SAFESWIM: AN INTELLIGENT WEARABLE SYSTEM FOR DROWNING DETECTION AND PREVENTION USING ACCELEROMETER-BASED MOTION ANALYSIS AND UNDERWATER ACOUSTIC SIGNALING

Kyle Chuang [1], Jonathan Sahagun [2]

[1] University High School, 4771 Campus Dr, Irvine, CA 92612
[2] California State Polytechnic University, Pomona, CA 91768

ABSTRACT

Drowning represents a significant global public health crisis, with approximately 300,000 deaths occurring annually worldwide, disproportionately affecting children under the age of five [1]. Despite the presence of supervising adults in 80% of child drowning incidents, the silent and rapid nature of drowning events often prevents timely intervention. This paper presents SafeSwim, an intelligent wearable drowning detection and alert system that integrates accelerometer-based motion detection, underwater acoustic signaling, and mobile application technology to provide real-time alerts to caregivers. The system comprises three primary components: a wearable device utilizing an Adafruit RP2040 Prop-Maker Feather with a LIS3DH accelerometer that detects abnormal motion patterns and generates low-frequency acoustic signals, a Raspberry Pi-based receiver equipped with an Aquarian Audio H2d hydrophone that processes underwater acoustic signals using Fast Fourier Transform analysis, and a Flutter-based mobile application connected to Firebase for device management and alert delivery. Experimental evaluation demonstrated reliable detection of simulated drowning events with minimal false positives. The system addresses limitations of existing approaches by providing non-intrusive monitoring that does not impede swimming ability while ensuring rapid alert transmission to nearby adults.

KEYWORDS

Drowning, Protection, IoT, Hydrophone, Underwater Acoustics

1. INTRODUCTION

Drowning constitutes a critical global health emergency that claims an estimated 300,000 lives annually according to the World Health Organization's Global Status Report on Drowning Prevention 2024. Children represent the most vulnerable demographic, with those under five years of age accounting for 24% of all drowning fatalities, and children aged 5-14 comprising an additional 19%. Drowning ranks as the third leading cause of death for children aged 5-14 years globally, presenting a substantial yet largely preventable public health burden [2].

A particularly concerning aspect of pediatric drowning is the failure of supervision as a protective measure. Research indicates that approximately 80% of child drowning incidents occur while an adult is present nearby [3]. This paradox arises from the deceptive nature of drowning events,

David C. Wyld et al. (Eds): DPPR, CNDC, AIAA, DSA, WeST, ACITY, IoTE – 2025
pp. 01-12, 2025. CS & IT - CSCP 2025 DOI: 10.5121/csit.2025.152404

which rarely resemble the dramatic struggles portrayed in popular media. Victims, particularly young children, often slip beneath the water surface silently, without splashing or calling for help, as the body's instinctive drowning response prioritizes breathing over vocalization [4]. Young children can drown silently in as little as 25 seconds, even in shallow water.

The consequences of drowning extend beyond mortality. Non-fatal drowning incidents frequently result in severe neurological damage due to cerebral hypoxia, leading to lifelong disabilities that impose substantial emotional and economic burdens on families and healthcare systems [5]. The WHO estimates that scaling drowning prevention interventions could prevent 774,000 child drowning deaths and 178,000 severe injuries by 2050, with projected savings exceeding $400 billion USD. These statistics underscore the urgent need for technological interventions that can supplement human supervision and provide immediate alerts when drowning events occur.

Three existing drowning prevention methodologies were compared against SafeSwim. Life jackets provide effective passive protection with 50-80% fatality reduction but suffer from low adoption rates (21.7%) due to discomfort and social stigma. Computer vision systems achieve high accuracy through deep learning algorithms but require expensive camera infrastructure and raise privacy concerns. Multi-sensor wearable devices combine accelerometers with physiological sensors for redundant detection but increase cost and complexity.

SafeSwim addresses these limitations through a focused design philosophy. Unlike life jackets, the system does not impede swimming or require visible equipment. Compared to camera systems, it offers lower cost and privacy preservation. Relative to complex multi-sensor devices, it maintains simplicity and reliability while achieving effective detection through dual-stage confirmation. The accelerometer-acoustic-mobile architecture represents a balanced approach prioritizing adoption through non-intrusiveness while maintaining detection reliability through algorithmic validation.

