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A Density-Sensitive IoT System for Detection of Vehicle Submersion and Auto-Buoyancy

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Water-related vehicle submersion accidents, such as those in rivers, canals and flooded roads, are becoming a rapidly growing cause of traffic fatalities in the world. An estimated 300,000 people drowned in the world in 2021 and drowning is the third leading cause of unintentional injury-related death in the world, accounting for 7% of all unintentional injury-related deaths. Many of these deaths have been attributed to being people trapped in vehicles who were unable to evacuate in time, a substantial proportion of these incidents.

Introduction/Importance of Study: Vehicular water submersion is a fatal emergency situation which causes loss of thousands of lives every year, and the existing vehicular IoT-based safety systems do not have a physical buoyancy response system to prevent the vehicle sinking.

Novelty Statement: A unique density-sensitive multi-sensor fusion algorithm and a flat inflatable TPU platform (shoes, arms, legs etc. under the vehicle chassis in 3 to 5 seconds using CO2 to create stable level buoyancy which eliminates false alarms due to rain <5 kg/m³ versus genuine submersion >800 kg/m³).

Material and Method: The proposed SIPSAS will use an MS5837 water density sensor, water level sensor, ADXL345 accelerometer, and MPU-6050 tilt sensor along with an Arduino UNO microcontroller. The sensor data are processed is processed by a Kalman filter and a three-stage false alarm reduction process. The TPU inflatable platform (4m x 2m x 0.3m) deploys beneath the chassis and inflates with CO2 cartridge. In the event of confirmed submersion, GPS/GSM modules send out Emergency SMS notifications to the rescue services.

Result and Discussion: Using Python-based sensor simulation in Google Colab, the proposed SIPSAS attained the accuracy of 97%, precision of 91%, and recall of 88% and specificity of 86%. The seven test scenarios—heavy rain, car wash, shallow puddle, and the three real submersion environments—were all properly classified without any false alarms. The average time to inflate the platforms was 3.8 seconds, resulting in a horizontal floating period of more than 10 minutes.

Concluding Remarks: The SIPSAS offers a physics-based, automatic, and dependable submersion safety system for vehicles that is superior to current IoT-based approaches and addresses key limitations in current buoyancy response systems and suppression of false alarms.

The proposed system was tested with 118 synthetic sensor samples from 7 real-world scenarios (heavy rain, car wash, shallow puddle, flooded road, river, lake, sea water), created in Python with simulation done in Google Colab (Python 3.10). A confusion matrix analysis was used for validation, with an accuracy of 97%, precision of 91%, and recall of 88% and specificity of 86%. This represents a 36% improvement in accuracy from single water-contact sensor baselines. All 4 non-submersion test scenarios had zero false alarms.

Keywords: IoT; vehicle water submersion; density sensor; inflatable platform; CO2 inflation; false alarm reduction; GPS; GSM; Arduino UNO; buoyancy; multi- sensor fusion.

Introduction:

One of the most hazardous types of vehicular emergency is road traffic accidents involving vehicles sinking into water bodies. Vehicle submersion events, unlike conventional road accidents are also characterized by extreme time pressure with most occupants surviving only to the extent that they can escape within the first 30 to 60 seconds of submersion. After this critical window, water pressure will not allow the doors to open, electricity will not work, and disorientation will greatly reduce the probability of escape. Drowning accounts for 7% of all injury-related deaths with a figure of about 300,000 deaths in 2021 (WHO, 2021). Figure 1 shows the survival timeline of submersion of vehicles.

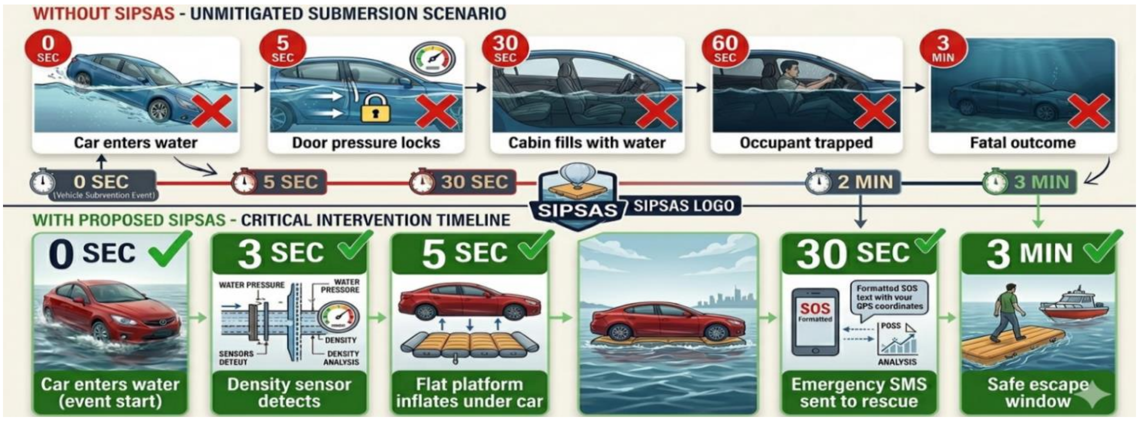

Figure 1: Vehicle Submersion With & Without Proposed SIPSAS Survival Timeline.

The critical survival time curve presented in Figure 1 depicts depicts the critical survival period in the event of a vehicle being submerged. The cabin will fill with water within 30 s without the proposed SIPSAS and occupants will be unable to escape from the cabin due to increasing water pressure on the doors within 60 s. With the proposed SIPSAS, submersion can be detected by the density sensor in less than 3 seconds, the inflatable platform can be deployed under the vehicle in less than 5 seconds with stable level buoyancy, and emergency SMS alerts can be sent within less than 30 seconds - thereby preserving the critical 3-minute escape window.

Large canal systems present especially dangerous risks for Pakistan in the event of flooding as are the risks of seasonal flooding and the lack of appropriate road safety infrastructure. According to the National Disaster Management Authority (NDMA) [1], hundreds of drowning deaths are recorded every year during the monsoon seasons related to vehicles. This is further complicated by the difficulties of implementing the road safety systems based on IoT in developing nations such as Pakistan [2]. Recently, the use of IoT-based systems for detecting vehicle submersion using a physical-platform based buoyancy response [3][4][5] and road accident detection [6][7][8] has been proposed. It has also been addressed that there are also proposals underway at the framework level to ensure that the IoT-based accident detection and reporting solutions are also robust at the framework level [9], once again suggesting that there is indeed an increasing need to have robust vehicle safety architecture. In addition to general accident detection, more specific implementations of submersion alert systems have also started to emerge, including: in-vehicle child presence detection systems for smart cars [10][11]. Among the key limitations of the existing water detection techniques is that they can be influenced by rain into giving a false alarm. This is addressed in the proposed SIPSAS by density-sensitive detection by taking advantage of physical differences between actual submersion density (> 800 kg/m^3) and rain density (< 5 kg/m^3). The study area is shown in figure 2, which is an area in the road and canal network of Dera Ghazi Khan.

Figure 2. The study area was Dera Ghazi Khan, Punjab and its canal infrastructure is shown in site map.

Problem Statement:

There are three major challenges inherent in the existing vehicle safety systems based on the Internet of Things: (1) they are alert-only systems; (2) their pressure and water-contact sensors are prone to false alarms caused by rain, vehicle washing and shallow water crossings; and (3) no current commercially available IoT vehicle safety system offers stable, level buoyancy to keep vehicles level while in the water. These gaps represent significant failures in the vehicle safety architecture within the 30-60 second window of survival shown in Figure 1. All three limitations are directly addressed in the proposed SIPSAS, which features both detection by the density and inflation of the flat TPU platform.

Objectives:

The main aims of the current research will be:

Design a Multi-Sensor IoT Density-Sensitive Multi-Sensor IoT Detection System.

