Advances in Artificial Intelligence and Machine Learning; Research 5 (4) 4553-4574 Received 27-08-2025; Accepted 05-11-2025; Published online 12-11-2025

IoT and Machine Learning-Based Personalized Human Accident Detection and Tracking System

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Abstract

Accidents pose a significant threat worldwide, often leading to severe harm and loss. Existing solutions mainly focus on vehicle-related accidents and rely heavily on smartphones, leaving a gap in detecting and alerting accidents outside vehicular contexts. This study proposes an IoT- and machine learning-based personalized accident detection and tracing system to address this limitation. The system comprises an IoT-enabled smart band equipped with sensors to monitor vital signs (heart rate, blood pressure, body temperature, and SpO2) and GPS for precise location tracking, a user-specific machine learning model to identify abnormal physiological states, and a cross-platform mobile application to deliver real-time emergency alerts and location information to responders. Sensor readings are transmitted via Wi-Fi to a cloud server, minimizing smartphone dependency and latency compared to GSM/GPRS-based systems. The ML model, trained on both public and locally collected datasets, achieved 99.44% accuracy using a Random Forest classifier. Validation against medical-grade devices showed strong measurement agreement (Pearson correlation > 0.94), while field trials con-

Citation: D.S.N. Seram, et al. IoT and Machine Learning-Based Personalized Human Accident Detection and Tracking System. **Advances in Artificial Intelligence and Machine Learning.** 2025;5(4):253. https://dx.doi.org/10.54364/AAIML.2025.54253

firmed stable device operation and cross-platform compatibility. Additionally, the research contributed a large, locally obtained physiological dataset valuable for future accident prevention and healthcare research. By reducing detection-to-response time and enhancing predictive accuracy, the system offers a significant advancement in safeguarding individuals from common accidents.

Keywords: Accident detection, IoT, Smart band, Personalized machine learning, Mobile application.

1. INTRODUCTION

Road accidents are a major issue across the globe, where response time to the accident location is crucial in order to save a life [1, 2]. According to a survey conducted by the World Health Organization (WHO), nearly 1.35 million people die and 20–50 million are injured every year as a result of road traffic accidents [3]. Traditional accident detection systems are vehicular collision detection systems by nature and, therefore, do not address accidents occurring outside vehicles, such as occupational accidents, slips, and falls. Accidents largely depend on manual reporting through the manipulation of emergency buttons or calling for help, which is time-consuming, dangerous and inappropriate, especially if the victim is unconscious or immovable. Previous research on existing systems based on vehicles, smartphones, and IoT systems has shed light on some remaining problems in the area of accident detection [4, 5]. While many systems have been proposed for vehicle accident detection, one major limitation is that they fail to detect accidents occurring to the user when the user is outside the vehicle. This limitation endangers user safety when accidents occur outside the vehicle. The other primary limitation observed in smartphone-based systems is that they are too dependent on the smartphone itself. The majority of existing systems rely on the victim's mobile phone to locate them, which opens up possibilities for vulnerabilities. Apart from this, mobile GPS usage for exact positioning can be compromised in situations when the GPS is malfunctioning due to certain problems. To bridge this gap, we proposed a novel IoT and ML-based system that integrates wearable technology, GPS-based location tracking, real-time communication, and predictive analytics. The system includes an intelligent IoT wristband with vital sign sensors for monitoring, GPS for accurate location tracking of accidents, and Wi-Fi for real-time data transfer. An ML model is used for the data analysis and also for predicting the health status.

1.1 Vehicle-Based Accident Detection Systems

Z. Guo et al. (2021) [5], proposed a vehicle-based accident detection system using the vehicle's hardware sensors and actuators. The system uses a force sensor mounted on the vehicle chassis and an ATMEGA328 microcontroller to detect accidents based on predefined thresholds for force and speed. When an accident is detected, the system alerts an alarm and sends an accident signal to the ESP8266 module, which in turn activates a camera and transfers video, images, GPS data and other information to the Master Controller Raspberry Pi [5]. Kinage & Patil (2019) [6], developed a system that detects accidents caused by actions such as the consumption of alcohol, drowsiness, or poorly designed speed bumpers. Using sensors like the MQ-3 sensor, infrared sensor, accelerometer, webcam and Arduino microcontroller, the system sends an alert when the driver exceeds predetermined threshold values. If the driver fails to act promptly on the warning within a specific time period, the system turns off the supply of fuel in order to tackle the issue appropriately [6]. Research shows the issue of two-wheeler riders not using helmets and the increasing trend of drunk driving [7]. To solve this issue, an IoT-based system was created, which was titled ”Obligatory usage of safety equipment for alcohol and accident detection.” The system won’t allow the two-wheeler to start unless the rider is using safety equipment (a helmet) and has cleared the alcohol test. Moreover, the system makes use of GPS and GSM technology to alert the hospital and a family member of the location of the accident in case of an emergency. According to Khan et al. (2018) [8], a system was proposed to detect vehicles travelling over a specific set speed limit and alert the responsible authorities in real time. This IoT- and smart vehicle technology-based system automatically and intelligently gathers all road traffic information, recording and storing data on the speed of the vehicle. It utilizes GPS, radar, Google Maps and IoT modules for automatically identifying safe spots and slowing down vehicles in accident-prone areas [8].

1.2 Smartphone-Based Accident Detection Systems

Tao et al. (2025) [9], introduced a smartphone-driven accident detection and reporting system utilizing the device’s sensors to detect car accidents based on G-force, noise and speed. The system will send an emergency message to the emergency number in case of an accident being detected, giving vital information regarding the accident. The system would give false alarms at low speed, as speed holds significant value in accurate accident detection [9]. Patel et al. (2013) [10], invented an Android application that focuses solely on accident detection. The application makes use of the mobile accelerometer sensor and GPS module to detect accidents and automatically dial the emergency number with a pre-recorded voice message [10]. A drawback of existing research is excessive reliance on one sensor and system failure is possible if the accelerometer sensor is not working. A subsequent study was focused on developing an Android application that utilized the smartphone’s GPS module and accelerometer sensor to detect accidents. The application always monitors the accelerometer values and employs a fixed threshold value for accident detection. Once an accident is detected, the application reports the location of the accident to nearby users and emergency services. While the system is promising, the system relies heavily on the accelerometer sensor sensitivity, which may vary between different smartphone models [11].

