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Silentsos: A Review of Multimodal Context-Aware Wearable Systems for Silent Emergency Detection and Intelligent Assistance

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Abstract—Many personal safety devices depend on the user pressing a panic button or unlocking a smartphone, yet in a fall, a sudden medical event, an assault or harassment the person may be unable to do either. A wearable that recognises such situations by itself and calls for help silently can close this gap. This review examines the technologies needed for such a device and organises them around SilentSOS, a multimodal context-aware wearable concept. It surveys physiological sensing of heart rate and blood oxygen saturation by photoplethysmography, motion sensing and fall detection with inertial sensors, skin and ambient temperature monitoring, acoustic analysis of surrounding sounds, satellite positioning and cellular alerting. It then reviews how machine learning combines these signals so that the decision does not rest on a single sensor, which reduces both missed events and false alarms. A layered architecture is presented in which an ESP32 microcontroller acquires data from MAX30102, MPU6050, temperature and microphone sensors, extracts features, classifies the situation as normal, suspicious or high-risk, and sends an SMS with location and readings through a GSM module, with a discreet gesture available for manual activation. Design trade-offs including battery life, privacy, on-device inference and validation are discussed, together with future extensions such as ECG and blood-pressure estimation.

Index Terms—Silent emergency detection, wearable technology, multimodal sensor fusion, machine learning, ESP32, fall detection, health monitoring, acoustic analysis, GPS tracking, GSM communication.

I. INTRODUCTION

Emergencies often happen when a person is alone or unable to act. An elderly person who falls at home may lie injured for hours. A person with a heart condition may lose consciousness without warning. Someone facing harassment or a threatening situation may not be able to take out a phone and make a call without escalating the danger. In each case, the time taken to raise an alarm strongly affects the outcome.

Existing personal alarm systems usually rely on a manual action: pressing a button on a pendant, shaking a phone, or using an emergency application. These actions assume that the person is conscious, has free hands and can act safely. Automatic fall detectors remove this assumption for one type of event, and research on them is well established [1], [2].

Wearable health monitors similarly track vital signs and can warn of abnormal values [3]. However, real emergencies are diverse, and a device that looks at only one signal either misses events or produces many false alarms.

The SilentSOS concept addresses this by combining several sensing modes in one wearable and using artificial intelligence and machine learning (AI/ML) to judge the overall context. The device monitors heart rate and blood oxygen, motion and posture, temperature and surrounding sound, determines its location by GPS, and sends alerts over the cellular network. This paper reviews the technologies and research behind each of these functions and presents a layered system architecture. Its contributions are:

- A review of sensing technologies for physiological, motion, thermal and acoustic monitoring in wearables.
- A review of machine-learning and sensor-fusion methods for detecting emergencies from multiple signals.
- A layered architecture and decision process for the SilentSOS wearable.
- A comparison with existing approaches and a discussion of design challenges and future extensions.

Section II surveys emergency detection approaches, Section III reviews sensing technologies, Section IV reviews AI/ML fusion methods, Section V presents the architecture, Section VI compares approaches, Section VII discusses challenges, and Section VIII concludes.

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II. EMERGENCY DETECTION APPROACHES

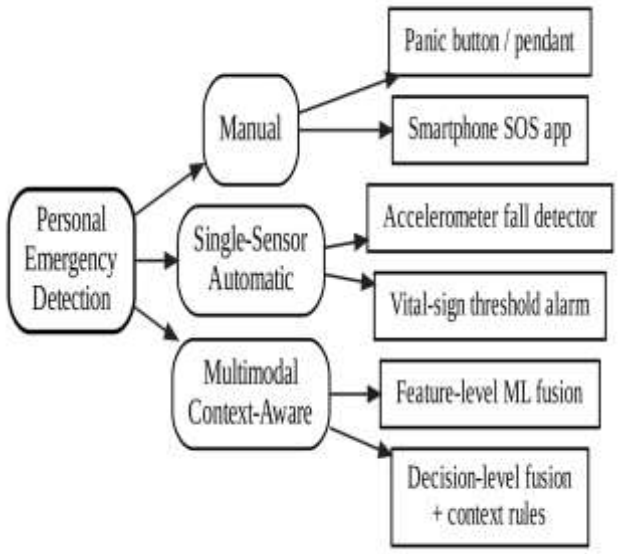


Fig. 1. Classification of personal emergency detection approaches.

1. Manual Alert Devices

Panic buttons and smartphone SOS functions are simple and reliable when the user can operate them, but fail when the user is unconscious, restrained or under observation by an aggressor.

2.Single-Sensor Automatic Detection

Fall detection is the most researched automatic method. Mubashir, Shao and Seed classified fall detectors into wearable, ambient and vision-based types [1], and Igual, Medrano and Plaza discussed their challenges, including the gap between laboratory and real-world performance [2]. Threshold-based algorithms on tri-axial accelerometers, such as that evaluated by Bourke, O'Brien and Lyons, detect the high acceleration peak of an impact [4]. Wearable vital-sign monitors detect abnormal heart rate or oxygen saturation [3], [5]. Each of these addresses only part of the problem.

