impact tests being performed on the headgear, a baseline reading without motion was taken in two different positions: lateral position where x-axis predominated (readings 1-6) and vertical position where z-axis predominated (readings 7-10). The formula for resultant acceleration is:

$$a_{\{resultant\}} = \sqrt{\{a_x^2 + a_y^2 + a_z^2\}} \quad (1)$$

In ten measurements in both orientations, the mean resultant value was 10.20±0.02 ms^{-2}, equivalent to gravitational acceleration (9.81 ms^{-2}), indicating the invariance of the magnitude of the resultant vector to helmet orientation. This feature is particularly important when deployed because the orientation of the helmet when impact occurs is impossible to predict.

4.1.2 Crash Test Data and Selection of Thresholds

For the helmet-mounted MPU-6050 sensor, physical actions were considered that ranged from normal riding conditions to those more characteristic of crashes. For each of these actions, the acceleration amplitude was calculated based on Eqn. (1). The results are shown in Table 3.

TABLE 3 Crash Detection Threshold Calibration Results

Action	Event type	Readings (ms^{-2})	Mean (ms^{-2})	Classification
Stationary-idle baseline	Baseline	10.17 – 10.23	10.20	Non-crash
Swinging	Normal riding	17.64, 17.65	17.65	Non-crash
Shaking	Normal riding	31.59, 29.60	30.60	Non-crash
Sudden stop (on motorcycle)	Normal riding	35.72, 29.91, 29.88, 29.75, 30.45, 29.79	29.7930.92	Non-crash
Tapping (light hit)	Normal riding	30.55, 36.03	33.29	Non-crash
Throw onto ground	Impact event	59.43, 50.69	55.06	Crash
Drop (1 m)	Impact event	73.97, 85.73	79.85	Crash
Smash into wall	Impact event	86.90, 87.03, 81.00, 86.20, 94.59	87.14	Crash

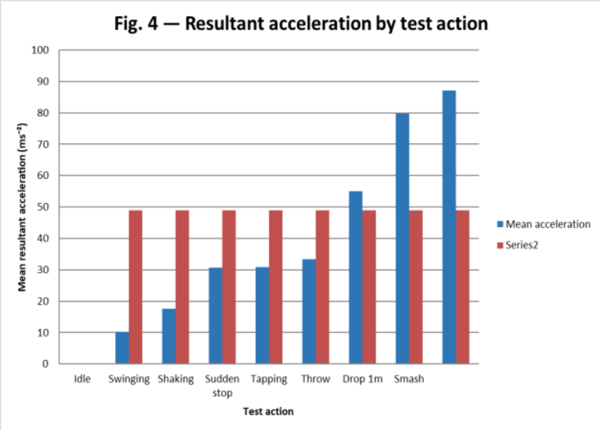


Figure 4. Crash Threshold Bar Chart

From the results obtained, there is a clear distinction between the largest value of the resultant from the maximum normal ride (35.72 ms^{-2}) obtained during a quick motorbike stop and the smallest result from the lowest crash scenario (50.69 ms^{-2}), giving a window size for design of about 14.3 ms^{-2}.

A threshold level of 29.415 ms^{-2} (3g) was first considered and found inadequate due to high false positives for both shaking and sudden-stop scenarios. This value was later raised to 49 ms^{-2} (≈5g), which is 13.28 ms^{-2} higher than the highest normal ride value and 6.06 ms^{-2} lower than the lowest crash value. At this threshold, all normal ride actions fall under while all the crashing values exceed, resulting in no false positives or false negatives (Figure 4).

The above findings show that the threshold levels as derived in other literature studies, which were mostly based on road conditions in Europe and North America, cannot simply be extrapolated to the Ghanaian setting. The value of the sudden stop of 30.92 ms^{-2} is itself above the often quoted threshold level of 3g.

4.1.3 Detection Accuracy

Crash detection accuracy was assessed for all 19 threshold calibration events – nine crash representative impacts and ten normal riding movements – using the selected 49 ms^{-2} threshold value. Detection accuracy is determined as follows:

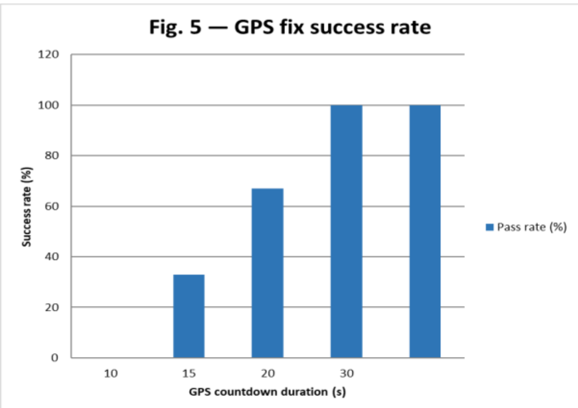
$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \; \boldsymbol{X\ 100\%} \qquad (3)$$

Accuracy was perfect at 100% since the algorithm was able to classify all 19 events correctly using the calibration data. When the threshold value is set to 3 g for the first time, shaking and sudden stops were causing false alarms, leading to an accuracy score of around 70% using the calibration data. Thus, this new threshold value removes all false alarms and exceeds the 75% accuracy goal.