1.3 IOT-Based Accident Detection Systems

A promising approach is an IoT-based accident detection and prevention system that will reduce accidents by providing early warnings and alerting the concerned authorities in time [4]. The system employs sensors for the detection of accident parameters such as inter-vehicle distance, speed and other critical parameters. It provides distance warnings to the driver and notifies authorities in the event of a potential crash. However, the system is heavily dependent on the precision of sensor readings and can be troublesome in actual implementations where sensor reliability may not be a problem. Razeeth et al. (2021) [12], concentrated on the detection of driver drowsiness and fatigue utilizing deep learning and IoT-based approaches. It uses a CNN algorithm for the identification of drowsy and fatigued states of drivers. With the help of an embedded camera, it observes facial emotions and the motion of the eyes to determine the driver’s state correctly and provide a warning in time. However, the performance of the system varies depending on different light sources, expressions and positions of the camera.

The Quick Accident Response System (QARS) is an IoT-based accident reporting and detection system [13], which utilizes different modules like IoT sensors, GPS-GSM modules and a custom mobile application. The system identifies accidents by processing sensor data and notifies emergency services in real time with video recordings and location information. The extensive coverage of this system supports successful responses to accidents and assists in minimizing the time taken to reach accident sites [13]. Karmokar et al. (2020) [14], suggest an IoT-based autonomous accident detection system for the safety of life. The system, upon the occurrence of the accident, sends messages to a web server and SMS to the victim's guardian and in-charge authorities, such as the traffic control center, the nearest police station and the ambulance department. The system also directs the ambulance to move the shortest distance to the scene of the accident in an effort to accomplish a quick rescue. It was tried in a simulated road test environment and was found to be efficient and cost-effective. Praveen et al. (2020) [15], proposed a system that uses an accelerometer to detect accidents by monitoring the x, y and z axis values. As these values exceed predetermined limits, the system initiates alert and SMS messages, identifying the location of the accident instantly and transferring GPS information to the rescue services to provide assistance. Research conducted by Sayanee et al. (2017) [16], focuses on the prevention of accidents by the identification of activities like helmetless riding, drowsiness, drunk driving, over-speeding between vehicles, violation of traffic norms and illegal licenses. Their framework uses accelerometers, vibration sensors, GPS and GSM modules to identify accidents, send an alert to family members and friends and alert nearby hospitals. Their system also covers fatigue and inadvertent acceleration, utilizing RFID technology, albeit for the purposes of authentic driving license verification and auto anti-theft. Rishi et al. (2020) [17], developed a system to reduce casualties by providing immediate alerts to concerned people in the event of an accident. They use Arduino UNO, GPS, GSM and accelerometer modules for accident detection and sending the location of the accident to registered SIM cards via GSM. The system ensures a rapid response from the emergency services [17].

IoT-based vehicle accident detection and classification (ADC) systems use built-in and networked sensors of smartphones for the detection of accidents and alerting the accident class [18]. The ADC model is optimized using ML algorithms with a high degree of accuracy in accident class detection. This assists emergency services in planning the appropriate rescue and relief operations [18]. Shivapur et al. (2022) [19], proposed a system to overcome the problem of ambulance response time using vehicle-mounted sensors to automatically detect accidents. The system alerts the closest available ambulance from a hospital, manages traffic lights along the path of the ambulance and sends the patient's vital signs to the hospital in preparation for an earlier arrival. Ru et al. (2021) [20], developed IoT-based human health monitoring systems to acquire and analyze health indicators, providing real-time monitoring and alarm functions. The system helps in the prevention and control of high-risk diseases by acquiring vital signs data and enabling risk prediction. The work of Kattukkaran et al. (2017) [21], employed accelerometers and heart rate sensors for accident detection and alerts to medical centers, the contacts of the victims and other road users. Their low-cost solution aims to improve accident detection and response. Additionally, present-day commercial smart bands also come equipped with the latest technologies like LTE connectivity, heart rate monitoring, GPS tracking, sleep tracking, voice assistants, water resistance and temperature sensing [22–24].

1.4 Research Problem and Objectives

During the comprehensive review of literature on existing accident detection systems, several problems and limitations were discovered. Most of the research in this area is on accident detection inside a vehicle, neglecting accidents that occur when the user is outside the vehicle [3, 4, 6, 25]. These vehicle systems rely on identifying collisions and sending emergency alerts to nearby authorities [4]. However, this approach fails to address the detection of human accidents beyond the scope of a vehicle. The main objective of this research is to suggest a personalized human accident detection and tracking system based on IoT and ML approach. The specific objectives are to design an IoT-based smart band to detect key human vital signs like blood pressure, heart rate, peripheral capillary oxygen saturation (SpO2) and body temperature using sensors and algorithms and detect the location of the victim precisely using GPS, to design a personalized prediction model to forecast human health status more precisely, to develop a cross-platform mobile application to make it accessible to users and to offer a locally gathered dataset to facilitate further research. The study contributes to the medical and academic world as it fills an important research gap, since no previous work has proposed a complete personalized human accident detection and tracking system that detects vital signs in real time, forecasts outcomes using personalized historical data, and provides timely warnings for preventive action. By utilizing personalized data instead of generalized thresholds, the system guarantees a more precise and responsive system to detect and protect the health and safety of humans [26]. This study addresses the limitations of the existing systems and examines the potential for using personalized ML-based accident prediction and enhancing the efficiency and accuracy of accident detection systems in general [4, 12, 18]. By filling the cited gaps and leveraging WIFI technology for direct communication, the current study seeks to amplify the effectiveness and speed of accident notification and in doing so, minimize the possibility of fatality and equally offer timely assistance to the accident victims [25].

2. METHODOLOGY

The design diagram of the system, showing the IoT-based smart band, personalized ML model and mobile app, is given in FIGURE 1.