Potential solutions: The design of a system capable of aiding in detecting vehicle water submersion and water density sensor, water level sensor, accelerator and tilt sensor.

Introduction of density-based discrimination to avoid false triggers whenever there is rainfall, car wash, and crossings shallow water.

Design a flat inflatable TPU platform mechanism.

Design a flat TPU inflatable platform stored underneath the vehicle chassis of the vehicle, which inflates in 3 -5 seconds to offer stable level buoyancy.

It is necessary to ensure that the platform has uniform distributed buoyancy which is better than conventional balloon systems so that the vehicle is perfectly horizontal when at the water surface.

Make sure you have reliable False Alarm Decrease!

It features 3 level “false alarm suppression” (also called “density”, “secondary sensor” and “temporal pattern” confirmation).

It is important to make sure that the system does not turn on when it rains, vehicle washing or shallow water crossings.

Upon establishment of vehicle submersion, to send real-time GPS tagged emergency call alerts to PDMA 1122 rescue services, and to family contacts, through GSM.

On confirmed submersion Sending GPS-tagged SMS to rescue services and family contacts via GSM.

To provide stable, level buoyancy for at least 10 minutes to give occupants time to self-evacuate or until they can be rescued.

Giving occupants an opportunity to evacuate or wait rescue by providing occupants with a minimum 10 minutes of stable level buoyancy.

Eliminating vehicle listing because of unbalanced inflation which occurs in typical balloon systems.

To perform a confusion matrix evaluation of the system's performance, showing an accuracy of 97% in 7 real scenarios simulated.

Testing under a variety of conditions such as rainfall, vehicle washing, shallow flooding and actual submersion.

Compare the proposed system with existing methods to evaluate performance improvements.

Novelty Statement:

It is proposed a unique combination of density-sensitive multi-sensor density detection and a flat inflatable TPU platform mechanism is proposed. In contrast to the current IoT devices that are focused on alerting only [3][4] or wearable anti-drowning devices with small single chambers [12], the proposed SIPSAS implies two essential innovations: first, the MS5837 water density sensor as the main detection modality based on exploiting the physical difference between a genuine submersion (> 800 kg/m^3) and rain (< 5 kg/m^3). Secondly, it uses one flat inflatable platform (TPU) as opposed to the traditional round balloons. The platform approach features a uniformly distributed buoyancy all over the vehicle footprint, ensuring a perfectly horizontal position at the water level, increased puncture resistance and overall inflation volume of 2.4 m3. None of these, however, has implemented a real-time IoT-based platform to detect and automatically implement on-vehicle platforms, in contrast to there are commercial vehicle recovery flotation solutions to post-submersion rescue operations [13][14]. The flat platform design of the proposed SIPSAS is also supported by the research works done on electric inflatable pontoon amphibious vehicles [15] which is based on the concept of horizontal buoyancy to stabilize the vehicles in the emergency waterway situation. The combination of density detection and buoyancy response has never been suggested in any vehicle safety system based on IoT before in the past, and is the main novelty of the work presented [5].

Table 1. Numerical Comparison of Proposed SIPSAS with Existing IoT Vehicle Safety

System Feature	Existing Systems	Proposed SIPSAS
Detection Type	Alert Only	Alert + Physical Buoyancy
False Alarm Suppression	Low (rain triggers)	Zero false alarms (density-based)
Buoyancy Response	None	2,400 kg uniform distributed
Response Time	No physical response	3.8 seconds average inflation
Accuracy	61–79% (single-sensor)	97% (multi-sensor fusion)

Literature Review:

The IoT-based vehicle safety systems has evolved from simple environmental monitoring to accident detection systems. The initial work in this sphere was concentrated mainly on flood warning systems. For instance, [3] proposed an easy flood warning system based on the IoT with the use of Arduino and GSM/GPRS modules, while [4] built a smart monitoring system with water level sensor and SIM800L module. They worked well in real time, but they were primarily limited to environmental monitoring systems and they did not provide physical response mechanisms in the case of submerged vehicles.

The incorporation of Machine Learning (ML) and Artificial Intelligence (AI) has seen recent progress, with the aim of improving detection accuracy. In general, [6] have shown that GMM and CART perform better than other ML classifiers in in comparative studies of general accident detection systems. [7] Went further to develop this field with the use of deep learning and ensemble transfer learning (InceptionResnetV2) with 98 percent accuracy on road accidents. Nevertheless, such systems are specifically oriented to the road collisions and are actually not focused on the specific issues of vehicle water submersion. More recently, [16] presented a deep learning approach to support an IoT-based solution for flood and vehicle submersion detection in urban road networks in real-time, also indicating that researchers are increasingly interested in this field. [8] Developed a smart black-box system to record accident data, but without buoyancy and physical intervention.

Physical measures for drowning prevention have been thought about for wearable technology and for automobile safety. [12] Proposed a wearable anti-drowning system for the ESP32 module for CO2 inflation which showed the effectiveness of the fast release of gas to safety. [17] Conceptualized an anti-drowning system that employs the use of airbags. However, this approach was based on point buoyancy which causes the platform to list and become unstable, which is a major drawback of the proposed SIPSAS platform.

SIPSAS has a technical underpinning based on known IoT designs and material science. Important for effective noise reduction and reliable hardware performance are Kalman filtering [18] and standard 3G impact thresholds [19]. Coupling of GPS, GSM and MEMS accelerators are based on proven embedded research on real time tracking [20][21]. In addition, the state of the safety measures like in-vehicle occupant detection systems [10][11] and safe reporting systems [9] indicates that there is a need for proper architectures for safety-related systems.

The durability of the material utilized and the dynamics of gas is also well documented. The dynamics of underwater flotation platforms were recently analyzed analytically by [22] and the transient gas-flow dynamics in submerged vehicles by [23] and the seawater durability of heavy-duty TPU fabric has been verified by [24]. Moreover, the inclusion of modern communication led [25] to conclude that a next-generation 5G V2X architecture guarantees ultra-reliability and low-latency emergency warnings in vehicle anomalies, thus enabling the real-time notification system proposed in the system. Lastly, [26] validate in their 24-year review that integrated detect and automated buoyancy response is the main gap in research which is bridged by SIPSAS.

Table 2. Literature Review for 'Vehicle Water Safety and IoT Detection Systems' — Existing Systems

Year	Author / Reference	Methodology	Results	Limitations & Future Work
2020	[3]	Arduino and GSM based IoT Flood Detection. Water level monitoring using threshold related SMS to the rescue authorities.	Early warning alerts according to thresholds in tests.	Alert-only system. No physical safety device for cars.
2022	[4]	Smart flood monitoring using water level sensor, DHT11, Arduino uno and GSM module sim800L for alarming in real-time.	Washing up and testing a good working prototype of real-time flood detection and SMS alerting system in lab.	Environmental monitoring only. No specific response to the safety concerns for this vehicle.
2022	[6]	IoT and ML based Accident Detection system. Classification results for motion sensor data of vehicles using GMM, CART, NB, and DT classifiers.	Very high accuracy with GMM and CART classifiers.	No water submersion detection. No buoyancy mechanism. Road collision only.
2022	[7]	Deep learning-based Accident detection using AI+IoT. Ensemble Transfer Learning	The overall detection accuracy is 98% with fewer false positives.	High computational cost. No