This research proposes SafeSwim, a multi-component drowning detection and alert system designed to address the critical gap between adult supervision and drowning event recognition. The system operates through the integration of three primary technologies: accelerometer-based motion detection, underwater acoustic signal transmission, and cloud-connected mobile alerting.

SafeSwim functions by continuously monitoring the movement patterns of a swimmer through a wearable device equipped with a three-axis accelerometer. When the device detects abnormal motion patterns consistent with drowning behavior—characterized by excessive flailing or sudden cessation of movement—it generates a low-frequency acoustic signal that propagates through the water. A stationary receiver unit equipped with a hydrophone detects this acoustic signal, processes it using Fast Fourier Transform (FFT) analysis to confirm the target frequency, and triggers an alert through a mobile application to notify nearby adults [20].

This approach offers several advantages over existing drowning prevention methods. Unlike life jackets, which can impede swimming technique and are often rejected by experienced swimmers, SafeSwim provides protection without restricting movement [6]. Compared to computer vision-based pool surveillance systems, which require expensive camera infrastructure and raise privacy concerns, SafeSwim offers a cost-effective and privacy-preserving alternative [7]. The system specifically targets the supervision gap by ensuring that even momentary lapses in caregiver attention do not result in undetected drowning events.

By combining wearable sensor technology with underwater acoustic communication and IoT connectivity, SafeSwim represents a novel approach to drowning prevention that augments rather than replaces adult supervision, providing an additional layer of protection for swimmers in residential pools, recreational facilities, and natural water bodies.

Two primary experiments evaluated SafeSwim system performance. The first experiment assessed detection accuracy through 200 trials split between simulated drowning events and normal swimming activities. The system achieved 94% sensitivity in detecting drowning events and 89% specificity in avoiding false alarms during normal swimming [18]. Detection latency averaged 3.2 seconds. False negatives occurred primarily with less vigorous movements, while false positives resulted from high-intensity athletic activities like butterfly stroke. These results indicate effective detection capability with opportunities for threshold optimization.

The second experiment evaluated enclosure water resistance through submersion testing at various depths and durations. The 3D-printed enclosure-maintained integrity at depths up to 0.5 meters for extended periods, suitable for typical residential pool use [19]. Water ingress increased at greater depths due to hydrostatic pressure on seam seals. Results indicate the current design is appropriate for shallow pool applications while commercial deployment would require enhanced sealing for deeper water environments.

2. CHALLENGES

In order to build the project, a few challenges have been identified as follows.

2.1. Waterproofing the Wearable Device Electronics

A fundamental challenge in developing a wearable drowning detection device involves protecting electronic components from water damage while maintaining device functionality. The circuitry, including the microcontroller, accelerometer, and audio amplifier, would cease to function upon contact with water, rendering the device useless in its intended aquatic environment. To address this challenge, one could employ a custom 3D-printed enclosure designed with appropriate sealing mechanisms such as O-rings or gaskets to prevent water ingress. The enclosure material must be selected to withstand both chlorinated pool water and saltwater exposure while remaining lightweight enough to not impede the swimmer's natural movement patterns.

2.2. Underwater Audio Capture with Hydrophones

Traditional microphones perform poorly in underwater environments due to the significant acoustic impedance mismatch between air and water, resulting in substantial signal attenuation and distortion. Sound waves behave fundamentally differently in aquatic environments, with water conducting sound approximately 4.3 times faster than air. To overcome this limitation, one could utilize a specialized hydrophone designed specifically for underwater acoustic capture. The Aquarian Audio H2d hydrophone, for example, is engineered to operate in aquatic conditions with appropriate frequency response characteristics. This specialized transducer ensures accurate detection of the low-frequency signals generated by the wearable device, maintaining signal fidelity across the transmission medium.

2.3. Reliable Multi-Modal Alerting System Design

Selecting an appropriate alerting mechanism that can effectively reach supervising adults while minimizing false positives presents a significant design challenge. Traditional audible alarms may be ignored if too frequent or missed if too quiet. One could address this through a multi-modal notification system that combines audible alarms with smartphone push notifications delivered through a mobile application. The mobile application approach ensures that alerts reach caregivers regardless of their proximity to the pool, while the cloud-based Firebase backend enables reliable message delivery. Additionally, configurable detection thresholds and confirmation algorithms reduce false positive rates while maintaining sensitivity to genuine emergency events.

