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AI-PaaS: Towards the Development of an AI-Powered Accident Alert System

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***Abstract*— The development of an accident detection system is a crucial step towards improving emergency response times, saving lives and achieving the ambitious projection of the United Nations General Assembly to drastically reduce the global fatality rate of road traffic crashes by half by the year 2030. It is also cardinal to the attainment of the United Nation's SDG 11 goal of making cities and human settlements inclusive, safe, resilient and sustainable. In this study we present a preliminary development of an AI-powered Accident Alert System (AI-PaaS). The system has four modules namely, sensors module, detection module, registration module and messaging module. The detection module is powered by sensing technology and the Hidden Markov Model to intelligently and correctly detect that an accidents sound. The MPU 6050 containing both accelerometer and gyroscope is also integrated to detect any sharp variation in the acceleration and angular vis-à-vis a predefined threshold value. Once an accident has been detected, the messaging module is triggered to communicate first responders and the victims' pre-registered kin. Preliminary results are presented. The system can potentially reduce road accident fatality by providing accurate and timely location-based information to emergency service providers.**

Keywords*— *Hidden Markov Model, Accident detection and alert, IoT, Machine Learning, Artificial Intelligence, Sensors.

I. Introduction

An accident is an undesired, unplanned incident, typically resulting in damage or injury. Perhaps the most common form of accidents is road accident. Road accident is one of the leading causes of death in the world, accounting for about 1.8 million deaths as at 2015, and is projected to top 2 million deaths by 2030 [1]. Road accident fatalities is the leading cause of death for children and young adults aged 5-29 and low to middle-income economies accounts for 93% of these fatalities [2]. Specifically, road mortality ranks among the top leading cause of death in low-income countries (see Figure 1) [3].

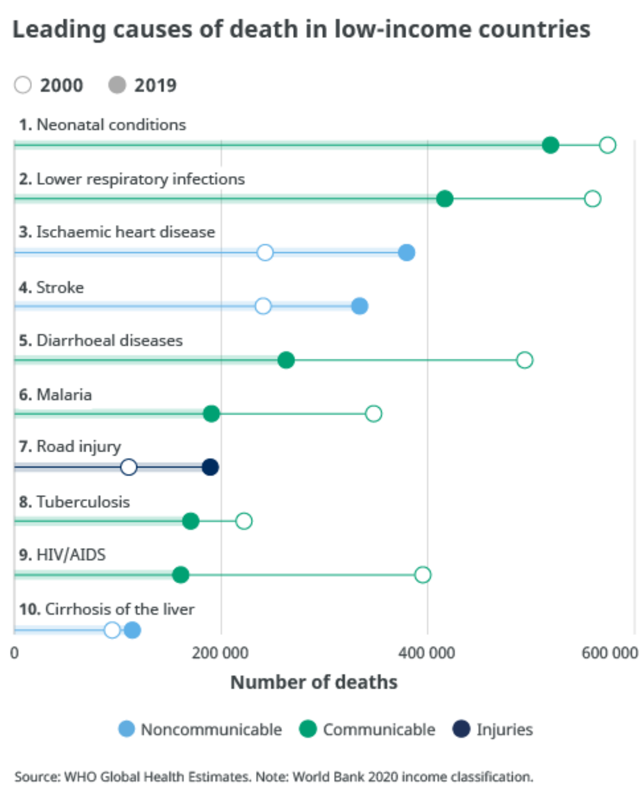

Fig. 1. The top 10 causes of death in low-income countries (World Health Organization, 2020) [3]

Most Sub-Saharan African countries are classified as low-income countries. In Nigeria, it is estimated that road accidents are the second most prominent cause of violent deaths after insurgency [4]. Figure 2 shows a chart of the extent of the fatality of road accidents from 2007 to 2013.

Fig. 2. FRSC and Nigeria Watch records of fatalities caused by road accidents, 2007-2013 [5].

In the second quarter of 2018 alone, 2,608 occurrences of road accidents and 1,331 fatalities were recorded [6]. According to Statistica, (2023) [7], during the fourth quarter of 2021, more than 11,800 road traffic casualties were reported in Nigeria. 10.2 thousand of the reported road traffic casualties were injuries, while 1,700 were registered deaths. In the previous quarter, approximately 8.8 thousand injuries and 1.4 thousand deaths, both resulting from road traffic crashes, were counted in the country. Most road accidents occurring in Nigeria are classified as serious and there appear to be a gradual increase in accident fatalities. With an average of more than 4 deaths per day, Nigeria accounts for arguably the highest accident-related death cases on the African planet. This high rate of accidents has its attendant economic consequences and is most undesirable; the United Nations has estimated that accident fatalities gulp up to 3% of nations' GDP globally [2].

