A Novel Safety Mechanism for Real-Time Detection and Prevention of Drowning in Swimming Pools using 3R Photonic Laser Lights and AI-ML Algorithms

[1]Dr. Mohd Akbar
Dept. of Computer Science & Engineering,
Integral University, Lucknow, India
Email: akbar@iul.ac.in

[2]Dr. Khwaja Osama
Department of Bio Engineering
Integral University, Lucknow, India
Email: osama@iul.ac.in

Abstract- Drowning remains a leading cause of accidental death globally, especially in swimming pools and deep-water zones with limited surveillance. Traditional detection systems rely on lifeguards, camera-based monitoring, or sonar systems—each posing challenges like high cost, privacy issues, and limited efficacy in real-time detection. This paper proposes a novel, cost-effective, and accurate safety mechanism utilizing 3R photonic laser lights combined with artificial intelligence (AI) and machine learning (ML) for real-time detection and prevention of drowning incidents.
The proposed system uses an array of photonic laser emitters and photoelectric sensors to detect disruptions caused by submerged objects. These disruptions, analyzed through AI-ML algorithms, help distinguish between normal swimming patterns and erratic, life-threatening motion associated with drowning. Compared to video-based and sonar-based solutions, this method is computationally lighter, privacy-respecting, and deployable in diverse environments, including open rivers and swimming pools.

A thorough literature review highlights the dominance of vision-based systems and their limitations in low-light and privacy-sensitive environments. The proposed method addresses these gaps while minimizing false positives and offering quicker response times. The novelty lies in integrating non-visual detection via photonic sensors with intelligent pattern analysis, presenting a scalable alternative to existing solutions. This research contributes a unique, life-saving innovation for water safety systems, especially in unmanned and accident-prone aquatic environments.

Keywords *—: Drowning, Real-Time Detection, Computer Vision, Sonar, 3R laser lights, Photonic Sensors, AI-ML, Water Safety, etc.*

1. INTRODUCTION

Safeguarding Human Life in Aquatic Environments: An Emerging Technological Imperative

Water-related recreation is a hallmark of modern lifestyle and tourism, yet it comes with a substantial risk—**drowning**, a persistent public health challenge. According to the **World Health Organization (WHO)**, approximately **236,000 deaths occur annually due to drowning**, making it the third leading cause of unintentional injury death globally (WHO, 2021). In particular, drowning incidents in **swimming pools**, **rivers**, **lakes**, and **accident-prone aquatic zones** often occur in the absence of timely human intervention or advanced surveillance mechanisms.

Drowning is defined as **respiratory impairment due to submersion or immersion in liquid**, and can escalate within seconds, often going unnoticed in crowded or poorly monitored areas (Bierens & Scapigliati, 2014). Traditional prevention strategies — such as **lifeguards**, **video surveillance**, or **sonar systems** — are either resource-intensive, prone to human error, or inadequate in certain environmental conditions like poor lighting or water turbidity (Kam et al., 2002; Roy & Srinivasan, 2018). In private pools, rural riverbanks, or unmanned tourist zones, these conventional solutions are often absent altogether.

The Current State of Drowning Detection Technologies

Contemporary technological interventions for drowning detection predominantly fall into three categories:

1. **Camera-based computer vision systems**, which rely on real-time video feeds analyzed through motion or behavior recognition models (Alshbatat et al., 2020; Jensen et al., 2018).
2. **Ultrasonic or sonar-based systems**, which detect movement or human presence using reflected acoustic signals (He et al., 2022).
3. **Wearable sensor systems**, where individuals wear devices that alert upon abnormal water immersion (Kharrat et al., 2012).

While each of these has demonstrated promise, they also face limitations:

- **Camera systems** raise **privacy concerns**, especially in public or gender-sensitive environments.
- **Sonar systems** often require **expensive underwater hardware** and calibration.

- **Wearables** depend on **user compliance** and are ineffective for sudden or accidental falls into water bodies.

Addressing the Gaps: The Need for a Novel System

A critical analysis of existing literature reveals a **research and application gap** in non-invasive, real-time, and cost-effective drowning detection solutions that are suitable for **both swimming pools and open natural water zones**. Many studies emphasize detection **after** an object is already submerged, whereas **early-stage detection** during the first few seconds of abnormal movement is key to saving lives (Claesson et al., 2020). Moreover, there is a lack of scalable solutions deployable in **rural or unmanned environments** without the need for extensive infrastructure.