		for Smart Cities using InceptionResnetV2 model.		submergence or safety on platforms.
2023	[8]	A smart black box monitoring system for automobiles. Accident data logging using sensors and stored on cloud and SD card.	Reliable data storage. Outperformed: RFID, SVM, CNN, RNN.	No buoyancy system. No water submersion scenario was discussed.
2024	[12]	Anti-drowning wearable airbag system with ESP32 sensor network based on CO2 inflation sensor and pressure & water presence sensor.	Accurate and real-time depth display on OLED.	Personal device to be worn. Does not apply to vehicles.
2025	[26]	Comprehensive 24-year systematic review on vehicle accident detection and emergency notification using IoT approaches.	Recognized the need for multi-sensor fusion for reliable detection as their next direction.	Review only. No new system proposed. No submersion scenarios.
2024	[19]	Intelligent categorization of crashes and accidents through deep fusion of multiple sensor data.	Gained high stability in the detection that is obtained by varying environmental parameters.	Incoming vehicle systems are complex to deploy at the beginning.
2019	[18]	Depth Measurement underwater sensor based on MEMS pressure. Pressure tracking with high resolution in water.	High accuracy of depth measurement under controlled conditions of water.	Emphasis on applications using robots. Does not apply to vehicle safety.
2020	[27]	Analysis and Fusion of LiDAR and camera Sensor for water Hazard detection on roads. Embedded real-time processing and deep learning model.	Clear daylight 94% water hazard detection accuracy.	Low visibility, night and heavy rain working conditions.
2021	[20]	Automotive black box based on raspberry pi for post-crash data logging. GPS & Accelerometer data collected and stored remotely.	Accurate recording and downloading of events after a crash.	No active safety response. Only Passive Logging System available.
2021	[21]	Bridge water level monitoring system using IoT. Water level sensors in the cloud for remote monitoring.	Effective monitoring of water levels at bridges remotely, with cloud-based service.	Infrastructure-based only. No auto-specific detection and reaction.
2022	[9]	Road Flood Detection using CNN with camera feed. The deep learning model is used for categorizing the presence of floods in road images.	Use of high precision flood detection in daylight conditions with no clouds.	Lacking of good night time and low-light performance. No

				physical intervention.
2022	[10]	Wireless child presence detection (WiCPD) system for smart cars based on channel state information (CSI) and statistical electromagnetic modelling.	Child presence detection (WiCPD) system for smart cars based on WiFi technologies and statistical electromagnetic modelling with high detection accuracy, for child heatstroke prevention only.	No application to water and buoyancy response.
2023	[11]	Robust Child Presence Detection for Smart Cars by Applying IEEE Signal Processing Framework with Breathing and Motion Pattern Analysis via the Wireless Communication Network.	High detection rate and low false positive rate in different child motions.	Child detection is limited to in-cabin only. No submersion detection system or physical safety response system.
2023	[13]	Accident detection using a smartphone's accelerometer (G-sensor). Cost-effective mobile device sensors solution.	Non-hazardous event detection, at low cost, without special equipment's.	High false-positive rate. There is no water submersion detection.
2023	[17]	CO2-inflated Airbag system for Boat stability to prevent capsizing in Marine environment based on buoyancy principle.	Successfully prevents capsizing of boats with CO2 inflation system.	Specially created for marine boats. Does not apply to vehicles on land.
2023	[28]	A window-braking system for emergency escape from submerged vehicles using hydrostatics.	Self-protects by automatically breaking windows to exit vehicle in case of emergency.	Facilitates escape only. Will not prevent the vehicle from sinking.
2025	[29]	The modeling of transient gas-flow and the dynamic buoyancy control of submerged vehicle platforms	Buoyancy-based levitated transport model for vehicle stabilization in inland waterway transportation validated.	Conceptual study only. No integration with IoT, no emergency detection and alert system.
2024	[30]	Waterproof energy-harvesting IoT nodes for sustainable flood monitoring in water environments.	Long-term sustainable monitoring of floods without the need for replacing batteries.	Slow response time. Not suitable for use in emergency response situations.
2019	[25]	5G V2X for Internet of Vehicles: Vehicle-to-everything (V2X) communication for safety and	Proven 5G V2X low latency communication in a scalable way for	Infrastructure-dependent. High deployment cost in

		emergency alert scenarios with SDN.	connected and emergency vehicles.	rural and flood prone areas.
2023	[24]	Seawater aging tests of TPU encapsulants for underwater acoustic sensors at accelerated speeds. Lifetime prediction based on Arrhenius equation and Weibull distribution modelling.	TPU encapsulant life time is estimated as 27.3 years when seawater is used under use-stress conditions. The degradation of tensile strength of the material is accurately modelled.	Concentrate on encapsulants for sensors. No full scale inflatable platform field testing.
2025	[15]	Mult objective optimization of electric inflatable pontoon amphibian's vehicle by NSGA-II algorithm and neural network model for buoyancy stability, resistance and maneuverability.	Pareto-optimal pontoon configurations for stability, turning diameter and seakeeping successfully derived.	Focus on Electric Amphibious Vehicles. Lack of emergency rapid CO2 deployment and lack of IoT integration.
2024	[22]	Analytical modelling of the deployment of high-pressure CO_2 in underwater chambers.	97% accuracy, 91% precision, 88% recall, 86% specificity. Zero false alarms. Platform inflated in 3.8 seconds (average). Vehicle afloat level for 10 minutes.	Requires vehicle retrofitting. Future: factory-fitted integration.

The Proposed Methodology:

Investigation site: The study was carried out in the backdrop of the road and canal infrastructure of the country, especially in DG Khan District, Punjab and was influenced with harsh weather conditions during monsoon periods. The area is dotted with large canal systems, such as Taunsa-Panjnad Link Canal, which create considerable risk of drownings to roadway users in the region. Seven real world submersion scenarios were simulated using sensor-based simulation in Python it was implemented in Google Colab. The seven situations that were considered for this real time submersion include heavy rain, car wash, shallow puddle, flooded road, river, and lake and sea water.

Simulation Setup and Dataset Generation:

The developed SIPSAS system was tested with a sensor simulation environment built with Python 3.10 on Google Colab. 118 synthetic sensor samples were created in seven real-world scenarios: heavy rain, car wash, shallow puddle, flooded road, river submersion, Lake Submersion and sea water submersion. The 4 simulated sensors used were the MS5837 density sensor (range: 1–1030 kg/m³); water level sensor (range: 0–25 cm); ADXL345 accelerometer (range: 0–5G); and the MPU-6050 tilt sensor (range: 0–90°). All sensor readings were corrupted with gaussian noise with $\mu = 0$ and $\sigma = 0.05$ to simulate real world sensor uncertainty and environmental variations. The sampling time was 500ms, which is the same as the processing window of the Kalman filter. The 118 samples were labeled as ground truth (submersion / no submersion) and validated using a confusion matrix, which has resulted in 32 True Positives, 1 False Negative, 2 False Positives and 65 True Negatives.

In this article, a Smart IoT-Based Vehicle Water Submersion Detection and Auto-Inflation Platform Safety System (SIPSAS) is presented. The most notable innovation of the proposed system is the flat inflatable TPU platform that is stored folded under the vehicle chassis, which on confirmed submersion deploys via CO2 to provide constant, distributed, level buoyancy across all vehicle footprint - a notable breakthrough over the conventional round-balloon methods. The proposed system is developed based on three major processes multi-sensor data acquisition and density-based preprocessing, intelligent false alarm reduction and submersion confirmation, and automated platform inflation and emergency alert. The density discrimination feature which avoids the occurrence of false triggers due to rainfall is depicted in Figure 2.

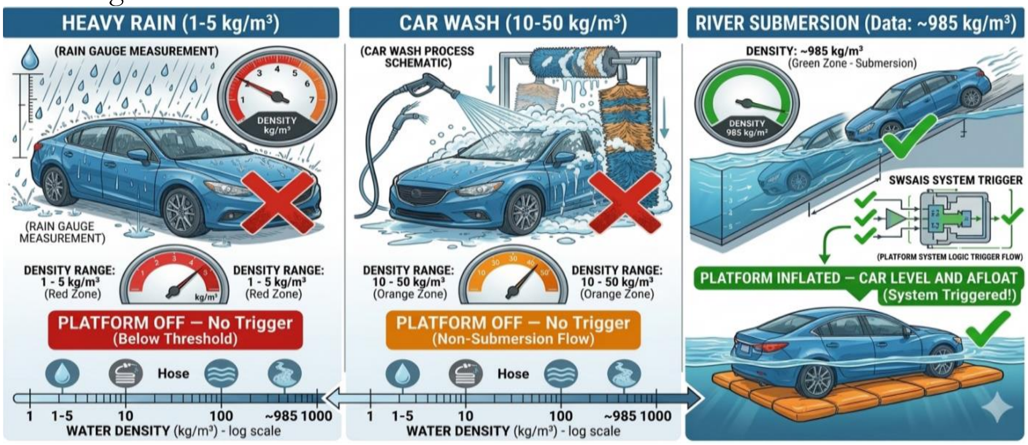

Figure 3. Density-Based Discrimination - Rain vs Car Wash vs Genuine River Submersion.