Getting emergency aid after the occurrence of an accident may be a major factor in the survival or otherwise of accident victims. The most prevalent way of disseminating accident information, especially in low-income countries is through 'word of mouth'. This method is both unreliable and slow. Unreliable, because the accurate location of the accident may not be effectively communicated by the reporter. Furthermore, the delayed time of reportage leads to delayed emergency response time resulting in many cases to avoidable death. It is a common scenario that people die in the event of an accident as a result of a delay or lack of medical attention. Accident victims have to rely on eye witness to call an ambulance or first responders. One of the drawbacks of this existing method is that people must be present where accidents occur. This is not always the case for accidents that happen late at night.

The aim of this study is toward the development of an IoT enabled system, which is able to detect the occurrence of an accident and accurately alert responders about the location of the occurrence. In achieving this aim, we set five research objectives which include the design a model for the automatic detection of accidents; the integration of modules such as sensing and location awareness; the development of the integrated A.I powered Low-Latent Accident Alert System (AI-PaaS); the deployment of the system on a wearable IOT based device; and, an evaluation of the model vis-à-vis some existing systems.

II. Statement Of The Problem

Getting emergency aid after the occurrence of an accident may be a major factor in the survival or otherwise of accident victims. The first post-accident hour is often referred to as the "golden hour" as victims stand a chance of survival if offered access to emergency care. It is estimated that low-income communities record twice as much post-accident fatalities compared to their high-income counterpart, due to longer response time and time taken before taking victims to the hospital [8]. Longer emergency response time can easily be traced to longer "accident notification time". According to Evanco, (1996) [9], rapid notification of accident emergencies has the potential of reducing post-accident fatalities by at least 11%. In Nigeria, post-accident responses are extremely poor [10][11]. Only a few urban communities such as Abuja, Lagos, and Port-Harcourt have a fairly organized emergency service. Even the available emergency services are deficient in the dissemination of timely accident notification. Hence, the need for an information system to provide timely notification in the occurrence of an accident. A lot of the fatalities recorded are avoidable with a timely and accurate accident notification system. This project is towards the development a low-latent IoT enabled intelligent accident alert system, equipped with an integrated automatic accident detection system as well as a location-aware alert functionality. Internet of Things (IOT) devices are computing devices that connect wirelessly to a network and have the ability to transmit data. While IoT has been in existence since the 90s, the advances in recent years in a number of different technologies have made it more practical and mainstream. The result of this study is expected to reduce accident fatality rates by enabling first responders, police, and ambulances through the provision of timely and location-aware alert. It is also expected to resolve the issue of unidentified bodies in fatal accidents that claim lives as their data has been taken before the initialization of the system.

III. Review of Literature

Accidents are an unfortunate, and all too common occurrence in today's world. Therefore, the development of automatic accident detection systems has become a fulcrum for the reduction of deaths from road accidents. Many works in the previous decades have proposed decent systems with the use of new and old technology as well as the use of hybrid methods to attack the issue of accident fatalities.

Gopi *et al.,* (2016) [12] presented a system for accident tracking and visual sharing using RFID and software-defined networking (SDN). The authors proposed a novel approach to track accidents and share real-time video footage with emergency services, using RFID technology to detect accidents and SDN to manage and route the video stream. The system architecture, includes several components such as RFID readers, cameras, SDN controllers, and a cloud-based video streaming server. The video stream is then managed and routed by the SDN controllers, which optimize the network traffic to ensure fast and reliable delivery of the video footage to emergency services. Experimental evaluation showed that the proposed system is capable of detecting accidents in real-time and delivering high-quality video footage to emergency services within a few seconds.

Raja *et al.* (2021) [13] proposed a device that senses the occurrence of the accident and reports to an emergency team. In the event of no causality, a switching mechanism is used to shut it off. This system like many previously reviewed systems proposes the use of the Arduino UNO, GSM and GPS modules, an accelerometer and a mobile phone. When an accident has occurred as determined by the accelerometer, it sends a signal to the Arduino. The GPS then tracks the location and coordinates of the vehicle and sends to the GSM module. The GSM module then sends a message to the nearest hospital and/or appropriate and authorized personnels, such as family members. This system offers a quick method of responding to emergency situations.

Sumathy *et al.,* (2021) [14] developed an IoT-based Vehicle Accident Emergency Alert System. The system detects accident via an accelerometer and triggers the integrated GPS and GPRS Modules to both detect the location of the accident and initiate a message to emergency services as well as the victims' pre-registered kins. The accelerometer detects that an accident has occurred if there is an abnormal tilting of the longitudinal and latitudinal positioning of the vehicle along the X,Y,Z axis. The system was successfully simulated on an Arduino UNO controller.