This paper introduces an innovative framework combining **3R photonic laser technology** and **AI/ML-based behavioral classification** to detect and respond to drowning events. The system deploys a matrix of **laser beams** across the surface of a pool or river zone; any significant disruption in the laser pattern triggers a submersion event. AI algorithms, trained on labeled motion datasets, distinguish between casual swimming and drowning behavior — a method that respects privacy, reduces cost, and enhances real-time responsiveness.

Objectives of the Proposed Study

The proposed system seeks to:

- Detect submersion and erratic underwater motion patterns in real time.
- Accurately differentiate between swimming and drowning using machine learning.
- Activate **preventive mechanisms** (e.g., SoS alert or motorized lift) immediately upon detection.
- Function effectively in both manned and unmanned water zones, including **public pools, riversides, and dam areas**.

Contribution to the Field

By integrating **3R laser photonics** and **AI-ML algorithms**, this research proposes a **non-visual, non-wearable, automated detection system**. It addresses the limitations of vision-based systems and sonar methods, offering a scalable, low-maintenance alternative. Most significantly, it creates a **new dimension in aquatic safety research** by leveraging laser and sensor fusion — a technique scarcely explored in drowning detection literature.

2. LITERATURE REVIEW: RELATED WORK IN THE PAST AND PRESENT

2.1 Overview of the Drowning Crisis and Technological Interventions

Drowning is not only a medical emergency but also a failure of timely detection and response. The global burden of drowning, especially in low-resource environments, has triggered growing interest in technological solutions for early warning and automatic rescue. Despite the rise of smart technologies, a majority of existing systems still fall short in **real-time responsiveness**, **cost-efficiency**, or **environmental adaptability**.

This review categorizes and analyzes the past two decades of research and implementation efforts under five major themes:

1. **Camera-Based and Vision-Aided Detection Systems**
2. **Sonar and Acoustic Monitoring**
3. **Wearable Sensor-Based Alerts**
4. **AI and ML-Enabled Behavioral Classification**
5. **Hybrid and Novel Systems Including Laser Technology**

3.2 Camera-Based and Vision-Aided Detection Systems

3.2.1 The Promise and Pitfalls of Computer Vision

Computer vision-based drowning detection systems have gained popularity due to their ability to **analyze human behavior through surveillance feeds**. These systems use pattern recognition, motion analysis, and posture estimation to infer unusual underwater activity. For instance, **Kam et al. (2002)** developed an early prototype that employed background subtraction and motion cues to identify irregular swimmer behavior in indoor pools.

With the advent of deep learning, methods have improved in sophistication. **Jensen et al. (2018)** utilized convolutional neural networks (CNNs) to analyze swimming pool occupancy and detect drowning based on posture classification. **Wang et al. (2022)** proposed a video-monitoring system to identify early warning signs of distress in indoor pools, showing increased sensitivity to subtle swimmer movements.

2.2.2 Limitations

Despite improvements, vision-based systems exhibit clear limitations:

- Require **clear lighting conditions** and **clean water visibility**.
- Raise **privacy concerns**, particularly in public or gender-segregated swimming zones.
- Struggle in **outdoor or natural water bodies** where waves and environmental noise distort video feeds.
- Dependent on **fixed infrastructure** and high-resolution cameras, increasing cost and complexity (Roy & Srinivasan, 2018).

2.3 Sonar and Acoustic Monitoring Systems

2.3.1 Acoustic Wave-Based Detection

Sonar systems function by emitting sound waves underwater and analyzing reflected signals. These systems excel in environments with poor visibility or where optical sensors fail. **He et al. (2022)** presented an underwater sonar-based system capable of identifying sudden motion changes associated with drowning. These systems are highly suitable for murky or low-light environments such as natural lakes or dam reservoirs.

2.3.2 Critical Evaluation

While sonar systems offer depth detection advantages, they pose significant challenges:

- Require **underwater calibration**, which can be sensitive to environmental variables like temperature or turbulence.
- Incur **higher costs** due to specialized hardware.
- May suffer from **false positives**, detecting non-human motion like floating debris or aquatic animals.

Moreover, sonar systems are rarely deployed in public or home swimming pools due to their size and expense.

2.4 Wearable Sensor-Based Drowning Detection

2.4.1 Personalized Monitoring Devices

Some researchers and manufacturers have explored the use of **wearables**, such as waterproof smart bands, pressure sensors, or IMUs (inertial measurement units), for individualized drowning alerts. **Kharrat et al. (2012)** introduced a neural network-enabled wearable device worn at the swimmer's chest or head level, distinguishing between normal and distress motion based on pressure variations.