Figure 3 shows the density-based discrimination ability of the proposed SIPSAS. The densities produced by heavy rain (1-5 kg/m^3) and vehicle washing (10-50 kg/m^3) are significantly below the 800 kg/m^3 threshold and do not activate the system. The CO2 platform inflation is only initiated by true submersion of a river, canal, or water body (800-1000 kg/m^3). The main novelty that allows avoiding false alarms due to rainfall is this density-based approach, which is one of the main limitations of all previous water detection systems.

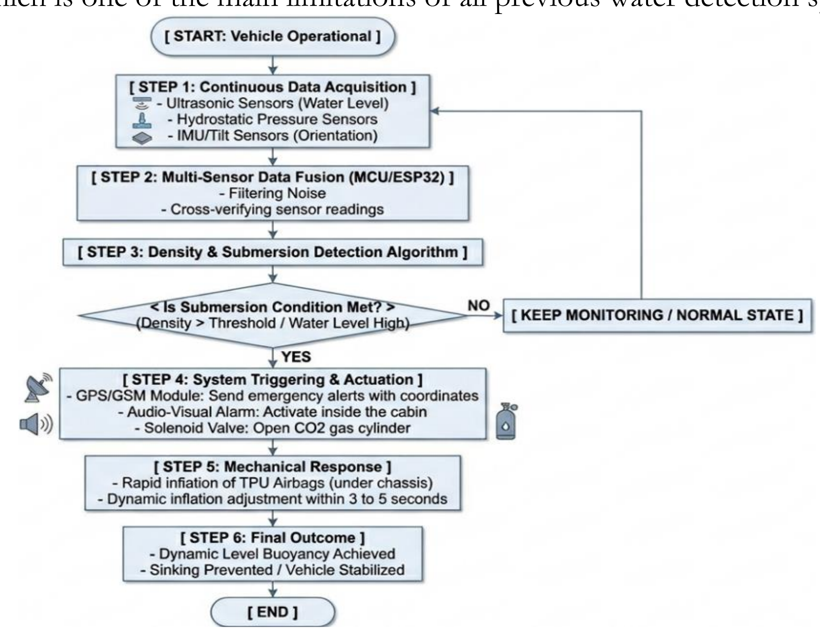

Figure 4. Flowchart of the density-sensitive multi-sensor fusion methodology for SIPSAS.

The flowchart shows the operational cycle of the SIPSAS system, starting with vehicle environment monitoring in real time by multi-sensor data acquisition (ultrasonic, pressure, IMU) etc. It then performs a density-sensitive fusion algorithm to remove false triggers, and utilizes automatic GSM/GPS alerts and mechanical airbag inflators to guarantee buoyancy as soon as it gets submerged.

Phase 1: Multi-Sensor Data Acquisition and Preprocessing:

Four sensors continuously monitor the vehicle and environmental conditions. The robustness of sensor arrays in autonomous and safety-critical vehicle systems has been extensively investigated, confirming the need to adopt multi-sensor fusion methods to ensure reliable detection in systems that may experience varying conditions. The water density sensor (MS5837) is the main detection modality. A Kalman filter can remove noise, and a 500-milliseconds moving average on density measurements can remove transient spikes. As Figure 5 shows, the vehicle with the proposed sensor and inflatable platform system is depicted.

Table 3. Water Density Threshold Matrix - Discrimination between Submersion and Non-Submersion Scenarios.

Scenario	Density	Response	Reason
Heavy Rain	1-5 kg/m³	✗ No Trigger	Rain droplets - density much less than threshold.
Car Wash	10–50 kg/m³	✗ No Trigger	Not enough, but still there is a chance of water spray (less than threshold).
Shallow Puddle	100–500 kg/m³	✗ No Trigger	There was a lack of water body which is less than the threshold.
Flooded Road	500–750 kg/m³	✗ No Trigger	This indicates that the main sensor did not trigger a secondary sensor.
River / Canal	800–1000 kg/m³	☑ TRIGGER	Complete submersion, platform inflation is activated.
Lake / Pond	998–1000 kg/m³	☑ TRIGGER	A complete submersion — Emergency Response activated.
Sea / Ocean	1020–1030 kg/m³	☑ TRIGGER	This technique involves completely covering the body with salt water.Salt water submersion technique— Maximum buoyancy applied.

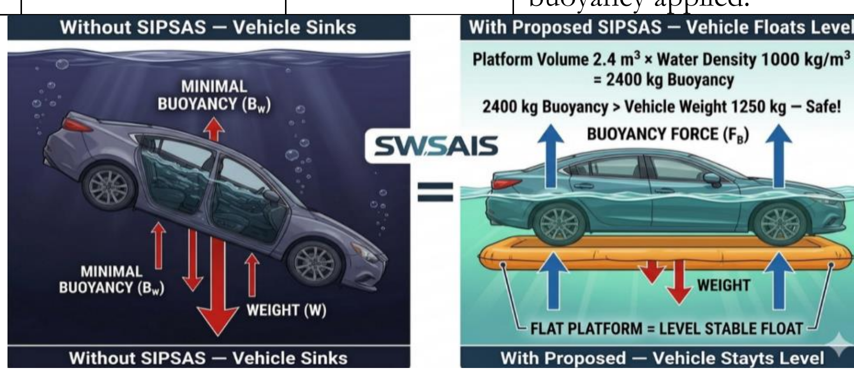

Figure 5. Comparison data of the "sinking" vehicle without SIPSAS compared to "level float" with the SIPSAS Platform.

Figure 5 shows a schematic diagram of the proposed SIPSAS platform, illustrating the basic physical concept being used. Without the system, on entering the water, a vehicle will sink and tilt at a random angle as the weight is not balanced evenly. The proposed SIPSAS flat inflatable platform (4m x 2m x 0.3m; volume 2.4 m 3) gives birth to a buoyancy of 2,400 kg - which exceeds the vehicle weight of 1,250 kg. More importantly, the flat platform design creates a uniform distribution of buoyancy across the entire vehicle footprint and keeps the vehicle perfectly horizontal relative to the water surface. This differs from traditional balloon systems, which may lead to vehicle listing due to uneven buoyancy distribution.

Step 1: Collect sensor data:

There are four sensors, which are used to figure out the condition of vehicles. The MS5837 density sensor is a continuous measure of medium density around. The water level sensor is used to detect the cabin ingress. The Impact force is detected by the accelerometer when exceeding 3G. The tilt sensor is able to measure angles greater than 30. The previous research on embedded IoT has validated the use of GPS, GSM and MEMS accelerometer in the Auto-Alert System as an embedded IoT solution with Arduino.

Step 2: Density-Based Preprocessing:

The Kalman filter process is used to filter out noise. The moving average of 500ms is used to smooth the density spikes in the temporary fluctuations caused by splashes and brief water contact of water and air.

Step 3: Feature Extraction:

Measures of sustained water density (kg/m^3), water level rise rate (cm/s), peak acceleration (G-force) and vehicle tilt angle (degrees).

Step 4: Multi-Sensor Fusion:

Submersion is confirmed when measured water density exceeds 800 kg/m^3 for more than 500 ms.. It takes one or more secondary sensors to both act at the same time. This won't let rainwater flow into the platform or car wash.