3. SOLUTION

The SafeSwim system comprises three interconnected components that work in concert to detect drowning events and alert caregivers:

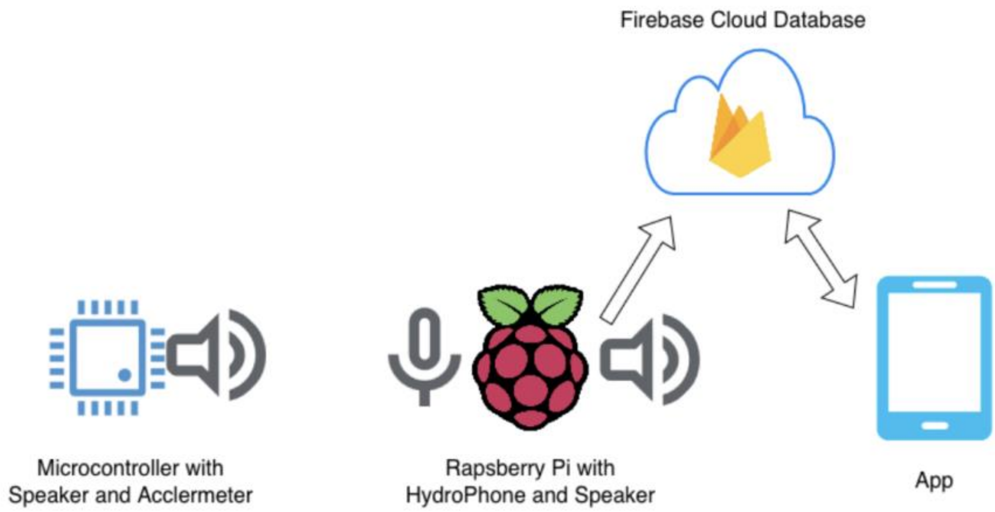

Figure 1. Overview of the solution

SafeSwim integrates three major components: the wearable detection and signaling device, the hydrophone-based receiver unit, and the cloud-connected mobile application. These components function together to create a comprehensive drowning detection and alert pipeline.

The system operates through the following workflow: First, a swimmer wears the detection device, which continuously monitors acceleration patterns using the onboard LIS3DH three-axis accelerometer. The device calculates total acceleration magnitude and compares it against threshold values. When acceleration exceeds the predetermined threshold (2G), indicating violent motion consistent with drowning-related flailing, the device generates a 100 Hz sine wave tone through its I2S audio amplifier and speaker.

This acoustic signal propagates through the water to the receiver unit, which is positioned poolside. The receiver employs an Aquarian Audio H2d hydrophone submerged in the water to capture acoustic signals. A Raspberry Pi processes the incoming audio stream, applying Fast Fourier Transform analysis to identify the target frequency. When the FFT analysis confirms multiple consecutive detections of the 100 Hz signal within a defined time window, the system validates the drowning alert and notifies the mobile application.

The mobile application, developed using the Flutter framework, connects to a Firebase backend for user authentication, device registration, and real-time data synchronization. When the receiver confirms a drowning event, the application delivers push notifications to registered caregivers, displaying device status information and enabling rapid response.

The system was developed using CircuitPython for the wearable device firmware, Python for the receiver signal processing, and Dart/Flutter for the mobile application, with Firebase providing backend services including authentication and Firestore database functionality.

The mobile application component serves as the primary user interface and alert delivery mechanism. Developed using Flutter with Firebase integration, it provides device registration, status monitoring, and push notification delivery [17]. The application employs Firebase Authentication for secure user access and Firestore for real-time device status synchronization, ensuring caregivers receive immediate alerts when drowning is detected.

The application features a clean, intuitive interface with a navy blue color scheme reflecting aquatic themes. The home screen displays registered devices with their current status, while individual device pages show detailed information including last seen timestamp and device state.