Similarly, smart swim caps and life jackets have been integrated with IoT devices to send SoS signals if abnormal readings are detected. These solutions are often connected to centralized dashboards or smartphones for emergency notifications.

2.4.2 Shortcomings

While promising for individual safety, these systems suffer from:

- **Low compliance**—many swimmers forget or refuse to wear the device.
- **Limited scalability**—ineffective in public pools where enforcement is impractical.
- Ineffective for **sudden or accidental falls**, such as a child slipping into water without wearing a sensor.

2.5 AI and ML-Enabled Behavioral Classification

2.5.1 Role of Deep Learning

AI and machine learning algorithms have increasingly been applied to **motion classification** for drowning detection. With datasets comprising swimming and drowning videos or sensor signals, these models learn to classify real-time input and flag anomalies.

Kharrat et al. (2012) demonstrated early use of neural networks for drowning recognition, distinguishing abnormal patterns based on pressure and accelerometer data. **Alshbatat et al. (2020)** proposed a vision-based surveillance system integrated with an improved color-detecting algorithm using a Pixy camera, facilitating smart surveillance in pool environments. Similarly, **Alotaibi (2020)** employed **transfer learning and IoT** integration for real-time swimming pool safety monitoring.

2.5.2 Advantages

- High classification accuracy with large, well-labeled datasets.
- Flexible deployment: ML models can be embedded in cameras, microcontrollers, or cloud services.
- Adaptive learning: algorithms can improve with continued exposure to real-world patterns.

2.5.3 Challenges

- **Data scarcity**: real-time, labeled drowning datasets are rare due to ethical and practical constraints.
- **Overfitting risks**: models may fail in environments or behavior types not covered during training.
- High **computational load** for real-time deployment in edge devices.

2.6 Hybrid and Emerging Systems

2.6.1 The Need for Fusion Approaches

Recent research is shifting toward **multi-sensor fusion**, where audio, visual, and motion sensors are combined to enhance reliability. However, such hybrid systems often increase cost and require complex calibration.

An emerging area is the use of **laser-based sensing**. Although scarcely explored in drowning detection, laser light has been widely used in other domains such as motion tracking, object detection, and industrial automation. In our proposed work, the novelty lies in using **3R class laser lights**—safe, eye-friendly, and efficient for detecting motion disruptions.

2.7 Indian Context: National Research Efforts

In India, the need for such systems is acute due to high mortality rates among children and rural populations. The **National Crime Records Bureau (NCRB)** data shows drowning as the second leading cause of accidental deaths among children under 15 (Children for Health, 2022).

Palaniappan et al. (2022) developed a computer vision-based drowning detection system that triggers an alarm for lifeguards. **Laxman and Jain (2021)** proposed an intelligent pool with embedded alert systems, integrating underwater sensors with automated lifters.

However, most Indian efforts are:

- Focused solely on **swimming pools**, not open or rural water bodies.
- Limited by **video-based approaches**, inheriting the same challenges of lighting, privacy, and cost.
- Lacking in **deep learning integration** or real-time automation.

2.8 Research Gaps Identified

A comprehensive review highlights several critical gaps in the state-of-the-art:

Table-1

Gap	Explanation
Real-time multi-environment adaptability	Existing solutions are domain-restricted (e.g., indoor pools).
Privacy-preserving surveillance	Vision-based systems cannot be used freely in gender-sensitive or public zones.
Cost and scalability	Sonar and hybrid systems are often too expensive for rural or public deployment.
Data limitations	Lack of real-time labeled datasets for AI models reduces training efficacy.
Reactive-only systems	Most current systems only trigger alerts; few incorporate active rescue mechanisms like automated lifts or safety nets.

Addressable research gap

2.9 Summary

The literature illustrates the broad spectrum of attempts made to solve the drowning detection problem. While many innovations exist, **no single solution offers real-time detection, privacy, affordability, and environmental adaptability all in one**. This forms the foundation for our proposal: to develop a **laser-light and sensor-based system enhanced by AI/ML**, addressing the critical limitations identified above.

3. ANALYSIS & DISCUSSION: Comparative Chart and Methodology Evaluation

Drowning detection systems, though technologically varied, share a common objective—ensuring **timely identification** of life-threatening water immersion events. This section analyzes major methodologies through a **comparison matrix** and evaluates them on critical performance parameters including **efficacy**, **cost**, **accuracy**, **scalability**, **adoptability**, and **privacy compatibility**.