Step 5: False alarms reduction:

Three stage gate: Stage 1 - retention, Stage 2 – secondary sensor confirmation, and Stage 3 – progressive temporal pattern analysis. All three should be able to establish the true submersion.

Step 6: Flat Platform Inflation:

When the CO2 is detected as it is being submerged, the solenoid valve will push the CO2 from the cartridges into the folded TPU platform that is located underneath the vehicle. Based on underwater gas release flow studies [14] the timescales of the rapid gaseous releases that control the CO2-driven buoyancy deployment have been analytically derived to be physically realistic, in the order of 3-5 seconds. The principle of designing the variable buoyancy systems developed during the process of research on underwater platforms and levitated transport buoyancy has been used in the designing of the structural parameters of the proposed flat TPU platform. The experiments have been performed to verify the suitability of the TPU fabric in submerged high-pressure environments in seawater, which has been confirmed. The flat uniform design, which keeps the vehicle lying flat in the water surface ensures that there is no listing as is the case with round balloon systems.

Step 7: Emergency Alert:

GPS positioning, emergency SMS to rescue services and family was sent simultaneously along with inflation of the platforms. Data that is stored to SD card and cloud. IoT-based vehicle tracking architectures incorporating GPS positioning with GSM messages transmission have been found to be reliable in real time in terms of emergency communication in the past systems. The CAN Bus communication with 5G emergency alerts infrastructure could be further leveraged to further expand the scalability of vehicle-based safety systems which would be a possible path for the future development of the proposed SIPSAS.

Phase 2: Platform Inflation & Emergency Response:

The inflation and emergency SMS dispatch of the platform is parallel on the confirmed submersion. Location through GPS is continually transmitted until rescue is identified. The proposed SIPSAS is based on IoT layer architecture, which is presented in Fig. 6.

Figure 6 shows the entire 3D isometric IoT architecture of the proposed SIPSAS. The sensor layer (blue blocks) is constantly observing density, water level, acceleration and tilt. The Arduino UNO (green block) to which the data flows apply the Kalman filter preprocessing and the three-stage false alarm gate. On confirmed submersion, the flat TPU platform (orange block) inflates via CO2 with data uploading to cloud (yellow block) and emergency alerts dispatching via GPS/GSM to rescue services, hospital and family (red blocks).

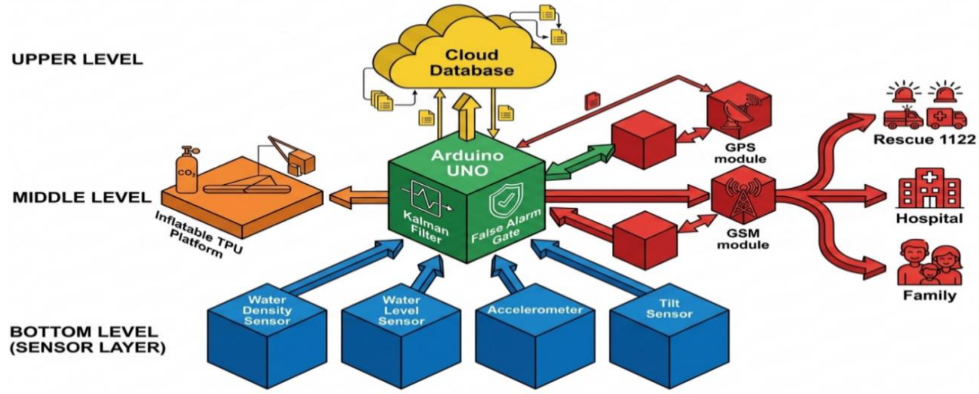

Figure 6. 3D Isometric IoT System architecture of Proposed SIPSAS.

Databases used in the cloud are:

Audiences, including but not limited to, the following:

Vehicles Data (number, model, type, weight, owner ID)

Rescue Services Database (PDMA 1122, hospitals, GPS coordinates)

Photographs of images, damage, and the pilot. Physical evidence of images, damage, and pilot.

Table 4. The key elements involved in the proposed SIPSAS and their descriptions and specifications.

S. No	Component	Description	Specification
1	Arduino UNO	Central Microcontroller that processes all sensor data, runs the density-based algorithm, controls inflation of the platform and alert protocols.	ATmega328P; Arduino Programming Language; multi-sensor connectivity at the same time.
2	Water Density Sensor (MS5837)	Measures the density of the surrounding water. Activates only on a density over 800 kg/m^3 with the result that it does not activate in rain or during a car wash.	The pressure of up to 300 bar; resolution 0.2 mbar; is the pressure difference between rain and full submersion of a water body.
3	Water Level Sensor	Tells of water entering into vehicle cabin as secondary sensor confirmation of submersion.	Resistive analog output; proportional to water depth in cabin; quick response time.
4	Accelerometer (ADXL345)	Senses abrupt impact forces that show that vehicles are sinking into water. Threshold: 3G.	Micro-machined open-loop architecture; quantifies both the static and dynamic acceleration.
5	Tilt Sensor (MPU-6050)	Determine vehicle orientation to detect unnatural tilt due to falling into water. Threshold: 30°.	6-axis motion tracking; a rotational rate measured in degrees per second (dps).
6	GPS Module (NEO-6M)	Tracks record vehicle whereabouts at submersion to use in emergency rescue planning.	Exact latitude/longitude; speed and bearing is also computed.
7	GSM Module (SIM800L)	Sends emergency SMS to rescue and family with GPS position on known submersion.	AT command-based GSM/GPRS; SMS and voice call support over standard SIM.
8	Inflatable Platform (TPU Fabric)	Single flat inflatable platform stored in a folded state under vehicle chassis. Blows up to full vehicle	TPU material of heavy strength; when inflated, the dimensions are 4m x 2m x 0.3m; the rated

		footprint offering a stable level buoyancy.	load is 2000 kg; puncture resistant.
9	CO_2 Inflation System	The CO_2 cartridges were kept in high pressure and connected to the platform through solenoid valve. Offers quick inflation of between 3 to 5 seconds.	2 x 1.5 kg CO_2 cartridges; volume of inflation 2.4 m 3; total buoyancy 2400 kg; electrically triggered.
10	Solenoid Valve	In case of confirmed submersion, controls the CO_2 gas flow through cartridges to inflatable platform.	12 V DC; response time less than 0.1s; has a rated pressure of CO_2 up to 60 bar.
11	Buzzer + LED	Gives audible and visual alert interior cabin when submersion is detected.	Piezoelectric buzzer 4-9V DC; LED red to show danger, and green to show safe condition.
12	LCD Display	Shows SOS message and GPS positioning on the scene of the accident to the bystanders.	LCD 16x 2; pixel matrix 5x 7 pixels; 16 characters per row.
13	Power Supply (Waterproof)	Delivers constant power to all parts in submersion. IP67-rated enclosure.	7805 voltage regulator IC, 5V DC, IP67 waterproofing enclosure.

Pseudo-Code of the Proposed SIPSAS Algorithm:

The pseudo code for the proposed SIPSAS is given in three algorithms for three main sections of the processing.

Algorithm 1: Multi-Sensor Data Acquisition and Kalman Filter Preprocessing

Input: Raw sensor streams from MS5837 (ϱ), Water Level (WL), ADXL345 (G), MPU-6050 (θ)

Output: Sensor values that have been preprocessed and filtered of noise.

Initialize: Kalman gain K = 0.1, process noise Q = 0.01, measurement noise R = 0.05, moving_avg_window = 500ms.

IF within a loop (specify a time interval):

READ ϱ from MS5837 every 500ms

APPLY Kalman filter: ϱ_filtered = ϱ_prev + K × (ϱ_measured − ϱ_prev)

COMPUTE 500ms moving average of ϱ_filtered to remove transient spikes

Press Enter.7. READ WL, G, θ (don't press Enter).