To determine the ability of the SIM868 GPS sub-module to establish a connection with the satellites, tests have been carried out using 4 different configurations of countdown durations: 10 seconds, 15 seconds, 20 seconds, and 30 seconds (Table 4). Before each test, the sub-module was turned completely off.

Table 4. GPS Polling Test Results

Countdown (s)	Trial 1	Trial 2	Trial 3	Trial 4	Remarks
10	Fail	fail	pass	33%	Insufficient time for reliable fix
15	pass	fail	pass	67%	Inconsistent; marginal
20	pass	pass	pass	100%	Consistent; **selected**
30	pass	pass	pass	100%	Consistent but extends EMS response time



Fig**ure 5.** GPS Fix Success Rate

The duration of 20 seconds for the countdown period was chosen since it allows for 100% fix success without delay before contacting the emergency service. Importantly, the GPS receiver is turned on at the beginning of the countdown process rather than after it, allowing for triangulation of the signal simultaneously with the rider's cancellation period, thereby reducing the total response time by about 20 seconds relative to a serial architecture (Figure 5).

GPS testing was performed entirely outdoors. During the integration phase, indoor testing revealed repeated failures in establishing GPS connectivity, which is expected since a passive GPS receiver will only establish line-of-sight connection to the satellites when outdoors. The GPS antenna is passed outside of the helmet through the shell.

4.2 Integrated System Testing

The integrated system was subsequently tested after individual subsystem tests were successful through two stages. In stage one, testing was carried out using the 29.415 ms^{-2} configuration, which revealed important hardware failure points (Table 5). In the second phase of testing, the configuration used was the calibrated 49 ms^{-2} setting.

Table 5. Phase 1 Integrated System Test Results (29.415 ms^{-2} threshold)

Trial	Crash detection	EMS dialing	GPS fix	Audio output	Overall	Remarks
1	pass	pass	fail	pass	fail	Indoor test; GPS obstructed
2	pass	pass	pass	pass	pass	
3	pass	pass	pass	pass	fail	Audio component damaged during trial
4	pass	pass	fail	fail	fail	Hardware damage unresolved from Trial 3

Trial 1 failed because the GPS system could not acquire satellites due to interference caused by being inside a building. The reasons for trials 3 and 4 failing were due to mechanical damage of an audio link between the DFPlayer system and the SIM868 microphone input, which occurred due to a sudden shock load.

Table 6. Phase 2 Integrated System Test Results (49 ms^{-2} threshold)

Test mode	Trial	Trigger/ detection	EMS dialing	GPS fix	Audio output	Overall
Crash detection	1	pass	pass	pass	pass	pass
Crash detection	2	pass	pass	pass	pass	pass
Manual trigger	1	pass	pass	pass	pass	pass
Manual trigger	2	pass	pass	pass	pass	pass
Manual trigger	3	pass	pass	pass	pass	pass
EMS cancellation	1	pass	N/A	N/A	Paa	pass
EMS cancellation	2	pass	N/A	N/A	pass	pass

There were no exceptions in any of the Phase 2 tests (Table 6). The crash trigger and manual trigger emergency response systems worked perfectly for all tests. The cancellation system effectively cancelled any attempt to contact the emergency service and provided an audio alert to the rider. The GSM module functioned properly in all possible edge cases automatically without any involvement from the rider. The average time required between sending the AT commands to having the call on the phone number was around 10 seconds.

4.4 End-to-End Response Time

Table 7 presents the complete end-to-end response time pipeline from crash detection to EMS call connection, derived from Phase 2 integrated test measurements.

Table 7. End-to-End Response Time Breakdown

Phase	Description	Duration	Cumulative
Detection + alert	Threshold confirmed; audio alert + GPS power-on	< 2 s	< 2 s
Countdown window	Rider cancellation window; GPS runs concurrently	20 s	~22 s
Dialing + connection	AT command to call confirmed on dialed device	~10 s	~32 s
Total	Crash impact to EMS call connected		~32 s

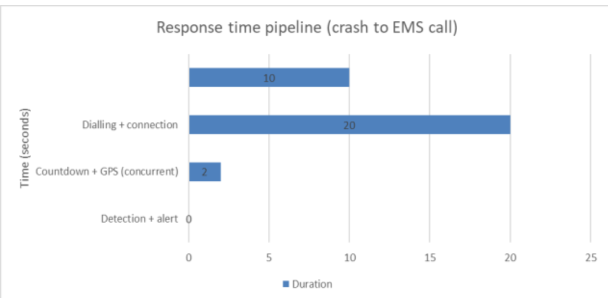


Figure 6. End-to-end emergency response time pipeline. GPS acquisition runs concurrently with the countdown window, eliminating ~20 s from a sequential design.