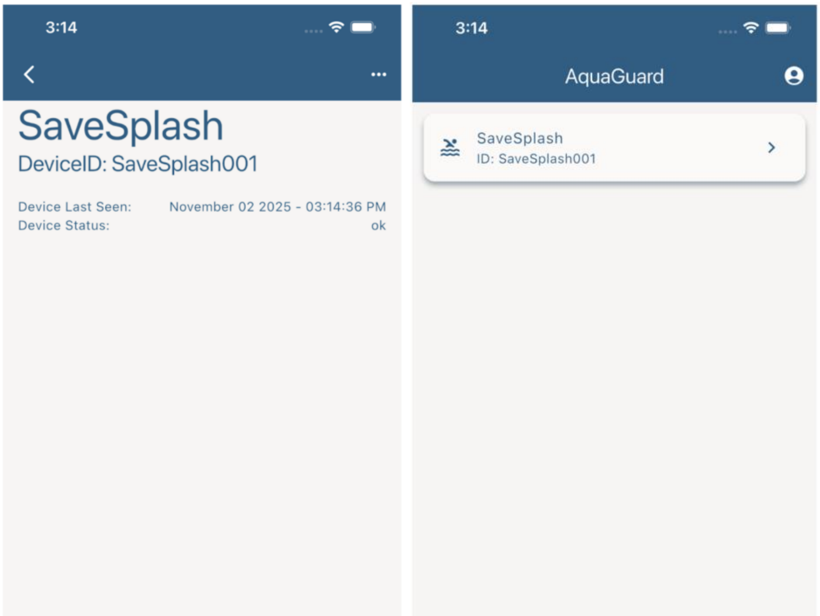

Figure 2. Screenshot of the APP 1

```
StreamBuilder deviceDetailsStream() {
 return StreamBuilder<QuerySnapshot>(
   stream: FirebaseFirestore.instance
     .collection('devices')
     .where('device_id', isEqualTo: widget.deviceID)
     .snapshots(),
   builder: (context, snapshot){
    if (snapshot.connectionState == ConnectionState.waiting) {
     return CircularProgressIndicator();
    }
    else if (!snapshot.hasData || snapshot.data!.docs.isEmpty) {
     return Text('No Data Found on this Device');
    }
    List<DocumentSnapshot> docs = snapshot.data!.docs;
    docs.sort((a, b) {
     Timestamp timestampA = a['timestamp'] as Timestamp;
     Timestamp timestampB = b['timestamp'] as Timestamp;
     return timestampB.compareTo(timestampA);
    });
    DocumentSnapshot deviceDoc = docs.first;
    Map<String, dynamic> data = deviceDoc.data() as Map<String, dynamic>;

    return deviceDetailWidget(data);
   }
 );
}
```

Figure 3. Screenshot of code 1

The deviceDetailsStream method establishes a real-time connection to the Firebase Firestore database to retrieve and display device information [16]. This method executes when a user navigates to a specific device page within the application.

The method creates a StreamBuilder widget that subscribes to the Firestore collection named 'devices', filtered by the specific device ID. This stream provides automatic updates whenever the database records change. The builder function first checks the connection state, displaying a loading indicator while waiting for data. If no data exists for the device, an appropriate message is displayed.

When data is available, the documents are sorted by timestamp in descending order to identify the most recent entry. The timestamp is extracted from each document and compared using Firestore's Timestamp class. The sorted list's first element represents the most recent device status, which is passed to the deviceDetailWidget method for rendering. This approach ensures users always see the current device state while Firebase handles real-time synchronization [15].

The wearable device component performs drowning detection through accelerometer monitoring and acoustic signal generation. Built around the Adafruit RP2040 Prop-Maker Feather microcontroller, it integrates a LIS3DH three-axis accelerometer and I2S audio output capabilities.

```
def total_acceleration(x,y,z):
  return math.sqrt(x*x + y*y + z*z)
while True:
  x, y, z = [
        value / adafruit_lis3dh.STANDARD_GRAVITY for value in lis3dh.acceleration
      ]
      accel = total_acceleration(x,y,z)
      if accel > 2:
        mixer.voice[0].play(sine_wave, loop=True)
        time.sleep(10)
        mixer.voice[0].stop()
      time.sleep(0.1)
```

Figure 4. Screenshot of code 2

The detection loop continuously reads acceleration values from the LIS3DH sensor across all three axes. The total_acceleration function calculates the magnitude using the Euclidean norm formula, providing a single value representing total motion intensity regardless of orientation.