Yan and Ko, (2021) [15] proposed the development of an Accident Sound Detection algorithm by identifying tunnel accident sounds to detect traffic accidents accurately and timely prevent secondary accidents. Mel Frequency Cepstrum Coefficient (MFCC) delta-delta coefficients were used as the input data of the follow-up neural network sound detection system. The system uses deep neural network to classify tunnel sounds as either accident sounds or non-accident sounds. The system requires different sounds to be pre-processed, then their features extracted. Accident and Non-accident sounds were taken to help distinguish and establish the sound library. The features derived were then used for classifier learning. The limitation of the system is that it only detects accidents, it does not report the accident to any of the appropriate authorities.

Many of the accident detection systems nowadays make use of the GPS to track and locate the vehicle that has just been involved in an accident. In this proposed system Pathik *et al*., (2022) [16] an accident emergency system that uses a force sensor, GPS module, alarm controller, ESP8266 controller, camera, Raspberry Pi, and GSM module to automatically detect that an accident has occurred. The system is able to collect and transmit accident-related information to the cloud/server. The proposed Accident Detection and Reporting System (ADRS) comprised of 2 phases. The first phase is the detection of accident using an IOT device and deep learning methods. The IOT device developed consists of several sensors which work hand in hand to make the ADRS successful. The force sensor which is the major component of this system is used to detect and measure the impact on a vehicle, if the value of the force is above 350pa the ATMEGA328 which is a micro controller unit that controls various devices including the alert system triggers the alarm and sets a 30 seconds timer and if this timer is not reset after 30 seconds, it sends a signal to activate the NodeMCU- ESP8266. The NodeMCU- ESP8266 is a master micro controller that enables micro controllers to connect to the internet, and hence transfers all the information as regards the accident to the cloud. Raspberry pi is a small computer with an OS that allows for the connection of IOT devices. It is connected to a Pi camera which takes images and videos of the accident scene and also uploads to the cloud database. The system contains 5 databases; User personal details database, vehicle database, Hospital database, Police station database and Mechanics database. Deep learning is used in this system to help improve the accuracy of accident detection to minimize false detection rate and to tell how severe the accident is. The deep learning technique used in this model is ResNet and InceptionResnetV2. The aim of this model in the system is to inspect the video sent to the cloud and classify the videos into two 'Accident or No accident'. Once the signal is sent and the timer is reset before 30 seconds, nearby mechanics will be sent to the registered mobile number and if it is not, the location of the accident is immediately sent to nearby hospitals and police stations. The modified ResNet-50 model achieves the training and test accuracy of 99.3 and 99.4, respectively. The accident recall rate of the model is 1. Which means that all accidents that occurred were detected and recorded as accidents.

Consequently, our project proposes to reduce accident notification and response times as well as improve on the latency of accident emergency systems with the use of a wearable accident detection and reporting system embedded with a GPS sensor, an accelerometer, a pulse oximeter sensor and an optical heart rate sensor to monitor passengers' vitals throughout the entire duration of travel.

IV. THE PROPOSED METHOD

The goal of this study is to develop a working prototype of an intelligent IoT system that is able to automatically detect that an accident has occurred and send alert to first responders and victim's pre-registered kin(s). The novelties of the proposed system are as follows:

1. Real-time data collection: The IoT-based device collects data from the interacting sensors in real-time.
2. Adaptive learning: The detection mechanism of the system is powered by the feature of adaptive learning properties of the Hidden Markov Model to adapt to changing circumstances and learn from new data. This improves the system's accuracy and reduce false alarms.
3. Contextual awareness

4. Integration of multiple sensing technology.

The system is classified into four major modules. The sensors module, registration module, the detection module and the messaging module. Figure 3 depicts the interacting component of the system.

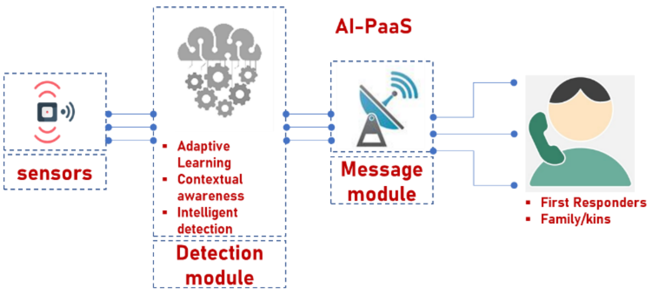

Fig. 3. Architectural depiction of the interacting components of the System

The registration is done on a networked mobile application to register the user's details and proposed system. The detection module is an integration of Machine Learning and interacting sensors. The messaging module is powered by integrated messaging controller to alert emergency responders as well as victims kins. The messaging module also integrates an incidence reporting functionality, which enables users to alert emergency responders about an incidence, such as kidnapping or robbery.