Parallel processing of GPS acquisition during the countdown phase is a consciously chosen edge-layer architecture approach. Sequential processing, consisting of countdown and GPS acquisition in sequence, would increase the overall response time up to around 52 seconds. Using the concurrent approach, this is brought down to an average of ~32 seconds, which is about 38% faster without compromising on position detection capabilities outdoors (Figure 6).

To put things into perspective, the average response time for EMS in Ghana has been shown to be between 30 to 60 minutes in cities, but much higher in peri-urban and rural areas (Deng, 2021; Sowah et al., 2024). With an approximate notification time of ~32 seconds, this framework saves an estimated 28–59 minutes in the notification to dispatch step alone compared to the manual approach – which is especially meaningful in light of the correlation found between EMS notification delay and trauma death (Mahama et al., 2018).

4.5 Cost Analysis and Commercial Viability

The prototype component cost is presented in Table 8. All prices reflect development board variants sourced from local Ghanaian suppliers.

Table 8. System Component Cost Breakdown

	Component	Unit Price (GH₵)	Quantity	Total Price (GH₵)
1	NodeMCU Microcontroller	71.00	1	71.00
2	SIMCom SIM868 Development Board	114.55	1	114.55
3	DFPlayer MP3- TF-16P SD Card Module	45	1	45
4	TDA2030 Amplifier	17.00	1	17.00
5	0.5 Ω 8 W Speaker	10.00	1	10.00
6	MPU6050 Accelerometer	42.00	1	42.00
7	2S Battery Charging Module	34.60	1	34.60
8	SPST Switch	5.00	1	5.00
9	Push Button	2.00	1	2.00
10	LM2596S Buck Converter Module	18.00	1	18.00
11	18650 Lithium-ion Battery	25.00	4	100.00
Total				459.15

The prototype costing GH₵ 459.15 is much higher than the price range for a regular motorbike helmet in the Ghanaian market, which is GH₵ 150-250. This poses a challenge to commercial viability for the current prototype model. Nevertheless, this cost is mainly due to the fact that the development board models are used for all main components. The development board comes with circuitry for voltage regulation, programming through USB, and breakout circuits, none of which is needed in the final design. Switching to a PCB-based design with raw ESP8266, SIM868, and MPU-6050 chips, which can be purchased from overseas vendors in bulk at a reduced price, will help bring down the cost of components to about GH₵ 300.00.

5. CONCLUSION

All the experiment results indicate that the designed three-layer cyber-physical system is able to fulfill all the five design requirements mentioned in Section I successfully. Calibration of 49 ms^{-2} was able to attain a detection accuracy rate of 100%, which is far higher than the minimum target of 75%. The GPS positioning system was successful in attaining 100% location fix within 20 seconds in outdoor conditions. The entire sequence of operations involved in handling emergencies performed successfully in all seven trials of Phase 2. Notification time of 32 seconds is an impressive achievement compared to the manual process observed in Ghana.

There are several limitations associated with the present evaluation that need to be recognized. First, the crash simulation used physical manipulation of helmets instead of instrumented drop tower or sled testing, which decreases the accuracy of the biomechanical response of the sensor and limits the ability to transfer the threshold from simulated conditions to reality. Second, although a data set of 19 crashes is adequate for defining the design threshold window, it is not adequate for any statistically significant claims, which is why more experiments are advised prior to publishing. Third, no evaluation of the false-positive detection rate was done under long-term, real-road riding on Ghanaian roads, including off-pavement conditions, speed bumps, and potholes. The only test done for 49 m/s^2 was performed in laboratory conditions. Fourth, although GPS signal loss indoors was managed well, it is still an operational limitation of the system in accidents occurring in covered areas. With respect to related work, the key aspects that distinguish the proposed model are threefold, in light of the circumstances in Ghana: absolute operational autonomy, which is independent of mobile app technologies, remote server systems, or centralized ACN hardware (Jo et al., 2021; Rodegast et al., 2024; Shi et al., 2016) threshold setting based on practical experiences with local riding conditions, rather than reliance on values established within other settings; and a dual GPS-countdown processing structure that significantly reduces system response time while relying on zero hardware infrastructure support. In return, the model sacrifices some accuracy with regard to edge case classification compared with other ML models (Melcher etal., 2015; Zirra et al., 2022) but this is more than compensated for by significant reductions in processing time and overheads.

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