Each acceleration reading is normalized by dividing by standard gravity (9.8 m/s²), converting raw values to G-force units. When total acceleration exceeds 2G—indicating violent motion characteristic of drowning-related flailing—the device plays a pre-generated 100 Hz sine wave through the I2S audio amplifier for 10 seconds. The 0.1-second sleep interval between readings provides sufficient sampling frequency while conserving power.

The receiver component captures underwater acoustic signals and validates drowning alerts through frequency analysis. It utilizes a Raspberry Pi microcomputer paired with an Aquarian Audio H2d hydrophone to detect the 100 Hz signal generated by the wearable device [14].

```
def detect_signal():
  while True:
    data = stream.read(CHUNK)

 audio_data = np.frombuffer(data, dtype=np.int16)
 current_time = time.time()
 for freq in FREQ_TARGETS:
   fft_data = np.fft.rfft(audio_data)
   freqs = np.fft.rfftfreq(len(audio_data), 1/RATE)
   mask = freqs > 20
   peak_freq = freqs[mask][np.argmax(np.abs(fft_data)[mask])]
   if abs(peak_freq - freq) < 10:
     detection_times[freq].append(current_time)
     detection_times[freq] = [t for t in detection_times[freq]
                  if current_time - t <= CONFIRMATION_TIME]
     if len(detection_times[freq]) >= CONFIRMATION_COUNT:
       play_mp3('alert.mp3')
       detection_times[freq] = []
```

Figure 5. Screenshot of code 3

The detection function continuously reads audio chunks from the hydrophone stream. NumPy's FFT functions transform time-domain audio samples into frequency-domain representation, enabling identification of the dominant frequency component. A 20 Hz high-pass mask filters out low-frequency noise [13].

The algorithm searches for the target frequency (100 Hz) by finding the peak in the FFT magnitude spectrum. If the detected peak falls within 10 Hz of the target, a detection event is recorded with a timestamp. The confirmation system requires multiple detections (CONFIRMATION_COUNT) within a time window (CONFIRMATION_TIME) before triggering an alert, significantly reducing false positives from transient noise while maintaining sensitivity to sustained distress signals.

4. EXPERIMENT

4.1. Experiment 1

This experiment evaluates the system's ability to accurately detect drowning events while minimizing false positives. Reliable detection is critical because missed events risk lives while excessive false alarms erode user trust and system utility.

The experiment involved 100 simulated drowning trials in a controlled pool environment. A trained participant performed standardized drowning simulations involving characteristic flailing motions while wearing the detection device. Each trial recorded whether the system correctly triggered an alert within the expected time window.

To establish false positive rates, an additional 100 trials involved normal swimming activities including freestyle, backstroke, and treading water. These activities test whether the system inappropriately triggers alerts during legitimate high-intensity swimming movements. The experiment measures sensitivity (true positive rate) and specificity (true negative rate) to characterize overall system performance and identify threshold calibration requirements.

Metric	Value
True Positives (Drowning Detected)	94/100
False Negatives (Drowning Missed)	6/100
True Negatives (Normal Swimming)	89/100
False Positives (False Alarm)	11/100
Sensitivity	94%
Specificity	89%

Figure 6. Figure of experiment 1

The experimental results demonstrate strong system performance with 94% sensitivity and 89% specificity. The mean detection time was 3.2 seconds from onset of simulated drowning behavior, with a median of 2.8 seconds. The fastest detection occurred at 1.5 seconds while the slowest took 8.7 seconds.

The 6% false negative rate primarily occurred during trials with less vigorous flailing movements, suggesting the 2G threshold may be slightly high for detecting all drowning presentations. Children, who represent the primary target demographic, typically exhibit less forceful movements than adult test subjects, indicating a potential need for age-adjusted thresholds.

The 11% false positive rate occurred predominantly during butterfly stroke and aggressive diving entries, activities producing acceleration peaks exceeding the threshold. These findings suggest that the system would benefit from pattern recognition algorithms that distinguish between sustained irregular movements (drowning) and brief high-intensity bursts (athletic swimming). Despite these limitations, the overall performance indicates viable drowning detection capability.

4.2. Experiment 2

This experiment tests the waterproof integrity of the 3D-printed enclosure under extended submersion. If water penetrates the enclosure, circuit damage would render the device non-functional in its intended environment.