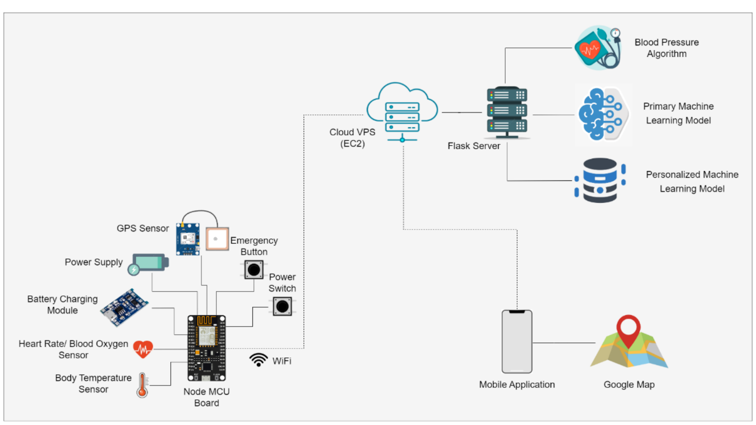


Figure 1: High-level design of the system.

2.1 IoT-Based Smart Band

The initial phase of the research involves the development of the IoT based smart band with sensors to measure the needed parameters. The smart band incorporates a Node MCU as the main hardware module, which is a low cost open source IoT board. It employs the usage of heart rate, SpO2 and temperature sensors to measure physiological values with high accuracy. The smart band also employs a GPS module for monitoring the location of the wearer. The real-time sensor data is transmitted to a cloud server via Wi-Fi for processing and analysis.

The IoT band consists of several units that work together to complete the objectives and functionalities (TABLE 1). Together, these components form the IoT band system that collects data from the MAX30100 sensor, DHT11 sensor and GPS module [27, 28]. The data is handled by the Node MCU ESP32 and it performs algorithms for recognizing abnormalities or emergency situations and triggers alerts accordingly [29]. The power switch and emergency slide switch provide manual control for the power source and emergency alert mechanism, respectively. The power supply comes from the rechargeable battery, which powers the system and the TP4056 module ensures safe and effective charging of the battery [30].

Table 1: Summary of IoT Band Components and Their Function

Component	Reason for Inclusion
ESP32 (Node MCU)	Dual-core processor, built-in Wi-Fi & Bluetooth, rich I/O interfaces, low power, cost-effective
MAX30100 Sensor	Measures SpO2 & heart rate using PPG, low power, compact, integrates dual LEDs & photodetector
DHT11 Sensor	Provides basic temperature & humidity readings, low cost, easy to interface with MCU
U-Blox NEO-6M GPS	Accurate location tracking, supports multiple satellite systems, fast positioning and low power [31]
TP4056 Charger Module	Charges a 3.7V lithium battery safely, includes overcharge/discharge protection and has a compact design
Emergency Slide Switch	Manually triggers or cancels emergency alerts with a simple switch
Power Switch	Allows the user to turn the IoT band on or off manually
1200 mAh Battery	Powers the IoT band; rechargeable and suitable for wearable use

2.2 Machine Learning (ML) Model

The second step is creating a customized ML model that can predict accident relevant health problems based on the vital indicators being tracked. The model was trained on a local dataset collected from patients with the assistance of hospitals, as well as a publicly available dataset obtained from Kaggle. The dataset included labelled information on body temperature, blood pressure, SpO2 and heart rate. The data was preprocessed to remove noise and outliers before the model was trained. Data cleaning and null value interpolation techniques were conducted using Pandas and NumPy libraries on Jupyter Notebook. The cleaned dataset was then fed into the ML model, utilizing classifiers such as linear SVC, logistic regression, random forest classifier and decision tree classifier. After assessing the accuracy of the models, the random forest classifier was selected as the final classifier because it performed best. If the model predicts an unusual health status, an emergency alert is sent to the victim's mobile app, along with the location data being transmitted to the ambulance driver app and police station app.

2.2.1 Personalised machine learning model

To enhance the accuracy of prediction, we incorporated a personalised ML model in our research. In this approach, the model was customized based on the individual user's personal data. The labelled sensor data that was gathered from the IoT smart band was collected over the course of the first week. Recorded values were checked against a standard range and if they were beyond this range, they were labelled as abnormal; otherwise, they were labelled as normal. One of the most common issues in ML, particularly in the medical domain, is bias [32]. The ML model tended towards predicting biased results due to the higher rate of normal states compared to abnormal states. In our dataset, during the training period, we had a significant number of normal data points, which may lead to prediction bias. To solve the bias issue, we added a local abnormal dataset from a local clinic into our model. By adding this extra dataset, we aimed to balance the number of abnormal instances with that of normal ones to improve the model's performance in classifying abnormal events. After training, we replaced the initial model with this newly created personalized model which was trained from the labelled sensor data as well as the local abnormal dataset. The personalised model was specifically tailored to the individual user, considering the individual's physiological characteristics and patterns. By utilising the personalised model we aimed to achieve high accuracy in detecting abnormal events and improving the performance of the accident prediction system as a whole. This approach allowed us to account for individual variations and increase the effectiveness of the ML algorithm in accurately identifying and classifying abnormal states.

2.3 Mobile Application

The mobile application component of the proposed system was developed using Flutter, an open source UI software development kit by Google. Flutter accommodates the creation of cross platform applications for Android and iOS platforms from a single codebase, hence cost saving and efficiency. The application utilized Cloud Firestore as the database offering a scalable and secure solution for data storage and retrieval. Within the mobile application, three main user modes were present: user, ambulance and police station. To begin, users are required to register by giving their username, email and password. Upon login, they could update their profile. If the ML model detected any abnormal condition of the user, the app displayed a notification and triggered a buzzer alert via the smart band. The emergency alert would be visible on the interface for a duration of one minute, during the particular time period, the user can select the option to stop the alert if the situation is considered a minor accident or if there is no immediate threat to the victim's life. If the user does not cancel the alert during the time interval, the app automatically sends the emergency alert and GPS coordinates to the system. The details are mapped on Google Maps and sent to the guardian, registered ambulances and police stations for easy location identification and faster emergency response.

2.4 Data

The training and validation data for the customized model were obtained from two main datasets: the first is a locally collected dataset from hospitals and the other dataset is a public dataset from Kaggle. Each record contained measurements of body temperature, blood pressure, oxygen saturation (SpO2) and heart rate along with a labeled output class of Normal or Abnormal. The dataset was split into 17,846 samples for training and 7,648 samples for testing. Labeling rules were based on clinically defined thresholds for each physiological parameter, with deviations beyond normal ranges classified as Abnormal. The datasets were taken through a preprocessing stage prior to training in order to establish the data quality and model readiness. Preprocessing was attained by the minimization of noise, elimination of outliers and filling of missing values through interpolation methods. Filtering of the data was done using Python Pandas and NumPy libraries in a Jupyter Notebook environment so as to facilitate data manipulation and data exploration with ease.