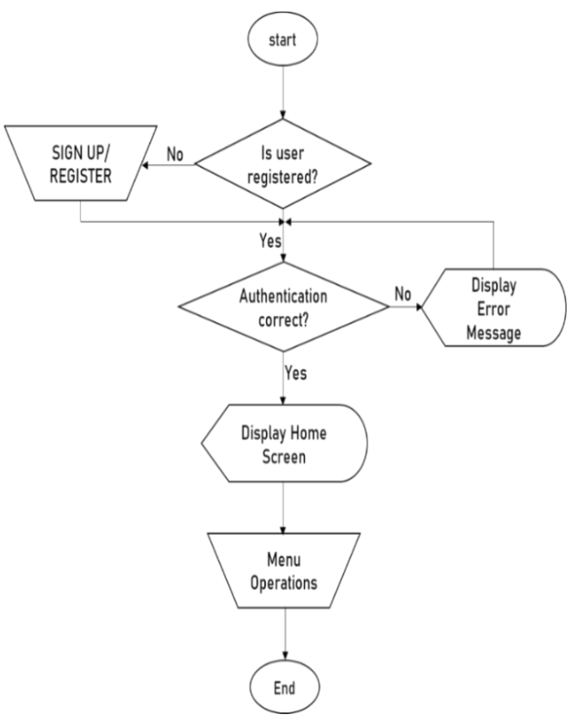

Fig. 4. Flowchart of registration module

During the registration phase, a user is required to register, his/her details, as well as that of first responders. A user may carry out other menu operation as he/she may deem fit. The flowchart of the registration module is presented in Figure 4.

The sensors module integrates four sensors, namely the acoustic sensor, pulse oximeter sensor, optical heart rate sensor, and the MPU 6050 sensor. The MPU 6050 sensor [17], is a low-cost, low-latent, low-power and light motion detection sensor that integrates 3 axis accelerometer and 3 axis gyroscope sensors. The accelerometer and a gyroscope supply complementary data about the motion of the device and the individual wearing it. The accelerometer helps determine the acceleration of the device along its three axes (x, y, and z). When an accident occurs, there may be a sudden change in the acceleration that exceeds the predefined threshold. The gyroscope provides support data on the "pose" or "orientation" of the device. A gyroscope measures the rotational velocity of the device around its three axes. In the case of an accident, the gyroscope can detect a sudden change in the rotation of the device. This change in rotation can be used as a complementary signal to the accelerometer data to improve the accuracy of the accident detection. Detecting an accident using an accelerometer and a gyroscope can be achieved by analyzing the sensor data in real-time to detect changes in movement patterns that are indicative of an accident. Algorithm 1 presents a general pseudocode for detecting an accident using these sensors.

The pulse oximeter sensor is low-cost and non-invasive and is used to monitors any spike in blood pressure, which may be indicative of a post-accident trauma or distress. The optical heart rate sensor is equally used to detect a spike in the heart rate of the user. These are possible post-accident accident health implication.

Algorithm 1: Pseudocode for detecting accidents using accelerometer and Gyroscope

Input: acceleration and rotational velocity device along x, y, and z axis

1. Collect data from the accelerometer and gyroscope sensors in real-time.
2. Calculate the magnitude of acceleration using the data from the accelerometer. This can be done using the following formula: $\boldsymbol{acceleration\_magnitude} = \boldsymbol{sqrt}(\boldsymbol{ax}^2 + \boldsymbol{ay}^2 + \boldsymbol{az}^2)$ where $\boldsymbol{ax}, \boldsymbol{ay}$, and $\boldsymbol{az}$ are the acceleration readings in the $\boldsymbol{x}, \boldsymbol{y}$, and $\boldsymbol{z}$ directions respectively.
3. Calculate the magnitude of angular velocity using the data from the gyroscope. This can be done using the following formula: $\boldsymbol{angular\_velocity\_magnitude} = \boldsymbol{sqrt}(\boldsymbol{gx}^2 + \boldsymbol{gy}^2 + \boldsymbol{gz}^2)$ where $\boldsymbol{gx}, \boldsymbol{gy}$, and $\boldsymbol{gz}$ are the angular velocity readings in the $\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{and}\ \boldsymbol{z}$ directions respectively.
4. Apply a threshold to the acceleration and angular velocity magnitudes to detect sudden changes in movement. If the acceleration and angular velocity magnitudes exceed the threshold, it is likely that an accident has occurred.

5. Determine the duration and intensity of the acceleration and angular velocity events to classify the event as a potential accident.
6. Initiate an emergency response if an accident is detected.