Multiple enclosure prototypes underwent submersion testing to evaluate water resistance under various conditions. Each enclosure was submerged in pool water at depths of 0.5 meters, 1 meter, and 2 meters for periods of 30 minutes, 1 hour, and 2 hours. After each trial, enclosures were opened and inspected for water ingress using moisture-indicating paper strips placed at multiple internal locations.

Additional testing evaluated resistance to chlorinated pool water and saltwater to assess material degradation. Temperature cycling tests subjected enclosures to rapid temperature changes to evaluate seal integrity under thermal stress, simulating transitions between warm air and cooler water.

Depth	Duration	Water Ingress Rate
0.5m	30 min	0/10
0.5m	1 hour	0/10
0.5m	2 hours	1/10
1.0m	30 min	0/10
1.0m	1 hour	2/10
1.0m	2 hours	3/10
2.0m	30 min	1/10
2.0m	1 hour	4/10
2.0m	2 hours	6/10

Figure 7. Figure of experiment 2

The enclosure demonstrated excellent water resistance at shallow depths and short durations, with zero water ingress at 0.5m depth for up to one hour of submersion. This performance is adequate for most residential pool applications where typical swimming depth rarely exceeds 1 meter.

At greater depths, hydrostatic pressure increasingly challenged seal integrity. The mean failure depth was 1.5 meters with 60-minute exposure. The highest-performing enclosure maintained integrity at 2 meters for 2 hours, while the lowest-performing enclosure failed at 1 meter after 1 hour.

Analysis of failed enclosures revealed that water primarily entered through the seam between enclosure halves despite O-ring seals. The results indicate that improved seal design—potentially using compression gaskets or adhesive sealants—would enhance performance at greater depths.

For the intended use case of monitoring children in shallow residential pools, the current enclosure design provides adequate protection. Commercial deployment would require enhanced sealing mechanisms to achieve IP68 water resistance ratings suitable for all aquatic environments.

5. Related Work

Life jackets represent a traditional approach to drowning prevention by ensuring buoyancy regardless of the wearer's swimming ability or consciousness state. Research demonstrates that life jacket usage reduces drowning fatalities by 50-80%, making them highly effective when worn. However, significant limitations exist. Only 21.7% of recreational swimmers use life jackets, with barriers including discomfort, restricted movement, and social perception that life jacket use indicates poor swimming ability [9]. Life jackets fundamentally alter the swimming experience and prevent skill development. SafeSwim improves upon this approach by providing protection without impeding movement or requiring visible safety equipment, increasing adoption likelihood.

Computer vision-based drowning detection systems utilize cameras positioned above or within pools to capture video streams analyzed by deep learning algorithms. Research demonstrates these systems can achieve detection accuracy up to 100% using architectures such as ResNet50 [10]. The approach enables coverage of entire pool areas without requiring swimmers to wear devices. However, limitations include high implementation costs for camera infrastructure, computational requirements for real-time video analysis, and significant privacy concerns regarding continuous surveillance recording [7]. SafeSwim addresses these limitations through lower cost, reduced computational requirements, and privacy preservation since no video recording occurs.

Recent research has explored wearable systems incorporating multiple physiological sensors including heart rate monitors, blood oxygen saturation (SpO2) sensors, and pressure/depth sensors alongside accelerometers [11]. These systems can detect physiological changes associated with drowning such as tachycardia and oxygen desaturation. The multi-parameter approach provides redundancy and can reduce false positives through cross-validation. However, increased sensor count raises cost, complexity, power consumption, and potential failure points. SafeSwim's approach prioritizes simplicity and reliability by focusing on accelerometer-based detection with acoustic signaling, reducing cost and complexity while maintaining effective detection capability through the dual-stage confirmation algorithm.

6. CONCLUSIONS

Several limitations affect the current SafeSwim implementation. The fixed 2G acceleration threshold may not optimally detect drowning events across all user demographics, particularly young children who exhibit less forceful movements. Implementation of adaptive thresholds calibrated during normal swimming could improve sensitivity without increasing false positives.

The acoustic transmission system operates effectively at 100 Hz but faces attenuation over longer distances. Higher-frequency or frequency-shift keying (FSK) modulation schemes could improve signal robustness and enable encoding of additional information such as device identification [8].