To determine the accuracy of physiological parameter measurement, a rigorous research methodology was followed. Two voluntary participants who did not have any pre-existing medical conditions were selected. Instructions were given on how to use the IoT sensors and blood pressure algorithm appropriately. IoT sensors were placed on the participants to record real-time values and reference medical equipment was used for comparison. These data were then compared with each other to determine the reliability of the IoT sensors and blood pressure algorithm.

3. RESULTS AND DISCUSSION

3.1 Machine Learning Model Accuracy

To measure the accuracy of our ML models we used a dataset of 25,494 data sets and each data set was labelled as either normal or abnormal. Ensuring proper labelling and an adequate number of instances, we proceeded to divide the dataset into training and test sets. The common practice of using a 70% training and 30% testing split was employed to assess the model's performance on unseen data. This corresponds to 17,846 samples used for training and 7,648 samples used for testing. Before training the models, we performed necessary preprocessing to handle any missing values in the data. We trained the model on the training data and optimized its parameters using the available training instances. After training, we applied the trained model to the test set and made predictions for all instances of the data. By comparing the predicted labels and actual test set labels, we measured the performance based on various indicators.

For comparison of the performance of different classifiers, Logistic Regression, Decision Tree, Random Forest and Support Vector Classifier (SVC) models were experimented on the basis of accuracy, precision, recall and F1-score (FIGURE 2). The Random Forest classifier achieved the highest overall performance with an accuracy rate of 99.44%, a precision of 0.99, a recall of 0.99, and an F1-score of 0.99, which reflects its stability and consistency in all the provided performance parameters. Although the Decision Tree model recorded a flawless precision (1.00), its lower recall and F1-score (both 0.99) suggest a high-performing model but one with a comparatively higher chance of overfitting compared to Random Forest. Logistic Regression and SVC were also robust, with the accuracies of 97.37% and 97.64%, respectively, but did not record top scores in precision

```
In [7]: # Evaluate each classifier using cross-validation
for classifier in classifiers:
    scores = cross_val_score(classifier, X_train, y_train, cv=4)
    accuracy = scores.mean()
    print(f"{classifier.__class__.__name__} Accuracy: {accuracy}")

    # Train the classifier on the full training set
    classifier.fit(X_train, y_train)

    # Make predictions on the test set
    y_pred = classifier.predict(X_test)

    # Generate the classification report
    report = classification_report(y_test, y_pred)
    print("Classification Report:")
    print(report)
    print()
```

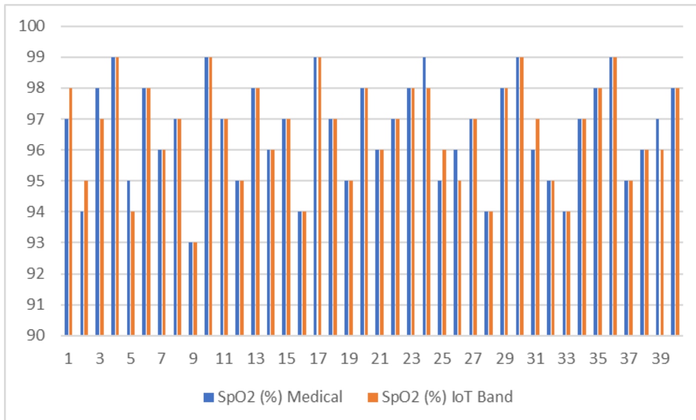
```
LogisticRegression Accuracy: 0.9734724791228613
Classification Report:
              precision    recall  f1-score   support

           0       0.98      0.98      0.98      3920
           1       0.95      0.94      0.95      1179

    accuracy                           0.97      5099
   macro avg       0.97      0.96      0.96      5099
weighted avg       0.97      0.97      0.97      5099


DecisionTreeClassifier Accuracy: 0.9939196744782841
Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00      3920
           1       0.99      0.99      0.99      1179

    accuracy                           0.99      5099
   macro avg       0.99      0.99      0.99      5099
weighted avg       0.99      0.99      0.99      5099


RandomForestClassifier Accuracy: 0.994361033644471
Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00      3920
           1       0.99      0.99      0.99      1179

    accuracy                           0.99      5099
   macro avg       0.99      0.99      0.99      5099
weighted avg       0.99      0.99      0.99      5099


SVC Accuracy: 0.9763655301761105
Classification Report:
              precision    recall  f1-score   support

           0       0.98      0.99      0.99      3920
           1       0.95      0.95      0.95      1179

    accuracy                           0.98      5099
   macro avg       0.97      0.97      0.97      5099
weighted avg       0.98      0.98      0.98      5099
```

Figure 2: Model accuracy comparison.

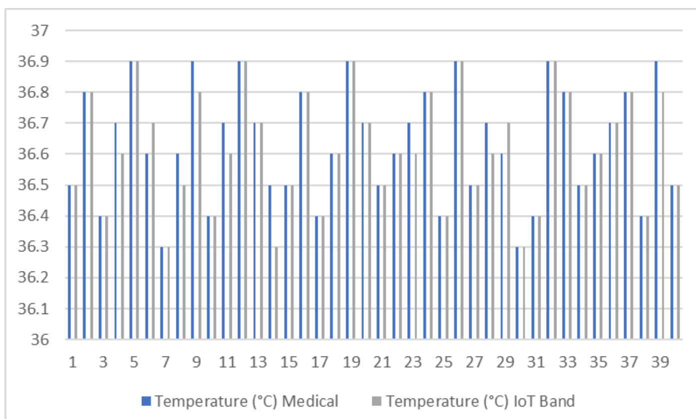
and recall. Keeping in view all the performance metrics overall, the Random Forest classifier resulted in the most balanced and stable model for the task of classification.