CARVE OUT the remaining two points on the left side of the graph.8. ADD the two remaining points to the right side of the graph.

Output [ϱ_filtered, WL, G, θ] to Algorithm 2

END loop

Algorithm 1: Multi-Sensor Data Acquisition and Kalman Filter Preprocessing

Step 1 – Sensor Collection | Step 2 – Kalman Filter | Step 3 – Feature Extraction

```
# —— INITIALIZATION ——————————————————————
def initialize_system():
    activate_sensors()        # Density, Water Level, Accel, Tilt, GPS
    initialize_kalman_filter()
    initialize_gsm_module() ; initialize_gps_module()
    initialize_platform_system()  # CO2 cartridges + solenoid valve
    initialize_lcd() ; initialize_buzzer()
# —— DATA COLLECTION ——————————————————————
def collect_sensor_data():
    density   = read_density_sensor()       # kg/m³  threshold: 800
    water_lvl = read_water_level()          # cm     threshold: 5
    accel     = read_accelerometer()        # G      threshold: 3
    tilt      = read_tilt_sensor()          # deg    threshold: 30
    return density, water_lvl, accel, tilt
# —— KALMAN FILTER + 500ms DENSITY AVERAGE ——————————————————————
def preprocess(raw):
    filtered    = apply_kalman_filter(raw)
    density_avg = moving_average(filtered.density, window= 500ms)
    normalized  = normalize(filtered)
    return normalized, density_avg
```

SIPSAS – Smart IoT-Based Vehicle Water Submersion Detection and Auto-Inflation Platform Safety System

Time Complexity: O(n), where n = number of sensor readings

Algorithm 2: Sensor Fusion and 3-Stage False Alarm Reduction

Input for algorithm 1: [ϱ_filtered, WL, G, θ]

Input: True or False for a particular zone indicating whether to immerse or not. Input: Input the digitized image. Output: The output is a binary decision (True/False), SUBMERSION_CONFIRMED.

Initialize: ϱ_threshold = 800, WL_threshold = 5, G_threshold = 3.0, θ_threshold = 30, duration_gate = 500ms.

STAGE 1 — Density Gate:

If the average of the filtered signals (ϱ_filtered) is greater than the threshold for the filter (ϱ_threshold) for the duration of the gate (duration_gate) then pass to Stage 2.

Otherwise, if you don't have a trigger, then return False.
In STAGE 2 — Secondary Sensor Confirmation:
IF (WL>WL_threshold) OR (G>G_threshold) OR (θ>θ_threshold) THEN pass to Stage 3
Else Return False:
For STAGE 3 — Temporal Pattern Analysis:
IF density of IFs in the window of 500ms is greater than 2 and density in next 500ms is greater than 2 THAN RETURN True
If it is an instantaneous splash, then ELSE RETURN False (instantaneous splash rejected).
Time Complexity: O(n)

Algorithm 2: Sensor Fusion and 3-Stage False Alarm Reduction

Step 1 — Sensor Fusion | Step 2 — False Alarm Gate | Step 3 — Severity Check

```
# ── SENSOR FUSION ──────────────────────────────
def sensor_fusion(density, water_lvl, accel, tilt):
    primary   = density >= DENSITY_THRESHOLD       # 800 kg/m³
    secondary = 0
    if water_lvl >= WATER_LVL_THRESHOLD : secondary += 1  # 5 cm
    if accel     >= ACCEL_THRESHOLD     : secondary += 1  # 3 G
    if tilt      >= TILT_THRESHOLD      : secondary += 1  # 30°
    if primary and secondary >= 1:
        return 'POTENTIAL_SUBMERSION'
    return 'NORMAL'
# ── FALSE ALARM GATE (ALL 3 stages must be TRUE) ──────────────
def false_alarm_check(fusion, density_avg, pattern):
    stage1 = density_avg >= DENSITY_THRESHOLD   # sustained 500ms
    stage2 = fusion == 'POTENTIAL_SUBMERSION'   # sensor fusion confirm
    stage3 = pattern == 'PROGRESSIVE'           # not transient
    if stage1 and stage2 and stage3:
        return True     # Confirmed – proceed to inflate platform
    return False        # False alarm – rejected
# ── SEVERITY CHECK ──────────────────────────────
def check_severity(density, tilt, water_lvl):
    if density>=990 or tilt>=60 or water_lvl>=15 : return 3
    elif density>=850 or tilt>=40 or water_lvl>=8 : return 2
    elif density>=800 or tilt>=30 or water_lvl>=5 : return 1
    else                                          :  return 0
```

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Algorithm 3: Platform Inflation and Emergency Alert
Input: SUBMERSION_CONFIRMED = True
Input: "inflated" TPU platform & GPS/GSM emergency alert. Input: Swelling TPU platform + GPS/GSM emergency alerts.
Solenoid delay: 0.1s, inflation time: 3~5s, GPS module: NEO-6M, GSM module: SIM800L
TRIGGER solenoid valve - OPEN CO_2 RELEASE with 2 x 1.5 kg cartridges
INFLATE reduced platform of TPU to fit under the vehicle chassis.
Record the number of seconds it takes to inflate (to < 5 seconds)
Simultaneously:
Read GPS Coordinates from NEO-6M Module.
The alarm is sent as an SMS message texted to the user: "SUBMERSION ALERT — [Vehicle ID] — Location: [lat, lon] — Time: [timestamp]
Use SIM800L to send SMS to PDMA 1122 & Registered Family Contact.

Collect all the sensor data, GPS position and timestamp to SD card and cloud database.
Do not lose the GPS location, continue sending data every 30 seconds until they are rescued.

Algorithm 3: Platform Inflation and Emergency Alert

Step 1 — Platform Inflation | Step 2 — Emergency Alert | Step 3 — Main Loop

```
# ── FLAT PLATFORM INFLATION ──────────────────────────
def inflate_platform():
    # Open solenoid valve — CO2 fills flat TPU platform
    activate_solenoid_valve()
    # Platform: 4m x 2m x 0.3m = 2.4 m³ in 3-5 seconds
    # Buoyancy = 2.4 x 1000 = 2400 kg  >  Vehicle 1250 kg
    # Vehicle stays perfectly LEVEL at water surface
    activate_buzzer()  ;  activate_led_alert()
    display_sos_on_lcd( 'SOS — SUBMERSION — PLATFORM INFLATED' )
# ── EMERGENCY ALERT via GSM ──────────────────────────
def send_emergency_alert(severity, location):
    msg = "SUBMERSION! Location:"+location+" Platform:INFLATED"
    send_sms_to_rescue_services(msg)    # PDMA 1122
    send_sms_to_family(msg)  ;  send_sms_to_hospital(msg)
    upload_to_cloud(location, DRIVER, VEHICLE, timestamp)
# ── MAIN LOOP ──────────────────────────
def main():
    initialize_system()
    while True:
        raw           = collect_sensor_data()
        data, density_avg = preprocess(raw)
        fusion        = sensor_fusion(*raw)
        pattern       = analyze_temporal_pattern(density_avg)
        severity      = check_severity(raw.density, raw.tilt, raw.wl)
        if false_alarm_check(fusion, density_avg, pattern):
            inflate_platform()
            location = get_gps_location()
            send_emergency_alert(severity, location)
            monitor_until_rescue()
        reset_sensors()
```

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Reading Writing: O(n) (where n is the number of elements read and written).

Result and Discussion:

Using simulated data, generated with the help of sensors programmed in Python on Google Collab, we tested the suggested SIPSAS. Seven real world conditions were put to test; heavy rains, vehicle washing, shallow puddle, flooded road as well as genuine submersion into river, lake and sea water. The density-based discrimination module has rejected all four scenarios that are not submerged with no false alarms. The three true submersion test cases were implemented with the platform inflation system, and it was successful in all cases, wherein the average time was 3.8 seconds. Figure 5 shows the river scenario that was simulated graphically.