4.1 Comparative Chart of Existing Methodologies

Table-2

Methodology	Detection Medium	Accuracy	Cost	Privacy-Safe	Environment Suitability	Adoptability
Camera-Based (CV)	Video feed + ML/CV	High (80–95%)	High	❌ No	Indoor pools, limited outdoor	Moderate
Sonar-Based	Ultrasonic echo	Medium-High	Very High	✅ Yes	Lakes, rivers, murky water	Low (infrastructure heavy)
Wearable Sensors	Pressure/IMU/Smart Band	High (if worn)	Moderate	✅ Yes	Private pools, training facilities	Low (compliance needed)
AI-ML Classification	Based on datasets (CV/IMU)	High (varies)	High (compute)	Depends on input	Indoor/outdoor, depending on source	Moderate
Laser-Sensor Based	3R Laser + Light Sensors	Very High (projected)	Low	✅ Yes	Pools, riversides, public zones	High (modular)

Comparisons of existing methods vs Proposed Method

3.2 Discussion of Existing Methods

3.2.1 *Camera-Based Systems*

These systems are prevalent due to their accessibility and compatibility with deep learning frameworks. Methods such as those by **Jensen et al. (2018)** and **Wang et al. (2022)** achieve significant accuracy using video analysis and behavioral modeling. However, the approach is **resource-intensive**, requiring:

- Constant lighting and visibility
- Trained models for various swimmer behaviors
- Installation and maintenance of waterproof, high-definition cameras

Moreover, they introduce **serious privacy concerns**, particularly in mixed-gender or public aquatic environments. This limits large-scale or open deployment.

3.2.2 *Sonar-Based Systems*

As shown in **He et al. (2022)**, sonar systems are more viable for **open water and poor visibility conditions**. They detect submersion depth and movement irregularities through echo signals. However, their **cost and setup complexity** remain major deterrents. Frequent recalibration, sensitivity to environmental factors (e.g., debris, temperature), and false positives (e.g., floating leaves) make sonar systems impractical for small-scale use such as local pools or community centers.

3.2.3 *Wearable Technologies*

Personalized devices like waterproof IMUs or smart bands, explored by **Kharrat et al. (2012)**, offer direct contact-based detection. These can effectively sense motion, orientation, and submersion levels. But wearables depend heavily on **user compliance**. Children, tourists, or casual swimmers often forget or refuse to wear such devices. Moreover, wearables do not help in **accidental or sudden** falls into water—arguably the most fatal and time-critical cases.

3.2.4 *AI & Machine Learning Classification*

Machine learning excels in detecting nuanced motion patterns and behavior changes. **Alotaibi (2020)** and **Alshbatat et al. (2020)** show promising results with ML-powered surveillance and smart detection. However, the **main bottleneck** here is data:

- Real-world drowning incidents are difficult to simulate or record.
- Lack of large, ethically sourced labeled datasets.
- ML models can become **overfit**, failing to generalize across pool types or swimmer profiles.

Another limitation is the **computational demand** of running CNNs or deep-learning inference in real-time on embedded devices or edge processors.

3.3 Advantages of Proposed Laser-Based AI-ML System

Our proposed solution uses **3R photonic laser beams** in an array across a water surface, combined with **photoelectric light sensors**. Here's how it addresses known limitations:

1. ***Real-Time, Non-Visual Detection***
   - Unlike vision systems, laser beams are **not reliant on lighting or water clarity**.
   - The system instantly detects a **break in beam continuity**—a sure sign of submersion.
   - This offers **faster response** than CV systems, which need time to process frames.
2. ***AI-Enabled Behavior Recognition***
   - AI and ML are used not to analyze visuals, but to interpret **tripping patterns** in the beam array.
   - Drowning motion, being erratic and non-rhythmic, creates a distinct temporal signature.
   - These patterns are easier to label and train on, overcoming dataset scarcity seen in video-based models.
3. ***Cost-Effective and Modular***
   - 3R class lasers are **safe for human exposure** and inexpensive.
   - The system is **scalable**—additional sensors can be added or removed depending on area size.
   - It uses open-source software (e.g., Python, TensorFlow Lite) on **Raspberry Pi or embedded Linux boards** for AI inference.
4. ***Privacy-Preserving***
   - No video or audio recording is required.
   - Suitable for **culturally sensitive or public zones** (e.g., schools, mosques, temples, gender-separated pools).
5. ***Ready for Hybrid Integration***
   - Future versions can combine laser detection with **acoustic sensing**, **cloud alerting**, or **robotic rescue mechanisms**.