The acoustic sensor is the component that acquires sound/acoustic signals at the scene of the accident/crash. The acoustic signal acquired then becomes an input for the AI-powered sound detection module is enabled by the underlying Hidden Markov Model / Algorithm (HMM). First the sound detector, determines whether the sound has attained to the crash pitch threshold. 145 decibels is the average pitch of an accident crash. The algorithm is trained to determine whether the sound signal is an accident sound or not. To achieve this the HMM algorithm is trained on publicly available dataset of accident and non-accident datasets. The accident dataset used was retrieved from Kaggle https://www.kaggle.com/datasets/sobhanmoosavi/us-accidents with about 2.8 million instances consisting, a variety of intrinsic and contextual attributes such as location, time, natural language description, weather, period-of-day, and points-of-interest. An accident sound is a combination of sounds such as sudden breaking sound, crash, vehicular rollover sound, skidding wheels and so on. Another important feature of an accident acoustic signal is human distress sounds and call for help. The HMM was chosen because of its statistical ability to handle context awareness and underlying attributes. The detection framework is presented in Figure 5.

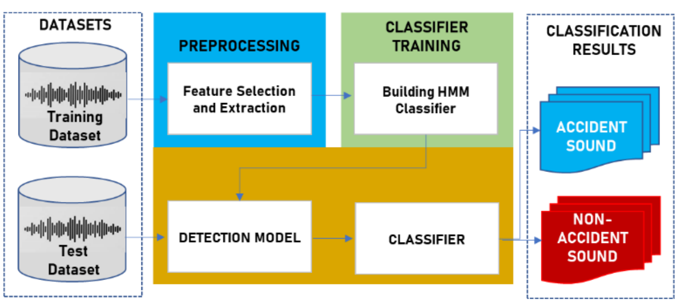

Fig. 5. Accident sound detection framework

The Hidden Markov Model (HMM) is a probabilistic graphical model used for modelling a sequence of observations. It is a generalization of the Markov chain model, which assumes that the probability of each state depends only on the previous state. The most common HMM algorithm used for classification is the Viterbi algorithm.

The Viterbi algorithm is used in a variety of applications, such as speech recognition, biological sequence analysis, and gesture recognition. The Viterbi algorithm is a dynamic programming algorithm that is used to find the most likely sequence of hidden states in a hidden Markov model (HMM). In an HMM, a sequence of observable events is generated by a sequence of hidden states according to a probability distribution. The Viterbi algorithm allows us to find the most likely sequence of hidden states given a sequence of observations and a model of the HMM. The Viterbi algorithm block diagram is presented in Figure 6.

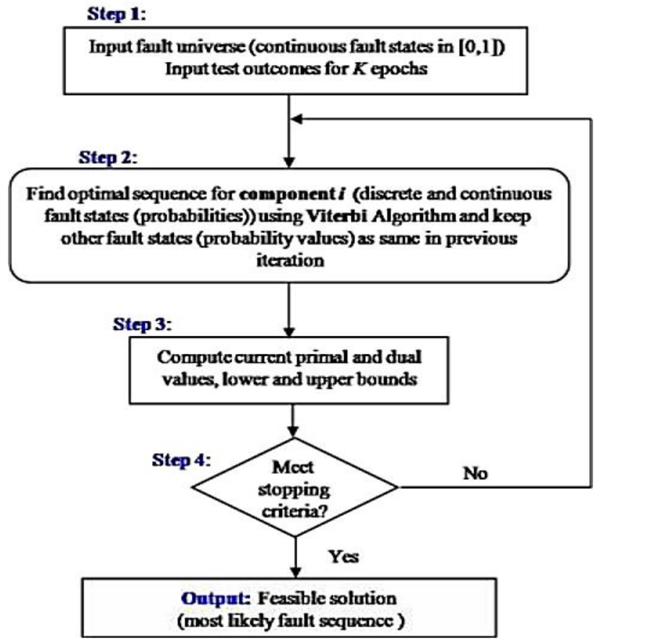

Fig. 6. Flowchart of the block coordinates of Viterbi algorithm [18]

The algorithm works by iteratively computing the probability of being in each possible state at each time step, based on the probabilities of transitioning between states and emitting observations from each state. The probabilities are stored in a matrix, and the algorithm uses the values in the matrix to backtrack and find the most likely sequence of states. In this context, sound signal is decomposed into five states as described by Vacher *et al.,* (2007) [19]. The states are "transient", "tonal" and "residual". The other two are the silent component of the audio at the beginning and end. A transition occurs from state q_i to q_j if $i = j$. Figure 7 presents the HMM state transition as proposed by Vacher *et al.,* (2007).