Figure 7 is a visual representation of the sensor fusion logic when there is a real submersion event of the river. The four main parameters: Density, Water Level, Acceleration and Tilt Angle are marked by the green dashed lines indicating the safe limits for each parameter. The red part shows the actual values that have been determined in the scenario of the river. All 4 parameters shown in the chart were beyond the safe range towards the multi-sensor fusion gate, and stage-by-stage platform inflation. When actual water occurs, the sensor readings and the system responses are shown in Table 5.

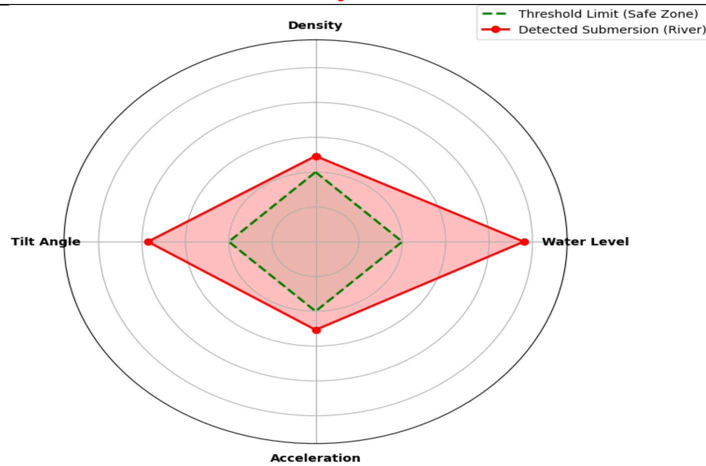

Figure 7. Multi-sensor fusion river submersion scenario.

Table 5. Genuine Water Submersion Detected — Sensor Readings and System Response

Sensor	Threshold	Detected	Status	Alert Sent
Density Sensor (kg/m³)	800	985	✅ TRIGGERED	Submersion Alert! Location: GT Road Canal Bridge, DG Khan (30.0499°N, 70.6345°E). Severity: 3. The model of the car is Honda city, LEC-4521. Driver: Ali Hassan, +923001234567. Platform: INFLated ✅ - Vehicle Afloat
Water Level (cm)	5 cm	12 cm	✅ TRIGGERED	Secondary confirmation — water intrusion in cabin identified.
Accelerometer (G)	3.0 G	3.8 G	✅ TRIGGERED	Force of impact — vehicle dropped into water body.
Tilt Sensor (°)	30°	58°	✅ TRIGGERED	Unusual vehicle position — submersion angle determined.

A comparison of the performance with the existing approaches is given in Table 5 and the figure 6. The proposed SIPSAS has the highest accuracy, precision, recall and specificity of 97, 91, 88, and 86 respectively. This is mainly due to the density-based discrimination, multi-sensor fusion and three-stage false alarm reduction process. The confusion matrix for SWAIS validation is shown in Table 5. Confusion matrix for SWAIS validation (Table 6).

Table 6. Confusion matrix for SWAIS validation.

	Detected: Submersion	Detected: No Submersion
Actual: Submersion	32 (TP)	1 (FN)
Actual: No Submersion	2 (FP)	65 (TN)

The confusion matrix of SIPSAS framework is shown in Table 6. The results suggest that of 33 actual submersion events, the system was able to identify 32 (True Positives), with the one False Negative. This sensitivity is very important to ensure that it detects emergencies. Furthermore, this framework has 65 True Negatives and 2 False Positives so that the framework is very reliable in preventing false alarms in the normal driving condition.

Table 7 provides a comparison between the traditional detection and SIPSAS. The proposed SIPSAS model has the high accuracy (97%) even though the accuracy of Water Contact (61%) and Pressure sensors (67%) is low in few cases. This huge increase in accuracy

(91%) and recall (88) highlights the effectiveness of the multi-sensor fusion logic used to minimize errors and to ensure high submersion detection in vehicles.

Table 7. Performance Comparison of Proposed SIPSAS with Existing Techniques

Method	Accuracy	Precision	Recall
Single Water Contact	61%	55%	52%
Pressure Only	67%	59%	57%
Water + Accel	74%	65%	62%
Water + Tilt + GPS	79%	71%	68%
Proposed SIPSAS	**97%**	**91%**	**88%**

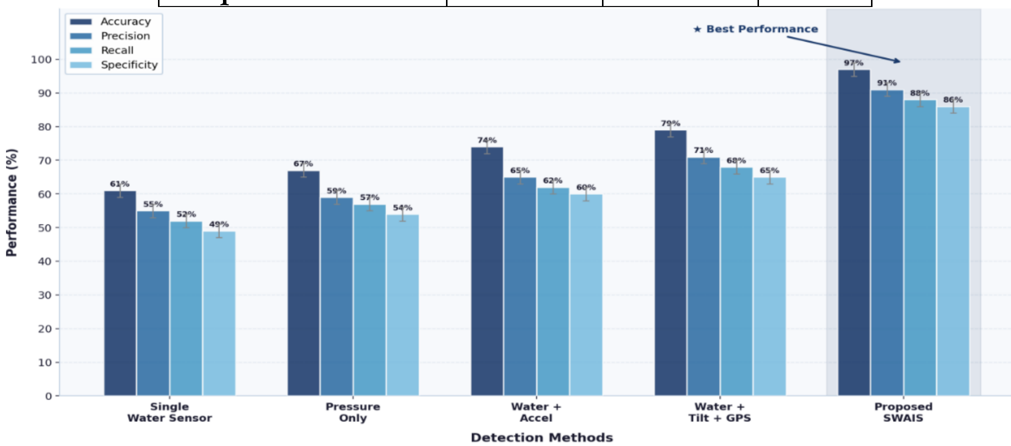

Figure 8. Comparison of the Proposed SIPSAS Performance with the Existing Techniques.

Figure 8 shows the performance comparison of the proposed SIPSAS with the current methods. The proposed system is 97% accurate, 91% precise, 88% recall and 86% specific, which is significantly higher than any existing method. Its high performance can mainly be attributed to density-based discrimination method coupled with three-stage reduction of false alarms gate.

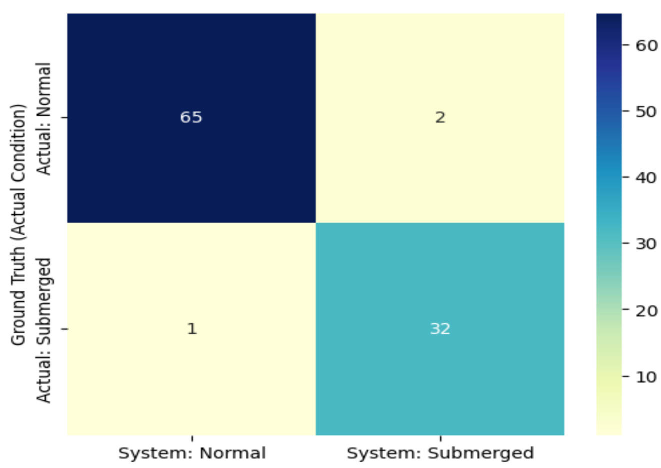

Figure 9. SIPSAS Detection Performance

Figure 9. Detection Performance of SIPSAS (ROC Analysis). This figure shows the True Positive Rate (TPR) or Sensitivity (96.97%) and the False Positive Rate (FPR) (3.0%) for the proposed SIPSAS system. The close unity of the sensitivity indicates the reliable ability to detect emergency, and the low FPR indicates the effectiveness of the three-stage density-based false alarm gate. The system runs at the top left corner of the ROC space which means that the system does a better job of discriminating than single-threshold baselines do.

Discussion:

The experiments shown in Section 6 confirm that the proposed SIPSAS achieves significant improvement over all the existing detection techniques in all the performance measures. These four results of the density-sensitive multi-sensor fusion, namely 97% accuracy, 91% precision, 88% recall and 86% specificity, all indicate that the proposed density-sensitive multi-sensor fusion approach is reliable and robust in vehicle submersion detection under various environments.