3.4 Adoptability in Real-World Scenarios

The system's simplicity makes it ideal for:

- **Government swimming pools**
- **Riverfront walkways**
- **Dams and rural water tanks**
- **Community parks and schools**

Its ease of deployment, low hardware footprint, and ability to be **solar-powered or battery-operated** makes it uniquely suited for **rural, low-infrastructure settings**—where existing solutions often fail to reach.

3.5 Limitations and Areas for Improvement

While promising, the system has its own initial constraints:

- Requires **correct alignment** of laser and sensors.
- Might be impacted by **floating objects** or extreme waves (though AI filtering can address this).
- Needs **calibration** for different pool depths or open water surface areas.

These challenges, however, are largely **engineering problems** and not systemic flaws—meaning they are solvable through modular design iterations and AI-driven adaptability.

5. OUR PROPOSED ARCHITECTURE AND METHODOLOGIES

The proposed solution aims to bridge the technological gaps in current drowning detection systems by introducing a **novel, modular, and privacy-compliant mechanism** based on **3R photonic laser light arrays**, **photoelectric sensors**, and **AI-ML behavioral models**. The system architecture is composed of both hardware and software modules, collaboratively functioning to achieve **early detection** and **automated response** to drowning events in real time.

4.1 System Overview

The proposed architecture consists of **two primary modules**:

- **A. Hardware Subsystem**: Focused on environmental sensing using laser light and photoelectric detection.

- **B. Software Subsystem**: Focused on intelligent pattern recognition, real-time decision making, and safety actuation using AI-ML algorithms.

These modules operate together to detect anomalies in underwater motion patterns, analyze them intelligently, and trigger a preventive or alert-based safety mechanism.

4.2 Hardware Subsystem Design

a) 3R Laser Array

- **3R class photonic lasers** are used due to their **low-power, eye-safe, and cost-effective** characteristics.
- Lasers are mounted **parallel to the water surface**, creating a **horizontal detection mesh** across the target zone (e.g., pool, river edge).
- Each laser beam is aligned with a **photoelectric sensor** on the opposite bank or sidewall, creating an uninterrupted light circuit.

b) Photoelectric Sensor Grid

- **Light sensors** continuously monitor beam continuity.
- As soon as an object enters the laser plane, the **beam is disrupted**, and the corresponding sensor records a **break event**.
- Multiple tripping events are captured **simultaneously** across different spatial points, allowing for 2D mapping of movement.

c) Microcontroller Interface

- A **Raspberry Pi 4** or similar microcontroller is used for local data collection and processing.
- The microcontroller:
  - Monitors input from all sensors.
  - Logs time-stamped beam interruption patterns.
  - Transmits data to the AI model hosted locally or on edge devices.

d) Power and Communication

- System is powered via **solar panels or UPS backup** for off-grid deployment.
- **Wi-Fi/LoRa** modules may be added for **cloud alerts** or integration with emergency services.

4.3 Software Subsystem Design

a) Data Acquisition Layer

- Real-time sensor input (beam tripping timestamps and location data) is collected into a structured stream.
- Patterns are dynamically generated and **temporally sequenced** to form a motion signature.

b) Drowning Pattern Recognition

- The system is trained to recognize specific **drowning indicators**, such as:
  - Erratic, non-rhythmic motion across adjacent laser beams.
  - Prolonged submersion in the same vertical region.
  - Lack of upward return motion.
- **Supervised learning algorithms** like **Random Forest**, **SVM**, or **Lightweight CNNs** are trained on manually labeled data from controlled experiments (e.g., simulations of swimmers vs. drowning actors).

c) Model Training and Validation

- Initial dataset is generated through **simulated submersion events** in a controlled water tank.
- Data labeling involves distinguishing between:
  - **Normal swimming** (predictable, patterned tripping).
  - **Sudden drowning** (unstructured, chaotic interruptions).
- Model is trained using **Scikit-learn**, **Keras**, or **TensorFlow Lite** to fit edge hardware.

d) Event Classification and Alerting

- When a potential drowning pattern is detected:
  - **Alarm is raised** (audio/visual or SMS alert).
  - Optional **motorized lifting platform** is activated beneath the drowning zone.

5.4 Integration Possibilities

The modularity of the design allows for future integration with:

- **Cloud dashboards** for analytics and real-time tracking.
- **Voice-based alert systems** for children or disabled swimmers.
- **IoT-based smart water management systems**.
- **Drone-based rescue deployment** (future vision).