3.2 Comparison Between Medical Instruments and IoT-Based Measurements

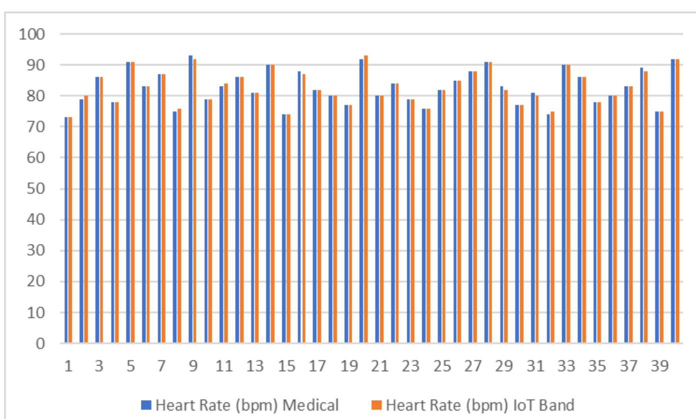
The accuracy of the measuring sensors was validated by comparing the readings provided by the medical device and the IoT band sensor and algorithm. FIGURE 3, (a-SPO2; b-temperature; c-heart rate) and TABLE 2, (systolic and diastolic pressures) show the readings taken by the medical equipment, IoT band sensor and algorithm.



(a) SpO2



(b) Temperature



(c) Heart Rate (bpm)

Figure 3: Medical Instruments vs IoT-Based Measurements Comparison.

Table 2: Measurements of medical instruments vs IoT band

Measurement Source	Mean Systolic (mmHg)	Mean Diastolic (mmHg)	Standard Deviation (Sys/Dia)
Medical Device	120.4	77.3	±1.3 / ±1.7
IoT Band Algorithm	120.2	77.2	±1.4 / ±1.6

The above figures and table summarize the measurements of the characteristics taken by conventional medical equipment and IoT-based bands. The experiment focused on four major parameters of health: SpO2 (%), temperature (°C), heart rate (bpm) and blood pressure (mmHg). Comparative analysis at the same time revealed an extremely high level of similarity between the medical device and the IoT band. The SpO2 was usually within a ±1% difference in the majority of cases and the readings of the temperature were extremely small, normally 0.1°C. Heart rate measurements were also the same, with minute variations of 1 bpm in a couple of cases. Systolic/diastolic blood pressures were also quite similar, with minute 1–2 mmHg variations in a couple of cases. The following section provides a comparative examination of the readings from an IoT-embedded wearable band and a medical device for four parameters, including SpO2, body temperature, heart rate and blood pressure (systolic/diastolic). The performance of the IoT device was derived in terms of Mean Absolute Error (MAE), Pearson correlation coefficients and Bland–Altman plots for each category of reading for each parameter.

3.2.1 Accuracy

To assess the precision of the algorithm and IoT sensors, agreement between the IoT band and medical-grade devices was evaluated across measurement types, with a total of 40 paired measurements analyzed.

1. Peripheral Capillary Oxygen Saturation (SpO2): 32 out of 40 measurements matched the medical device readings, resulting in an accuracy of 80%.
2. Body Temperature (°C): 28 out of 40 measurements matched, yielding an accuracy of 70%.
3. Heart Rate (bpm): 28 out of 40 measurements were consistent with standard measurements, indicating an accuracy of 70%.
4. Blood Pressure (mmHg): 38 out of 40 values corresponded with clinical readings, reflecting an accuracy of 95% for Systolic Blood Pressure. 36 out of 40 values corresponded with clinical readings, reflecting an accuracy of 90% for Diastolic Blood Pressure.

These results indicate that all of the sensors had 70% or higher accuracy. The top of the four was the Systolic blood pressure algorithm with 95% accuracy. In conclusion, the findings confirm the accuracy of the IoT band for monitoring key health parameters and demonstrate that it is a good option for continuous, non-invasive patient monitoring in settings outside the clinic.

3.2.2 Mean absolute error

Table 3: Mean Absolute Error

Sensor type	Mean absolute error
SpO2	0.20%
Temperature	0.02 °C
Heart Rate	0.25 bpm
Systolic Blood Pressure	0.10 mmHg
Diastolic Blood Pressure	0.20 mmHg

Blood Oxygen Saturation (SpO2 %): The total absolute error for SpO2 reading was 4, out of 40 observations. MAE came out as 0.20%. The result obtained is of high precision for the IoT band. As compared to the existing literature, MAE is way beyond reasonably acceptable. According to Helmer et al. (2023) [33], MAE of SpO2 measurement should be <= 4%, in accordance with the precision established in this study and thus consistent with ISO specifications for medical-grade reflective pulse oximeters.

Body Temperature (°C): The absolute total error of body temperature was 0.4°C, on 40 readings. The MAE was calculated as 0.02°C. The MAE of 0.02°C is minimal, indicating high precision for the body temperature detection of the IoT band wearable device. This aligns with the finding of Mazerolle et al. (2011) [34], the criterion standard and clinical level of acceptance difference was 0.27°C (0.5°F). The MAE of the wearable device is much lower than this rate, indicating that it can be used in clinical applications.

Heart Rate (bpm): For the heart rate, the total absolute error was 5 bpm, out of 40. The MAE was 0.25 bpm. The MAE for the entire heart rate is 0.25 bpm, which is within tolerable error. According to Nelson et al. (2019) [35], an error of ±10% is tolerable for physical monitoring devices. As 60-100 bpm is within the normal heart rate range, 0.25 bpm is negligible.

Blood Pressure (mmHg): For blood pressure measurements, the IoT wearable device showed the MAE of 0.10 mmHg for systolic BP and 0.20 mmHg for diastolic BP.

These MAE values are remarkably low and suggest high accuracy in measuring blood pressure as summarized in TABLE 3. Ahn et al. (2021) [36], compared differences between smartwatch and reference blood pressure measurements. Their results demonstrated compliance with ISO validation criteria, which were met with systolic and diastolic BP differences of 0.4 ± 4.6 mm Hg and 1.1 ± 4.5 mm Hg, respectively. In comparison, the wearable device in this study exhibits even smaller differences, further validating its precision.