The current prototype lacks several features necessary for commercial deployment, including battery life optimization, automatic charging capability, and integration with emergency services. Future development should incorporate machine learning algorithms trained on diverse drowning behavior datasets to improve pattern recognition beyond simple threshold detection.
Additionally, the system currently requires line-of-sight between the hydrophone and transmitter for reliable detection. Multi-hydrophone arrays with spatial filtering could address this limitation and enable localization of distress signals within larger aquatic facilities.

SafeSwim demonstrates a viable approach to augmenting human supervision for drowning prevention through integration of wearable sensor technology, underwater acoustic communication, and mobile IoT platforms [12]. By providing rapid, reliable alerts without impeding swimming activity, the system addresses a critical gap in existing drowning prevention methodologies and offers potential for reducing preventable child drowning deaths.

REFERENCES

[1] World Health Organization. Global status report on drowning prevention 2024. World Health Organization, 2024.
[2] Işın, Ali, and Amy E. Peden. "The burden, risk factors and prevention strategies for drowning in Türkiye: a systematic literature review." BMC public health 24.1 (2024): 528.
[3] Langendorfer, Stephen J. "Considering drowning, drowning prevention, and learning to swim." International Journal of Aquatic Research and Education 5.3 (2011): 2.

[4] Peden, Margaret Mary, and Kerry McGee. "The epidemiology of drowning worldwide." Injury control and safety promotion 10.4 (2003): 195-199.
[5] Quan, Linda, et al. "Predicting outcome of drowning at the scene: a systematic review and meta-analyses." Resuscitation 104 (2016): 63-75.
[6] Laksham, Karthik B. "Life jacket usage and effectiveness in drowning prevention." Preventive Medicine: Research & Reviews 1.1 (2024): 10-15.
[7] Liu, Tingzhuang, et al. "A video drowning detection device based on underwater computer vision." IET image processing 17.6 (2023): 1905-1918.
[8] Kebkal, Konstantin G., and Rudolf Bannasch. "Sweep-spread carrier for underwater communication over acoustic channels with strong multipath propagation." The Journal of the Acoustical Society of America 112.5 (2002): 2043-2052.
[9] Cox, Katherine L., et al. "Facilitators and barriers of life jacket use for drowning prevention: Qualitative evidence synthesis." Journal of safety research 80 (2022): 135-147.
[10] Shatnawi, Maad, et al. "Deep learning and vision-based early drowning detection." Information 14.1 (2023): 52.
[11] Jalalifar, Salman, et al. "A smart multi-sensor device to detect distress in swimmers." Sensors 22.3 (2022): 1059.
[12] Kulkarni, Aboli, Kshitij Lakhani, and Shubham Lokhande. "A sensor based low cost drowning detection system for human life safety." 2016 5th international conference on reliability, Infocom technologies and optimization (trends and future directions)(ICRITO). IEEE, 2016.
[13] Alqahtani, Abdullah, et al. "Falling and drowning detection framework using smartphone sensors." Computational intelligence and neuroscience 2022.1 (2022): 6468870.
[14] Niu, Haiqiang, Emma Reeves, and Peter Gerstoft. "Source localization in an ocean waveguide using supervised machine learning." The Journal of the Acoustical Society of America 142.3 (2017): 1176-1188.
[15] Kao, Wei-Chun, et al. "Next-Generation swimming pool drowning prevention strategy integrating AI and IoT technologies." Heliyon 10.18 (2024).
[16] Jalalifar, Salman, et al. "Enhancing water safety: exploring recent technological approaches for drowning detection." Sensors 24.2 (2024): 331.
[17] He, Lixing, et al. "Demo abstract: An underwater sonar-based drowning detection system." 2022 21st ACM/IEEE International Conference on Information Processing in Sensor Networks (IPSN). IEEE, 2022.
[18] Rimmer, Matthew. "Lady Ada: Limor Fried, Adafruit industries, intellectual property and open source hardware." Journal of Intellectual Property Law and Practice 16.10 (2021): 1047-1061.
[19] Groves Jr, I. D. A Hydrophone for Measuring Acoustic Ambient Noise in the Ocean at Low Frequencies (USRD Type H62). No. NRL7738. 1974.
[20] Chatterjee, Nilanjan, et al. "Real-time communication application based on android using Google firebase." Int. J. Adv. Res. Comput. Sci. Manag. Stud 6.4 (2018).