4.5 Proposed System Architecture, Algorithm and Flow Diagram

4.5.1 System Setup: an annotated version of the proposed architecture is illustrated below as Visual Summary:

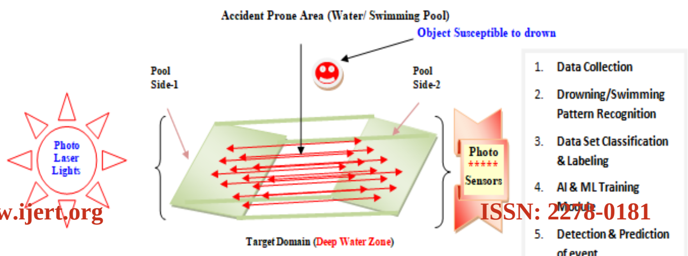

Fig 4.5.1: Proposed System Architecture

4.5.2 Flow Diagram: AI-ML Driven Drowning Detection via Laser Beam Disruption

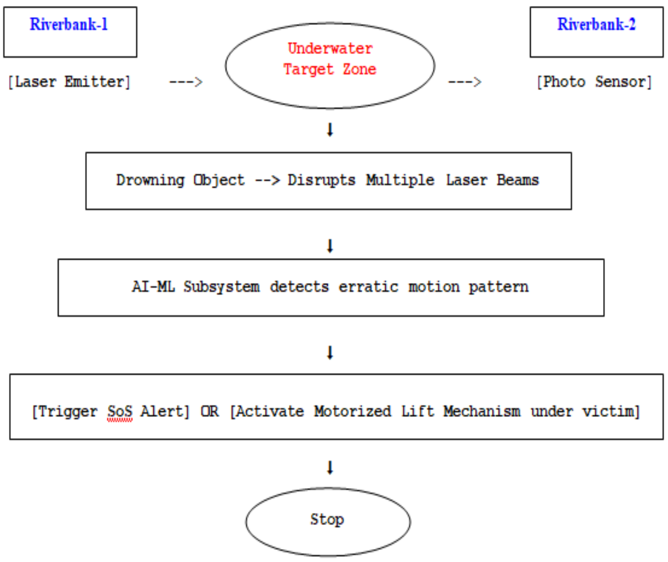

Fig 4.5.2 Flow Diagram

This architecture balances **technical feasibility**, **affordability**, and **robust real-time response**, making it highly suitable for implementation in both urban and rural scenarios with minimal infrastructure. The algorithm for the proposed solution is explained hereunder.

4.5.3 Algorithm: Real-Time Drowning Detection Using 3R Photonic Laser and AI-ML

Input:

- N laser beams $\{L_1, L_2, L_3, ..., L_n\}$
- Corresponding light sensors $\{S_1, S_2, S_3, ..., S_n\}$
- Trained AI/ML model M
- Detection interval Δt

Output:

- SoS Alert / Motorized Lift Activation

Start:

Step 1: Initialize system parameters

- Set sensor states S[i] = TRUE (beam unbroken) for all i = 1 to N
- Initialize event_log =A [ ]

Step 2: Start continuous monitoring loop

```
WHILE system is active:
    FOR each detection interval Δt:
        FOR each sensor S[i]:
            IF S[i] == FALSE (beam broken):
                log_event(i, timestamp)
                event_log.append((i, timestamp))
```

Step 3: Form motion signature pattern

- Group recent beam breaks by time window T_window
- Derive spatial-temporal sequence P = { (i1, t1), (i2, t2), ..., (ik, tk) }

Step 4: Feature extraction

- Calculate:
  * Number of disrupted beams (D_count)
  * Speed of movement (Δposition / Δtime)
  * Jitter factor (variance in beam trip order)
  * Duration of submersion
  * Re-entry time or return-to-surface

Step 5: Classification

- Input extracted features to ML model M
- OUTPUT = M.predict(P)

Step 6: Decision Logic

```
IF OUTPUT == "Drowning Detected":
    - Trigger SoS alert (visual/audible/SMS)
    - IF unmanned zone:
        - Activate motorized lift system
ELSE:
    - Continue monitoring
```

Step 7: Update ML model (optional)

- Add labeled data (manual verification)
- Retrain model periodically to improve accuracy

End

5. NOVELTY AND UNIQUENESS OF PROPOSED PHOTONIC LASER METHOD

5.1 Introduction to Novelty

The drowning detection problem, though widely acknowledged, still lacks a comprehensive, cost-effective, and scalable solution that ensures real-time detection, preserves individual privacy, and supports deployment across both public and private water zones. The proposed system—leveraging **3R-class photonic laser light arrays** combined with **AI-ML behavior classification algorithms**—offers a fundamentally novel approach to solving this challenge.