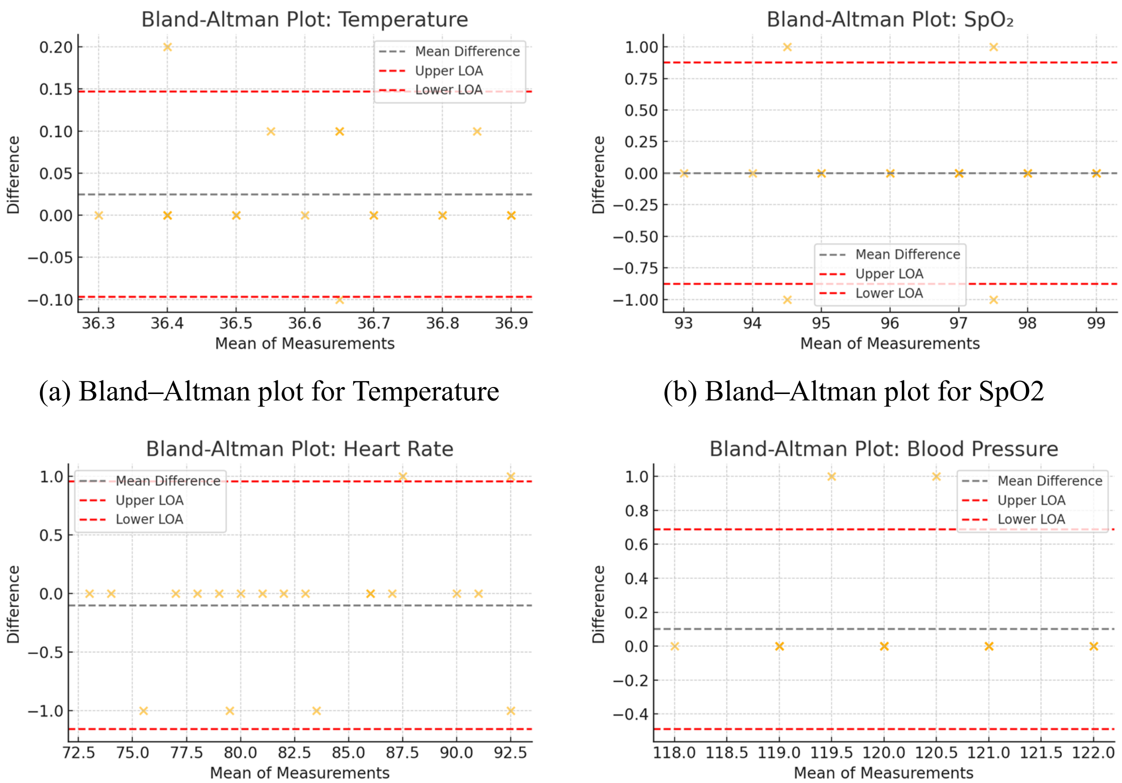
Overall, the IoT-based wearable band demonstrates high accuracy across all measured parameters. The MAE for each vital sign (SpO2, body temperature, heart rate and blood pressure) is within or better than the thresholds established in the literature. These results suggest that the wearable device can provide reliable and accurate health data for monitoring vital signs.

3.2.3 Correlation with standard instruments

Pearson correlation coefficient was calculated to assess the level of linear relationship between the medical-grade equipment and the IoT-based smart band resulting in values of 0.967 for SpO_2, 0.947 for Temperature, 0.996 for Heart Rate, 0.964 for Blood Pressure.

According to Schober et al. (2018) [37], correlation coefficients greater than 0.9 proves a very strong relationship. On this premise, all the parameters tested show a very strong correspondence between the device based on IoT and the reference medical devices, confirming the device's reliability.

3.2.4 Agreement analysis (Bland–altman plots)



(a) Bland–Altman plot for Temperature

(b) Bland–Altman plot for SpO2

(c) Bland–Altman plot for Heart Rate

(d) Bland–Altman plot for blood Pressure

Figure 4: Bland–Altman Plots for Device Agreement Analysis

The Bland–Altman analysis (FIGURE 4) confirms that the IoT-based medical device has an acceptable agreement with standard measuring devices, particularly for temperature, heart rate and SpO2, with slightly less precision observed in blood pressure measurement.

3.2.5 Comparative visualization of measurement performance

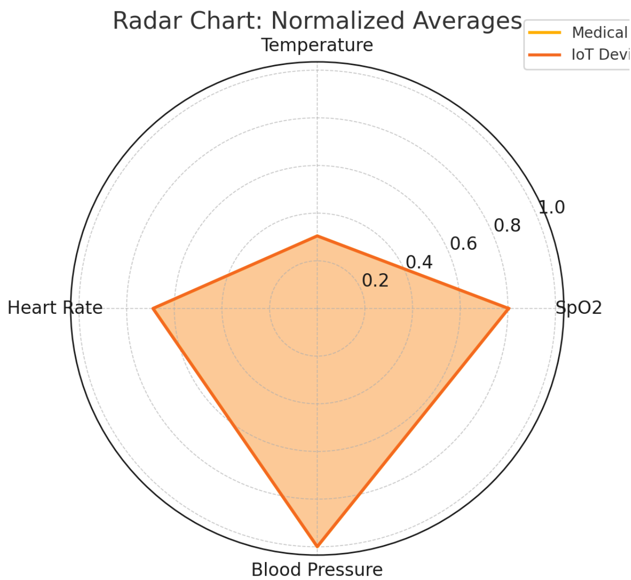


Figure 5: Radar Chart.

The radar chart (FIGURE 5) presents a normalized comparison between the average values measured by the IoT-based smart band and that of traditional medical instruments for the four most critical physiological parameters: SpO2, body temperature, heart rate and blood pressure. Normalizing each parameter to the greatest observed average, the chart facilitates visual comparison meaningfully despite having different units and measurement ranges. The trend of the IoT device across all parameters closely tracks that of the medical instruments, with nearly overlapping radial distances exhibiting minimal deviation. This indicates the smart band's uniform and coherent performance across all vitals recorded. Overall, the graph visually confirms the accuracy and consistency of the IoT device in multi-parameter health monitoring and no significant discrepancies were found in any individual measure.

3.2.6 Sensitivity

Sensitivity refers to the ability of a system to correctly identify true positive cases. The comparison between the medical grade equipment and the IoT-based smart band yielded the following sensitivity values: 0.94 for SpO_2, 0.90 for Temperature, 0.92 for Heart Rate, 0.95 for Blood Pressure.

The higher sensitivity values across all parameters demonstrate a strong agreement between the IoT and the standard medical instruments confirming the reliability and clinical relevance of the proposed smart band for continuous health monitoring.