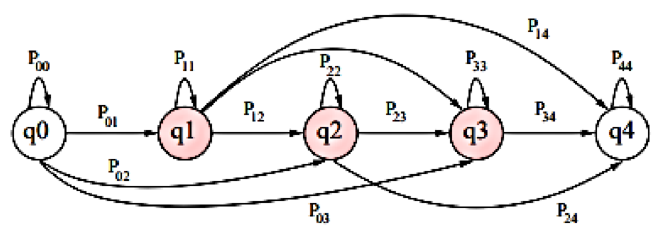

Fig. 7. HMM state transition (Vacher *et al.,* 2007)

Let $S = \{s_1, s_2, \dots, s_n\}$ be a set of states,

$A = \{a_1, a_2, \dots, a_m\}$, be a set of possible observations,

$P = \{p_{11}, p_{12}, \ldots, p_{1n}, p_{21}, p_{22}, \ldots, p_{2n}, \ldots, p_{n1}, p_{n2}, \ldots, p_{nn}\}$ be a set of transition probabilities from state S_i to S_j respectively,

$O = o_1, o_2, \ldots, o_m$ be a set of emission probabilities from state S_i to observation O_j respectively

$V = v_1, v_2, \ldots, v_n$ be a set of values of the Viterbi algorithm,

The mathematical model for the Viterbi algorithm can be written as follows:

$$V(1) = max\{p_{1i} * O(1, i) \mid i \in S\} \quad (1)$$

$$V(i) = max\{V(i-1) * p_{ik} * O(i, k) \mid k \in S\} \quad (2)$$

The most likely sequence of states is given by:

$$s* = argmax\{V(n) | n \in S \quad (3)$$

The system sounds a distinct beep sound to alert the user of its detection status and start a countdown of 30 seconds while it beeps. It is assumed that the user has been incapacitated if no user action is taken at the expiration of the 30 seconds. This triggers the messaging module.

The GPS sensor picks a pin-point longitude/latitude reading of the site of the accident and relays it on the google map API to identify landmarks for descriptive purpose. The geo-location of the accident site, with a description using the identified landmark, as well as possible status of the victim, based on the pulse reading are relayed as a message to emergency service providers nearby, and the victim's pre-registered next-of-kin. Figure 8 illustrates the working of the AI-PaaS.

Fig. 8. AI-PaaS Illustration

V. Proof of Concept

Proof of Concept is presented herewith in terms of description of devices to be used as well as preliminary results obtained.

ARM-based SOC (Advanced RISC Machine based System On Chip). An ARM-based SoC (System-on-a-Chip) is a type of computer chip that integrates various components of a computing system onto a single chip. It is based on the ARM (Advanced RISC Machines) architecture, which is a type of reduced instruction set computing (RISC) architecture designed for embedded systems and mobile devices. An ARM-based SoC typically includes a processor core, memory, input/output (I/O) interfaces, and other peripherals such as graphics processing units (GPUs), audio and video codecs, and network interfaces. These components are all integrated onto a single chip, which helps to reduce the size, power consumption, and cost of the computing system. In figure 9, the ARM-based SOC design is presented.

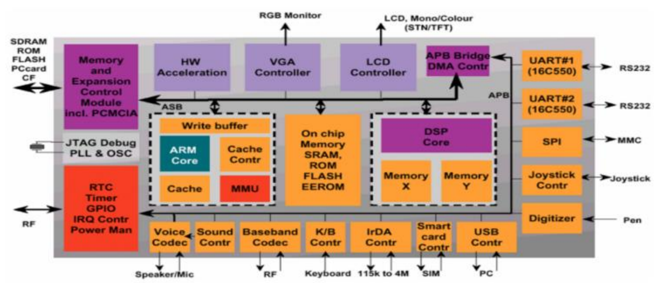

Fig. 8. ARM-based SOC design

ARM-based SoCs are widely used in smartphones, tablets, and other mobile devices, as well as in embedded systems such as smart home devices, automotive systems, and industrial control systems. They offer a balance of performance, power efficiency, and flexibility that makes them well-suited for these applications. Some examples of ARM-based SoCs include the Qualcomm Snapdragon series, Samsung Exynos series, and Apple A-series chips used in their respective devices.

Below is a part of code generated for the classification of sounds using HMM.

```
import numpy as np
from hmmlearn import hmm

# Load the data
accident_sounds = np.loadtxt('accident_sounds.txt')
non_accident_sounds = np.loadtxt('non_accident_sounds.txt')

# Create the HMM model
model = hmm.GaussianHMM(n_components=2, covariance_type="diag", n_iter=1000)

# Train the model on the data
X = np.concatenate((accident_sounds, non_accident_sounds), axis=0)
lengths = [len(accident_sounds), len(non_accident_sounds)]
model.fit(X, lengths)

# Test the model on new sound data
test_sound = np.loadtxt('test_sound.txt')
test_logprob, test_labels = model.decode(test_sound.reshape(-1, 1), algorithm="viterbi")
if test_labels[-1] == 0:
    print('The sound is classified as an Accident Sound')
else:
    print('The sound is classified as a Non-Accident Sound')
```

The mobile component of the system has been developed. Figure 10 depicts the registration module page. The page allows users to create an account, that is linkable to the IoT system.