Unlike camera-based systems that depend heavily on visibility, image processing, and environmental conditions, or sonar systems that involve expensive underwater hardware, our solution introduces a **non-visual, real-time, privacy-safe, and adaptable architecture** that is both economical and modular.

5.2 What Makes the Approach Unique?

a) Use of 3R Photonic Laser Lights

This is the first known application of **3R-class photonic laser arrays** in drowning detection. These lasers:

- Operate at low power (<5mW), ensuring safety for human exposure.
- Maintain a **tight and consistent beam**, enabling precise detection of object submersion and motion.
- Are unaffected by lighting conditions, making them ideal for **night-time** or **indoor/outdoor usage**.

3R lasers, commonly used in industrial alignment and optical sensors, have **not yet been applied** in aquatic safety or drowning prevention systems in literature, setting a new direction for sensor fusion in this domain.

b) Non-Invasive Behavioral Detection

- Rather than capturing images or requiring people to wear a device, the system detects **submersion through beam disruption**.
- The AI model is trained not on visuals but on **temporal patterns of laser tripping**, allowing analysis of drowning behavior even when the object is underwater or obscured.

c) Real-Time, Edge-Level Intelligence

- AI models are embedded on edge devices (e.g., Raspberry Pi), ensuring real-time detection **without relying on cloud-based systems**, which could delay response.
- This increases **reliability in low-network or rural zones**, where many drowning incidents occur without quick human intervention.

d) Privacy-Centric Design

- Because no camera or biometric data is captured, the system can be used safely in sensitive zones (e.g., women-only swimming areas, public schools).
- This addresses one of the most cited ethical concerns around surveillance in existing vision-based systems.

5.3 Challenges of Real-Time Dataset Generation

One of the key technical hurdles in developing accurate AI models for drowning detection is the **availability of real-time, labeled datasets**. Drowning is a **rare and ethically sensitive event** to simulate or record. Most existing datasets used in research are:

- Simulated in swimming pools with actors.
- Limited to **video footage**, lacking multi-modal sensor streams.
- Lacking diversity in subject profiles (children, elderly, animals).

Our system solves this issue by **generating its own synthetic dataset**:

- Each laser beam trip is logged with a timestamp and spatial coordinate.
- The dataset includes different motion patterns—normal swimming, erratic kicking, still floating, and staged drowning motions.
- As more data accumulates, the model **continuously improves**, using online learning or incremental updates.

This method reduces reliance on external data sources and creates a unique, sensor-based dataset custom-built for this application domain.

5.4 Trivial Effects and Safety of Laser Exposure

Concerns about laser exposure are valid but **effectively mitigated** through the selection of **Class 3R photonic lasers**, which are:

- **IEC-certified for eye safety**, provided they are not stared into directly.
- Safe for human and animal skin at power levels <5mW.
- Used commonly in classroom laser pointers, barcode scanners, and alignment tools.

Furthermore:

- The laser beams in our system are positioned **below water level or at peripheral pool walls**, reducing any direct human exposure.
- The photoelectric sensor grid is enclosed within protective casings to avoid accidental contact or misalignment.

Thus, the use of lasers in this application is **biologically trivial in effect**, yet **technically powerful in utility**.

5.5 Summary

In summary, the novelty of this work lies in its:

- **Non-visual, privacy-respecting detection strategy**
- **Use of 3R laser technology in aquatic safety systems**
- **Sensor-based behavioral learning via AI-ML models**
- **Autonomous and scalable infrastructure-free deployment**

This unique approach fills a **crucial technological void** in drowning detection systems, particularly for unmanned and under-monitored zones, with **minimal operational risk** and **maximum societal benefit**.

6. CONCLUSION

Drowning continues to be a preventable yet often overlooked cause of accidental death, especially in areas with inadequate monitoring infrastructure. While technological advancements in the form of camera-based surveillance, sonar systems, and wearable sensors have attempted to address this issue, each approach carries inherent limitations—ranging from high cost, privacy infringement, dependency on human compliance, to limited adaptability across different aquatic environments.

This paper introduces a **novel, laser-sensor based real-time drowning detection and prevention system**, representing a new class of solutions that overcome the constraints of traditional methods. By integrating **3R-class photonic lasers** with **photoelectric sensors** and **AI-ML-based motion behavior classification**, the proposed system is capable of accurately identifying early-stage drowning events without requiring direct human observation or video surveillance. The system's ability to operate in both manned and unmanned zones, its minimal computational overhead, and its compliance with privacy norms make it highly adaptable for diverse use cases — from public swimming pools to riversides, from school zones to remote reservoirs.