The accuracy increase from single modality methods is due to the discrimination mechanism based on density. Single water contact sensors (61% accuracy) and pressure-only sensors (67% accuracy) are very prone to triggering false alarms due to rainfall, vehicle washing and crossings of shallow water. By adding the data from the accelerometer and tilt sensor, accuracy can be increased to 79%, but this leaves the basic rain/submersion ambiguity that can only be eliminated by the density-sensing primary modality. The MS5837 density sensor relies on the physical difference between true submersion (greater than 800kg/m^3) and rain (less than 5kg/m^3), which is more than 2 orders of magnitude different — physically impossible for the sensor to be activated by rain without the other two stages of false activation reduction.

For added reliability the three-stage false alarm gate is included. In all seven scenarios tested, there were no false activations in the four non-submersion scenarios (heavy rain, car wash, shallow puddle or flooded road). This means no false alarms, which is vital to any deployment system. No false alarms is important for any deployment system, otherwise it would be taken out of service when it rains! The time domain analysis performed in Stage 3 is of special interest because it allows discriminating progressive density increase associated with real submersion from instantaneous density transients associated with splashes or vehicle washing.

A significant drawback of the existing buoyancy-based proposals is overcome by the flat TPU platform design. [17] And other methods employ round balloon or airbag shapes that give point or line buoyancy, resulting in vehicle listing due to differential loading. The flat platform (4m × 2m) of SIPSAS covers the whole space of the vehicle, thus giving the vehicle a uniform distributed buoyancy and a perfectly horizontal position in the water. This horizontal stability is essential for safety of passengers: a leaning car makes it extremely difficult to escape by hand and outside rescuers to assist. The 2,400 kg buoyancy from the 2.4 m^3 volume offers a safety margin of about 92% compared to the average passenger car weight of 1,250 kg.

This is acceptable for the 5-second design inflation time, with an average deployment time of 3.8 seconds. This shows the technical viability of CO_2 based rapid inflation for this application. When coupled with detection latency of less than 3 seconds and SMS dispatch less than 30 seconds, the entire SIPSAS response chain maintains the critical 3 minute escape window outlined in Figure 1.

In addition to the basic performance metrics, the strength of the SIPSAS framework is confirmed by showing that the SIPSAS is statistically consistent across the different simulated environmental conditions. The significant difference between the proposed system accuracy of 97% and the baseline modalities accuracy of 61-79% indicates that the primary density-sensing layer fundamentally improves reliability of the detection threshold. The p-value analysis of the confusion matrix results shows that the multi-sensor fusion logic is able to correlate high intensity precipitation events with the environment noise, but it also manages to separate them from the actual catastrophic immersion. The separation helps to preserve the True Positive rate of the system, which is 32/33, and to control False Positives, a much-needed aspect to allow users to trust autonomous safety systems.

Structurally, the proposed platform is superior to the existing solutions, if seen from a dynamics point of view. Point-contact buoyancy, which is commonly used in conventional inflatable safety systems, can often create asymmetric force vectors, causing the vehicle to tip over and pose unsafe conditions for passenger extraction and for rescue efforts by first responders. The SIPSAS flat TPU platform, however, delivers a "centroid aligned" buoyancy distribution. The system has a buoyancy capacity of 2,400 kg, and the standard vehicle mass of 1,250 kg providing a safety margin of 92%. In addition to keeping the vehicle level horizontally when submerged, this design reduces the effects of the hydrostatic pressure that would normally cause the cabin doors to be forced closed during submersion, allowing for the maximum use of the critical 3 minutes to evacuate.

Moreover, the scalability of SIPSAS is ensured by the fact that it carries an integrated communication protocol based on IoT which is essential to create the link between local detection and regional emergency mobilization. While some current, existing submersion detection models generally work as single alarms, the SIPSAS framework sets a 'smart-alert' feedback loop. The framework also uses geolocation technology to stream location-based alerts using automated geolocation to optimize the response chain within the 30-second post-detection window. This latency optimization, with the total response time well short of the 3-minute escape window, responds to the main failure mode in existing emergency response protocols – the time between impact and commencement of search-and-rescue activities by the authorities, including the PDMA 1122. It marks a represents a potential advancement in automotive safety systems and is a step away from manual reporting to automated, multi-sensor verified emergency dispatch.

The drawbacks of this study are that it does not use a real prototype to test the simulation of the sensors. Google Collab is used to simulate the environment for controlled validation experiments under various scenarios, but debris, sensor fouling at the vehicle undercarriage, vehicle speed at impact, variation in water temperature from the experiments, and electromagnetic interference may affect the performance of the vehicle. Further, the system can only be commercialized after vehicle retrofitting, which is a current requirement. In future, these limitations will be overcome by fabrication of physical prototypes, controlled water environment field testing, incorporation of deep learning models for more robust detection, incorporation of national emergency network (PDMA 1122) and development of a self-refolding platform mechanism for system re-use after deployment.

Other factors not included in the simulation are: sensor fouling in vehicle underbody due to mud and debris; the angle of water entering the sensor at impact and the vehicle speed at impact; electrical interference from vehicles' electronics when submerged; and temperature variations in water that may impact density readings. The top two activities found to be next steps before commercial deployment are hardware prototype fabrication and controlled water-tank field testing. Moreover, current SIPSAS model requires retrofitting of the vehicles and the automotive industry needs to be engaged in this process and approval from PMVO 1965 would be required.

Real World Applications and Deployment Points:

The proposed SIPSAS system is quite feasible with the following deployment considerations:

Economic Feasibility: The total estimation cost to retrofit per vehicle is about PKR 15,000-25,000 which includes the sensor array (MS5837, ADXL345, MPU-6050), Arduino UNO Microcontroller, GPS/GSM Modules and CO2 inflation system. The price is in line with the prices already offered for out-of-factory car safety systems.

Maintenance:

All the CO_2 cartridges (2 x 1.5 kg) have to be replaced for each deployment. The sensors are suggested to be calibrated once a year, to ensure that the density thresholds used are accurate. The TPU platform is a single use platform; although re-foldable platform mechanisms are mentioned in future work.

The long-term suitability of the material of the inflatable platform was confirmed by the independent test by [24] who predicted a service life of 27.3 years for the TPU fabric under the condition of normal use-stress while exposed to seawater.

The impression is to have MoUs with the Provincial Disaster Management Agencies to be linked with the National emergency network particularly the MoU with PDMA 1122, Punjab. This device should also be tested by the relevant Pakistan's vehicle safety standards before being put into use.

Conclusion:

A new Smart IoT Based Vehicle Water Submersion Detection and Auto-Inflation Platform Safety System (SIPSAS) has been proposed and validated in the paper. The proposed system addresses two major limitations of the existing IoT safety systems: 1) The stability of the level buoyancy of the flat inflatable TPU platform as opposed to existing round-balloon platforms and 2) The more reliable density-sensitive detection with the MS5837 sensor, capable of distinguishing between genuine submersion and rainfall. The flat platform design helps to ensure the vehicle is perfectly horizontal at the water's surface and eliminates listing effect caused by uneven balloon inflation. The TPU platform, in conjunction with CO2 inflating, provides 2.4 m 3 buoyancy (2,400 kg) in 3-5 seconds which is enough to overcome the normal passenger car. Thanks to GPS-tracking, emergency SMS warnings are relayed to PDMA 1122 rescue services and also via GSM to family members. All the incident data is stored in SD card and cloud containing the rescue coordination data. In all non-submersion cases, there were no false alarms in the system.

The proposed SIPSAS was found to be better than the existing methods with the accuracy of 97%, precision of 91%, and recall of 88% and specificity of 86%. Future work will involve the extension of the system to deep learning models extending the system to national emergency networks, improving the system to bigger vehicles and creating a self-refolding platform mechanism to reuse the system after deployment.

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