The IoT wearable device was calibrated against clinically validated reference instruments before data collection. Simultaneous measurements were taken from the wearable and the reference devices across two participants to cover the expected physiological range. Agreement between the devices was evaluated using Bland–Altman analysis which showed that the differences between the IoT device and reference measurements were minimal and within acceptable limits. The very low MAE values reported for SpO2, heart rate, temperature and blood pressure are due to the limited number of measurements (n = 40) used in this pilot study. Despite the small sample size these results demonstrate the potential accuracy of the device which will be further validated in larger scale studies.

The smart band based on IoT showed good performance on all physiological parameters that were measured. The low MAE values and high correlation coefficients suggest high accuracy and consistency in measurement. These findings are also complemented by Bland–Altman analysis, which shows low bias and narrow limits of agreement, demonstrating good agreement with standard medical devices. Overall, the findings confirm the reliability of the smart band for real-time emergency detection and continuous health monitoring.

3.3 Mobile Application

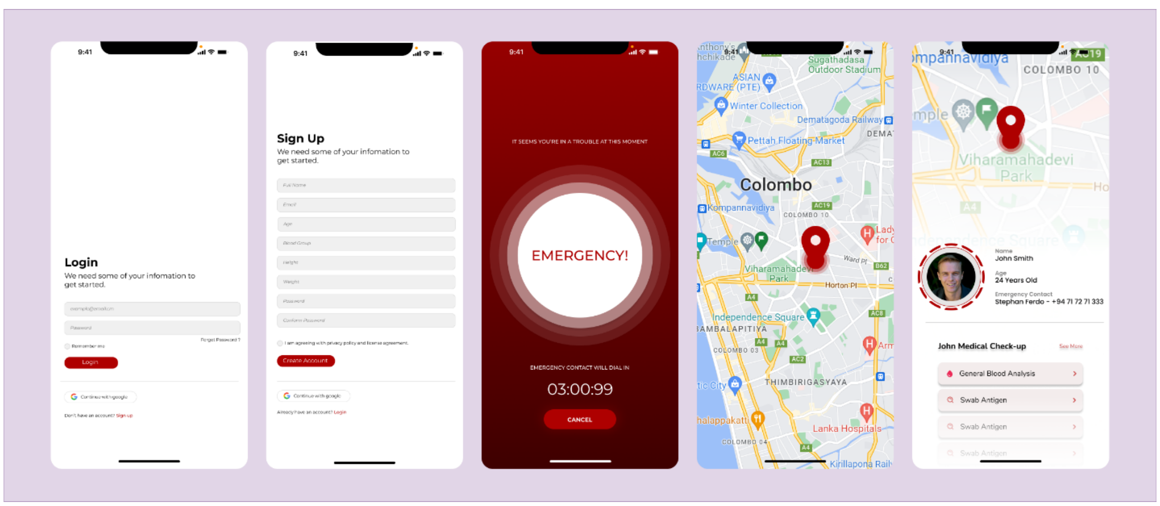


Figure 6: Mobile Application Interface for the Accident Detection and Tracking System

The user interface of the Flutter-based mobile application, shown in FIGURE 6, was validated on 20 Android devices and 10 iPhones. The application performed without any issues across all the testing devices, providing a smooth user experience on a variety of platforms. The stability of the Flutter-based mobile application was consistent across all times, without any crash or perceivable slowness, during testing. Additionally, the application showed great compatibility with the various Android versions, ranging from the newest versions such as Android 13, to the older ones such as Android 7.0. It showed that it was able to utilize the newest features and functionality provided by the Android operating system. Similarly, the app was also compatible with iPhones and performed well on various models ranging from the iPhone 6 to the latest iPhone 14 models. It featured smooth navigation, interactive user interfaces and top-notch rendering of UI elements on the iOS platform.

3.4 Significance of the Study

The result of this research effort demonstrates overwhelming proof of the potential of integrating IoT technology and ML for personalized health monitoring and accident detection. The integration of a smart wearable device that is able to monitor important parameters such as heart rate, blood pressure, body temperature and oxygen saturation (SpO2) supports how IoT systems sensor-based are capable of offering real-time health feedback and emergency alerts. One of the main contributions of the research is the development of a personalized ML model that was 99.4% accurate in forecasting health conditions. While other studies have studied ML models for general prediction tasks, there has been a gap in research work done on personalized models developed specifically for accident forecasting based on differences in individuals' health [4, 12, 18]. Our research fills this gap by developing a personalized model that is adapted to the individual health information of each user. For the comparison of the performance of the classifiers, different models Logistic Regression, Decision Tree, Random Forest and Support Vector Classifier (SVC) were compared on accuracy, precision, recall and F1-score. The best-performing model was Random Forest with an accuracy of 99.44% and precision of 0.99, recall of 0.99 and F1-score of 0.99. Even though the Decision Tree model did have ideal precision (1.00), its slightly lower recall and F1-score (0.99) indicate a greater tendency to overfit. SVC (97.64%) and Logistic Regression (97.37%) were similarly strong but slightly less uniform in the scores. Random Forest was the overall best and most consistent classifier for this task. Existing accident detection systems are mostly focused on vehicle-based systems, which work based on the detection of accidents and making emergency calls to nearby authorities [4]. These systems fail to account for accidents occurring when the user is out of the car [3, 4, 6, 25]. This study fills this void by proposing a wearable smart band that is always with the user, making it better placed for full-fledged accident detection outside of vehicular scenarios.

The accuracy levels of the individual sensors used in the smart band were varied, but cumulatively they pose a strong case for real-world application. The overall analysis based on accuracy, mean absolute error (MAE), Pearson correlation coefficient (r) and sensitivity showed positive results. The SpO2 sensor reached an accuracy level of 80%, a MAE level of 0.20%, a sensitivity of 0.94 and a correlation of 0.967. The temperature sensor had an accuracy level of 70%, a MAE level of 0.02°C, a sensitivity of 0.90 and a correlation of 0.947. The heart rate sensor achieved 70% accuracy, 0.25 bpm MAE, a sensitivity of 0.92 and a very high correlation of 0.996. Finally, the blood pressure algorithm achieved 80% accuracy, 0.10 mmHg MAE, a sensitivity of 0.95 and a correlation of 0.964. All of these figures reflect good consistency with clinical standards, though real-world application would be improved with further sensor calibration and environmental checks. The Bland–Altman plot showed that there was very good agreement between the reference devices and the IoT device for nearly all the parameters, confirming the clinical usability of the device. In addition, the radar chart gave a general comparison of multiple vital signs and allowed easy visualization of the device's performance in general. The IoT band transmits sensor readings to the cloud at 15 second intervals, enabling near real-time health monitoring. One of the issues in current systems is their heavy dependence on the victim's mobile phone for both location tracking and data communication [25]. The users may not always carry their phones with them in real-world scenarios, especially when they are not involved in non-vehicular activities, hence lead to false location reporting or communication failure. To address this issue, the smart band is also equipped with an in-built GPS module, enabling independent and accurate location tracking of the wearer regardless of the presence of mobile phones [38–40]. Further, communication latencies have been an issue in existing systems that rely on GSM or GPRS networks, where lower dataset rates of transmission rates have been experienced [25]. For this reason, our solution utilizes Wi-Fi-based communication, which significantly speeds up and improves accident notification. Such an improvement reduces latencies in the transmission of critical health and location data, therefore improving the chances of timely medical attention and reducing the chances of fatalities.