3. Multimodal Context-Aware Detection

Context-aware systems combine several sensors and interpret them together. Gravina *et al.* reviewed multi-sensor fusion in body sensor networks and showed that fusing data at the signal, feature or decision level improves the reliability of activity and event recognition [6]. SilentSOS belongs to this category.

III. SENSING TECHNOLOGIES

1. Heart Rate And Blood Oxygen

Photoplethysmography (PPG) shines light into the skin and measures the variation in reflected or transmitted light caused by blood volume changes with each heartbeat [7]. Using red and infrared light, the ratio of absorption gives an estimate of blood oxygen saturation (SpO_2). The MAX30102 integrates red and infrared LEDs, a photodetector and signal processing in a small package suited to wearables [8]. PPG is sensitive to motion artefacts and to how firmly the sensor touches the skin, so readings must be filtered and checked for quality.

2. Motion And Fall Detection

The MPU6050 combines a three-axis accelerometer and a three-axis gyroscope with a digital motion processor [9]. A common feature for fall detection is the signal vector magnitude of acceleration:

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

A fall typically shows a short period of reduced magnitude during free fall, a sharp peak at impact and a period of low activity afterwards [4]. Gyroscope data indicate rapid rotation and the final orientation of the body. Bulling, Blanke and Schiele provide a tutorial on recognising human activities from such body-worn inertial sensors [10].

3. Temperature

A skin temperature sensor provides information on fever or exposure to cold, while an ambient sensor indicates environmental conditions. Temperature changes slowly and is mainly useful as supporting context.

4 Acoustic Analysis

A microphone allows the device to recognise events in the surrounding sound, such as screams, shouting, breaking glass or a crash. Salamon and Bello showed that deep convolutional networks with data augmentation achieve strong accuracy in environmental sound classification [11]. On a wearable, privacy is important, so only short-time features such as spectral energy or mel-frequency coefficients should be processed locally, without storing or transmitting raw audio.

5. Location And Communication

A GNSS receiver such as a GPS module provides latitude and longitude outdoors [12]. Indoors or in dense urban areas, accuracy degrades, and the last known location should be reported. A GSM module sends SMS messages or makes calls over the cellular network, which works without a paired smartphone. The ESP32 microcontroller provides a dual-core

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processor, Wi-Fi and Bluetooth, and multiple serial interfaces to connect these modules [13].

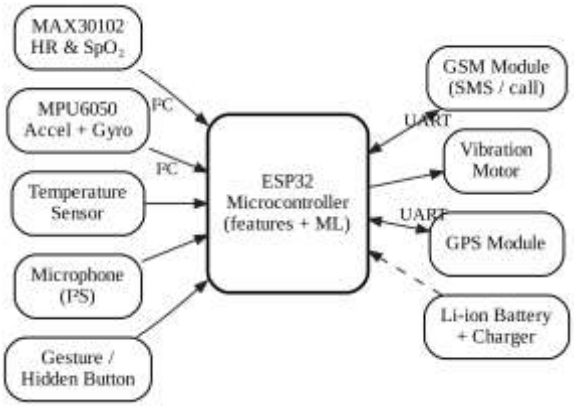


Fig. 2. Hardware block diagram of the SilentSOS wearable.

IV. AI/ML-BASED MULTIMODAL FUSION

Fusion Levels

Sensor fusion can take place at the data level, by combining raw signals; at the feature level, by concatenating features such as SVM, heart-rate change and sound energy into one vector; or at the decision level, by combining the outputs of separate detectors [6]. Feature-level fusion is a good compromise for a microcontroller because features are compact.

7 Classification Methods

Classical machine-learning methods such as decision trees and random forests are accurate on tabular features, robust to noise and easy to run on small devices [14]. Neural networks can learn more complex patterns, and frameworks for tiny machine learning allow small quantised models to run on microcontrollers with only a few hundred kilobytes of memory [15]. For SilentSOS, the classifier outputs three classes: normal, suspicious and high-risk.

8. Context Rules And Escalation

ML output is combined with context rules. For example, a detected fall followed by little movement and a rising heart rate is treated as high-risk, while a fall-like peak followed by normal walking is treated as normal. A suspicious state can trigger a short, silent vibration that lets the user cancel within a few seconds; if the user does not respond, the system escalates to an alert. This staged approach reduces false alarms without requiring visible interaction.