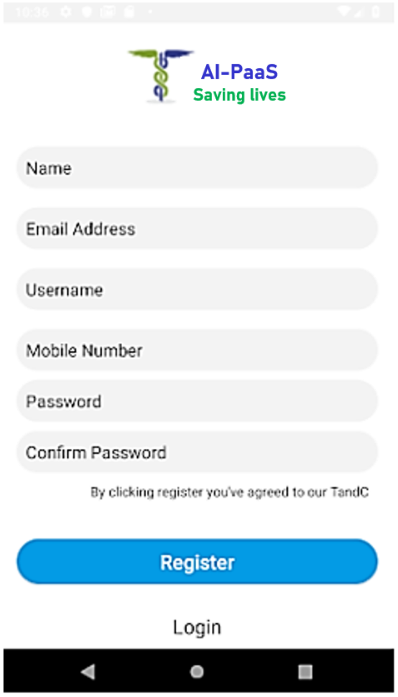

Fig. 10. AI-PaaS registration module

Figure 11 depicts the login page of the AI-PaaS

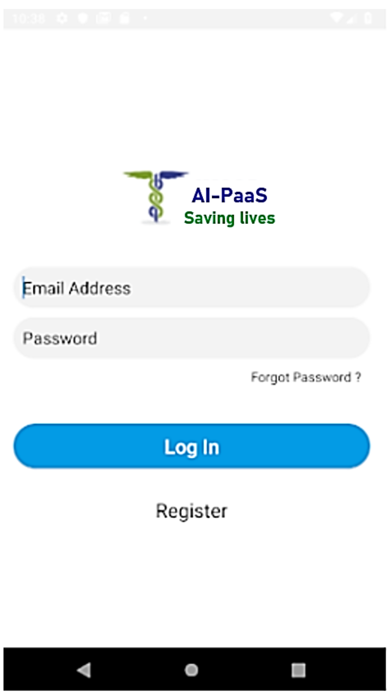

Fig. 11. AI-PaaS login

Figure 12 shows the AI-PaaS dashboard, where users can configure and pre-register next-of-kins.

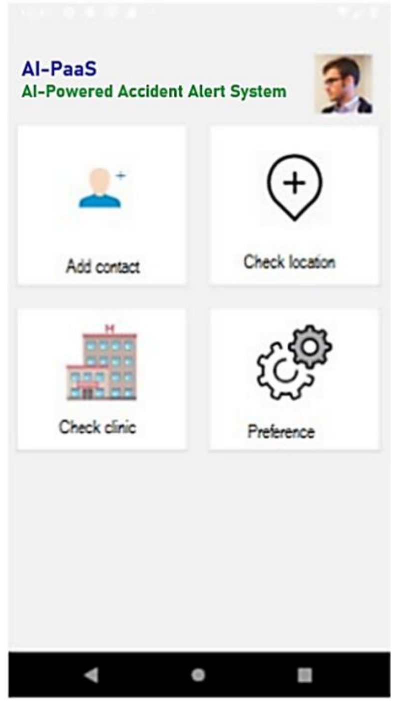

Fig. 12. AI-PaaS dashboard.

The CRUD (create, read, update or delete) contact page enables the user to create new contact, check (read) contact list, update already existing contact and delete contact. This is presented in Figure 13.

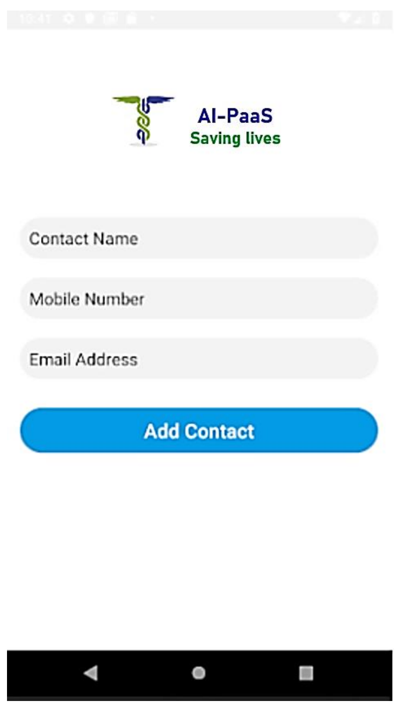

Fig. 13. The AI-PaaS CRUD page

VI. CONCLUSION

We have presented a preliminary prototype of the AI-PaaS. The proposed system is a wearable IoT enabled intelligent accident alert system. The system has features such as Location-Based Services, pattern recognition, incidence reporting packed with the HMM learning algorithm. Further studies include the development of the prototype using Arduino UNO and the commercialized production of the wearable system.