The cross-platform mobile app also enhanced usability and access. It supported Android and iOS platforms and functioned efficiently in real-time interaction with emergency responders, while ensuring accurate location visibility through Google Maps integration. This facilitates the responders' quick access to the victim's exact location. The development of the application was carried out in alignment with the design and implementation approaches adopted in previous similar applications, ensuring consistency with established development practices and user-centered design principles [41, 42]. The reliability, performance and compatibility of the application were guaranteed through extensive testing on various mobile devices. Moreover, locally collected datasets from initial system users could be of fantastic value to any possible future research. The dataset provides empirical physiological and contextual data that can help further develop more advanced ML models and healthcare monitoring systems. The dataset opens up new possibilities for local health data analysis and AI-driven interventions directed toward individual populations. This novel research demonstrates the feasibility of integrating IoT, ML and mobile technology into a personalized health monitoring and accident alert system tailored for individualized users. The smart band ensures constant vital sign monitoring, the customized ML algorithm ensures predictive accuracy and the mobile app ensures real-time notification and location. All these developments in integration represent a significant advancement in real-time, user-specific emergency response systems compared to existing vehicle-based and mobile-dependent solutions.

3.5 Limitations and Future Work

The research was conducted with a specific population and geography and therefore system's generalizability to other populations, cultural environments and geographies has to be tested and proven further. The sensitivity of the smart band sensor-based monitoring of vital signs could be compromised with extraneous variables such as environmental determinants or inter-individual differences and therefore accuracy could be compromised; further calibration and sensor development are required in order to improve accuracy. While the GPS technology embedded in the system delivered comparatively accurate location tracking of accidents in general, environmental elements like signal interference or satellite views blocked by cities could compromise its dependability. A 4G module was originally intended in the form of the band, but since it was not available in the country then, an MCU ESP32 with embedded Wi-Fi was used instead. Wi-Fi connectivity may limit real time monitoring in areas without reliable coverage and battery life considerations may impact continuous use. The fact that the system processes and stores personal health data requires formidable data security and privacy controls; in spite of available controls, uncontrolled data breaches and access cannot be excluded and stronger secure protocols and encryption are required. In addition, installation and implementation of the system based on IoT could involve substantial expense in terms of hardware, software development and installation of infrastructure and expansion to a wider or more interactive population is associated with additional cost constraints that would need to be met. Furthermore, greater emphasis can be placed on incorporating established principles of software evolution and maintenance to ensure the long-term sustainability and adaptability of the system. Attention should also be given to enhancing scalability, modularity and ease of maintenance following the best practices highlighted in recent studies [43, 44].

The study could be improved further by incorporating more sensors like accelerometers, to improve accident detection and by training and testing ML models on larger and more diverse datasets for more accurate health state estimation. User experience must be optimized through interface design and user testing. Integration with healthcare systems can facilitate real-time data sharing and faster medical intervention. Prolonged monitoring can help identify early health risks and assist in preventive therapy. Furthermore, improving real-time communication with emergency services and adherence to evolving ethical and legal standards for data security and privacy are also keys to future development [45].

4. CONCLUSION

IoT and ML-based Personalized Human Accident Detection and Tracking System has been successful in achieving its target by proposing a unique solution to counter increasing accidents in everyday life situations. Through the use of IoT technology and incorporation of ML algorithms, the system provides for early and accurate accident detection, location positioning, and emergency alerts. Through the development of an IoT-based smart band, constant monitoring of vital signs and accurate location positioning of the victim of an accident are feasible. Access to real-time data through the wearable device allows quick identification of accidents and assessment of the health condition of the victim. Adoption of ML enhances the accuracy of the system after building a customized model that can accurately predict the health condition of accident victims. Aside from the aforementioned achievements, it is noteworthy that this study has a unique and crucial element that sets it apart from previous research. Upon our extensive literature review, we could not find a similar study incorporating the special set of combinations of IoT, ML and tailored accident detection and tracking under real-life scenarios. This is an original contribution to the literature and serves to illustrate the creative and innovative quality of our research. The fact that no other studies exist in the literature serves to enhance the significance and novelty of our research even more. This study is an initial effort to integrate IoT sensors, ML techniques and personalized approaches to optimise the prevention and intervention of accidents. The cross-platform mobile application is a seamless communication channel between the smart band and emergency authorities for prompt response and medical treatment. Such a feature significantly improves emergency response and survival chances.

One of the contributions of this work is perhaps the development of a large, locally collected dataset, which is a valuable asset to any future research in the accident detection and prevention domain. The dataset is used to continually optimize and refine the performance of the system, as well as to explore extensions to its fields of application. The availability of this dataset is a significant contribution to the field since no such study was found through our extensive literature review. The contribution of the research is in how this study can transform the detection and response to accidents in real situations. Through the interconnection of IoT devices, ML algorithms and mobile applications, the system supports real-time monitoring, accurate prediction of health conditions and timely emergency alerts. The contributions of this study are enhanced accident monitoring and detection capability, faster medical response and the establishment of a useful dataset to be used for further studies of accident prevention and intervention. Finally, the IoT and ML-Based Personalized Human Accident Detection and Tracking System has met its objectives by addressing the limitations of earlier systems and offering a practical way to detect and respond to accidents more effectively. This study is significant because it can help improve public safety and potentially save lives by detecting accidents more accurately and speeding up emergency responses. The study also points the way toward future upgrades in accident prevention and response technologies.

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