Table I Summary Of Representative Studies Relevant To Silent Emergency Detection

Ref.	Focus	Method	Contribution	Limitation
[4]	Fall detection	Accelerometer thresholds	Simple, low-power detection of impacts	Single sensor; false alarms in sports
[1]	Fall detection survey	Wearable, ambient, vision	Classification of fall detection approaches	No multimodal emergency scope
[3]	Health wearables	System survey	Review of wearable vital-sign platforms	Medical focus, not safety threats
[7]	PPG sensing	Optical physiology	Basis of heart-rate and SpO2 measurement	Motion artefacts
[11]	Sound events	Deep CNN with augmentation	Accurate environmental sound classes	Computationally heavy for MCUs
[6]	Sensor fusion	Body sensor network fusion	Shows fusion improves recognition	General review
[15]	On-device ML	TinyML on microcontrollers	Enables local inference at low power	Model size constraints

9 Silentsos System Architecture

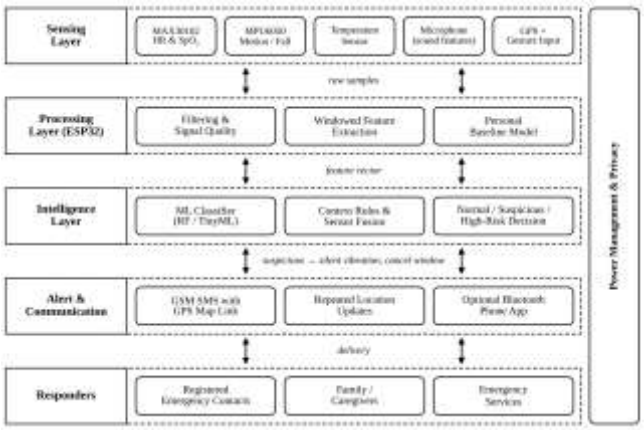


Fig. 3 presents the layered architecture of SilentSOS.Fig. 3. Layered architecture of the SilentSOS multimodal context-aware wearable.

10. Sensing Layer

The MAX30102 provides heart rate and SpO_2, the MPU6050 provides acceleration and rotation, a temperature sensor provides skin or ambient temperature, a microphone captures sound features, and a GPS module provides location. A discreet gesture, such as a specific sequence of taps detected by the accelerometer or a hidden button, allows manual activation.

11. Processing Layer
The ESP32 samples sensors at suitable rates, filters noise, and computes features over sliding windows, for example SVM peaks and post-impact stillness, heart-rate deviation from the user's baseline, SpO_2 level, temperature trend, and sound energy and class.

12. Intelligence Layer
A lightweight classifier, such as a random forest or a small quantised neural network, maps the feature vector to normal, suspicious or high-risk [14], [15]. Context rules confirm or override the output, and personal baselines adapt thresholds to each user.

13 Alert And Communication Layer
For a high-risk state, the GSM module sends an SMS to registered contacts containing a map link with the latest GPS coordinates, the time and key sensor readings. Messages are repeated at intervals with updated location until the user cancels the alert with a secure gesture. Optionally, a Bluetooth link to a phone can provide richer data and app notifications.

14 Power Management
A rechargeable lithium battery with a charging circuit powers the device. Sensors are duty-cycled, the ESP32 uses light-sleep modes between samples, and the GPS and GSM modules are woken only when needed, which extends battery life [13].

IV. COMPARATIVE ANALYSIS

Table II compares SilentSOS with other approaches.

Table Ii Comparison Of Personal Emergency Detection Approaches

Feature	Panic Button / Phone SOS	Fall Detector	Health Smartwatch	SilentSOS (Multimodal)
Works if user incapacitated	No	Falls only	Partly	Yes
Detects threats (sound)	No	No	No	Yes
Vital-sign monitoring	No	No	Yes	Yes
Location in alert	Phone dependent	Sometimes	Phone dependent	Yes (GPS)
Independent of phone	Device dependent	Often	Usually no	Yes (GSM)
False-alarm control	Not needed	Low	Medium	Fusion and silent cancel

V. CHALLENGES AND FUTURE DIRECTIONS

Several challenges must be addressed. Battery life is limited by the power demand of GPS and GSM modules, so careful duty cycling is essential. PPG readings at the wrist are degraded by motion, so physiological alarms should be trusted only when signal quality is good [7]. Acoustic monitoring raises privacy concerns; features should be computed on the device and raw audio should not be stored or sent [11]. Collecting realistic data for emergencies is difficult and sometimes unethical, so systems are often trained on simulated falls and acted scenarios, which may not reflect real events [2]. GPS does not work well indoors, so Wi-Fi-based positioning may be needed. Finally, a medical-grade claim requires clinical validation and regulatory approval. Future extensions include ECG sensing for arrhythmia detection, cuffless blood-pressure estimation, integration with dedicated continuous glucose monitors, LTE-M or NB-IoT modules for lower power, and personalised models that learn each user's normal patterns.

VI. CONCLUSION

SilentSOS represents a class of wearables that recognise emergencies automatically and request help without any visible action by the user. This review has examined the technologies involved: PPG for heart rate and SpO_2, inertial sensing for falls and motion, temperature monitoring, acoustic event recognition, GPS positioning and GSM alerting. Multimodal fusion with machine learning allows these signals to be judged together, which reduces dependence on any single sensor. The layered architecture

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built around an ESP32 provides a practical basis for a discreet and adaptable device for personal safety, emergency response and health monitoring.

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