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REFERENCES

[1]. World Health Organization (2015). *Global Status Report on Road Safety 2015*. Retrieved from https://www.afro.who.int/sites/default/files/2017-06/9789241565066_eng.pdf

[2]. World Health Organization. (2022). *Global status report on road safety 2021*. Retrieved from https://www.who.int/publications/i/item/9789240032507

[3]. World Health Organization. (2020). *The top 10 causes of death in low-income countries*. Retrieved from https://www.who.int/news-room/fact-sheets/detail/the-top-10-causes-of-death-in-low-income-countries#

[4]. Federal Road Safety Corps. (2010). *Road traffic crashes and casualties during the 2010 Eid-el-Kabir festival period*. Retrieved from https://frsc.gov.ng/wp-content/uploads/2019/02/Road-Traffic-Crashes-and-Casualties-during-the-2010-Eid-el-Kabir-Festival-Period.pdf

[5]. Ukoji, V. N. (2014). *Trends and patterns of fatal road accidents in Nigeria (2006–2014)*. Retrieved from http://www.nigeriawatch.org/media/html/WP6VitusV6Final.pdf

[6]. National Bureau of Statistics. (2018). *Road transport data (Q2 2018)*. Retrieved from https://www.nigerianstat.gov.ng/pdfuploads/Transport_Q2_2018.pdf

[7]. Statistica (2023). Nigeria: Number of road traffic casualties in Q4 2020 to Q4 2021. Retrieved from https://www.statista.com/statistics/1296025/total-number-of-road-casualties-in-nigeria/#:~:text=More%20than%2011%2C800%20road%20traffic,1.7%20thousand%20were%20registered%20deaths.

[8]. Roshanfekr P, Khodaie-Ardakani MR, Sajjadi H, Malek Afzali Ardakani H. Income-Related Inequality in Traffic Accident Health Outcomes (Injury, Disability and Mortality): Evidence from the Nationwide Survey in Iran. *Iran J Public Health*. 49(4) 718-726.

[9]. Evanco, W. E. (1996). *Impact Of Rapid Incident Detection On Freeway Accident Fatalities*. Retrieved from https://rosap.ntl.bts.gov/view/dot/3077/dot_3077_DS1.pdf?#:~:text=The%20analysis%20showed%20that%20the,fatalities%20resulting%20from%20highway%20accidents.

[10]. Oluwadiya, K. S., Olakulehin, A. O., Olatoke, S. A., Kolawole, I. K., Solagberu, B. A., Olasinde, A. A., & Komolafe, E. O. K. (2005). Pre-hospital care of the injured in South Western Nigeria: a hospital based study of four tertiary level hospitals in three states. *In Annual Proceedings/Association for the Advancement of Automotive Medicine* 49, 93-100

[11]. Solagberu, B. A., Ofoegbu, C. K. P., Abdur-Rahman, L. O., Adekanye, A. O., Udoffa, U. S., & Taiwo, J. (2009). Pre-hospital care in Nigeria: a country without emergency medical services. *Nigerian journal of clinical practice* 12(1), 29-33

[12]. Gopi, Divya , P. R., Rajan, Rajan, & Renjith. (2016). Accident Tracking and Visual Sharing Using RFID and SDN. *International Journal of Computer Engineering in Research Trends*, 3(10), 544-549.

[13]. Raja G.B., Keerthika, A., Keerthika, S. G. Nandhini A., & Pranitha K.J. (2021). GSM based Vehicle Accident Alert System. *International Journal of Engineering Research & Technology* 9(5), 309-312

[14]. Sumathy, B., Sundari, L., Priyadharshini, S. J., & Jayavarshini, G. (2021). Vehicle Accident Emergency Alert System. *IOP Conference Series: Materials Science and Engineering*, 1012, 1-14. https://doi.org/10.1088/1757-899x/1012/1/012042

[15]. Yan, L., & Ko, S. W. (2021). In-tunnel Accident Detection System based on the Learning of Accident Sound. *The Open Transportation Journal*, 15(1), 81–92. https://doi.org/10.2174/1874447802115010081

[16]. Pathik, N., Gupta, R. K., Sahu, Y., Sharma, A., Masud, M., & Baz, M. (2022). AI Enabled Accident Detection and Alert System Using IoT and Deep Learning for Smart Cities. *Sustainability* 14. https://doi.org/10.3390/su14137701

[17]. Invensense (2013). *MPU-6000 and MPU-6050 Product Specification Revision 3.4*. Retrieved from https://invensense.tdk.com/wp-content/uploads/2015/02/MPU-6000-Datasheet1.pdf

[18]. Kodali A., Pattipati K.R., Singh S., (2013). Coupled Factorial Hidden Markov Models (CFHMM) for Diagnosing Multiple and Coupled Faults. I*EEE Transactions on Systems, Man, and Cybernetics: Systems* 43(3):522-534 DOI: 10.1109/TSMCA.2012.2210405

[19]. Vacher M., Serignat J. & Chaillol S. (2007, May). *Sound Classification in a Smart Room Environment: an Approach using GMM and HMM Methods*. Paper presented at the 4th IEEE Conference on Speech Technology and Human-Computer Dialogue. Retrieved from https://hal.science/hal-00957418/document