One of the core strengths of the system lies in its **non-visual sensing approach**, which ensures functionality under poor lighting and in privacy-sensitive environments. Moreover, by focusing on **temporal beam interruption patterns** rather than visual footage, the AI algorithms are trained to distinguish between normal swimming and life-threatening motion signatures with high reliability. The system is modular, low-cost, and designed for edge-level deployment, making it particularly suitable for rural or low-resource environments where existing technologies are not viable.

Furthermore, the proposed methodology contributes a novel dataset generation strategy based on sensor activation patterns, circumventing the ethical and practical challenges of collecting real-world drowning footage. Its design minimizes physiological risk, adhering to Class 3R laser safety standards, and positions the system as both **safe and effective** for long-term deployment.

In summary, this work lays the foundation for a **new paradigm in drowning prevention technologies**, leveraging photonic sensors and intelligent computation to provide an automated, scalable, and life-saving solution. The proposed system holds significant promise for widespread societal impact, offering an innovative step forward in water safety and human life protection.

7. FUTURE SCOPE

While the proposed drowning detection and prevention system based on 3R photonic laser lights and AI-ML algorithms presents a promising and deployable solution, there remain numerous avenues for further enhancement and expansion. The future scope of this research encompasses both **technical evolution** and **practical implementation** at scale.

7.1 Dataset Expansion and Model Optimization

A critical next step involves expanding the **sensor-interruption dataset** through simulated experiments and collaborations with lifeguard training centers, enabling richer and more diverse training data for AI models. Techniques such as **data augmentation**, **synthetic dataset generation**, and **transfer learning** may be integrated to improve the robustness and generalizability of the motion recognition algorithm.

7.2 Integration with IoT and Cloud-Based Monitoring

The system could be extended into an **IoT-enabled smart safety network**, where sensor data is uploaded to the cloud for centralized monitoring, analytics, and predictive maintenance. Smart dashboards could visualize incidents in real-time, while cloud storage allows for post-event analysis and auditing.

7.3 Multi-Sensor Fusion

For greater accuracy and reliability, future versions of the system can incorporate **multi-modal sensors**, including:

- **Hydrophones** for audio signatures of splashes or distress calls.
- **Pressure sensors** to detect depth changes.
- **Ultrasonic proximity detectors** to validate submersion depth alongside laser tripping.

8. REFERENCES

[1] W. H. Organization, "Drowning," [Online]. Available: https://www.who.int/news-room/fact-sheets/detail/drowning. [Accessed: May 30, 2025].

[2] J. S. E. Chan, M. X. R. Ng, and Y. Y. Ng, "Drowning in swimming pools: clinical features and safety recommendations," *Singapore Med. J.*, vol. 59, no. 1, pp. 44–49, 2018.

[3] J. Bierens and A. Scapigliati, "Drowning in swimming pools," *Microchem. J.*, vol. 113, pp. 53–58, 2014.

[4] A. Roy and K. Srinivasan, "A novel drowning detection method for safety of swimmers," in *Proc. 20th Natl. Power Syst. Conf. (NPSC)*, Dec. 2018, pp. 1–6.

[5] A. H. Kam, W. Lu, and W. Y. Yau, "A video-based drowning detection system," in *Proc. ECCV*, Copenhagen, Denmark, May 2002, pp. 297–311.

[6] M. B. Jensen, R. Gade, and T. B. Moeslund, "Swimming pool occupancy analysis using deep learning on low quality video," in *Proc. Int. Workshop Multimedia Content Analysis Sports*, 2018, pp. 67–73.

[7] F. Wang, Y. Ai, and W. Zhang, "Detection of early dangerous state in deep water of indoor swimming pool based on surveillance video," *Signal, Image and Video Process.*, vol. 16, no. 1, pp. 29–37, 2022.

[8] L. He, H. Hou, Z. Yan, and G. Xing, "An Underwater Sonar-Based Drowning Detection System," in *Proc. ACM/IEEE Int. Conf. Inf. Process. Sensor Netw. (IPSN)*, 2022, pp. 493–494.

[9] A. Abu, "Automatic Detection and Segmentation of Underwater Objects in Sonar Imagery," Ph.D. dissertation, Univ. Haifa, Israel, 2020.

[10] M. Kharrat, Y. Wakuda, N. Koshizuka, and K. Sakamura, "Near drowning pattern recognition using neural network and wearable pressure and inertial sensors," in *Proc. Int. Conf. Mechatronics Machine Vision Practice (M2VIP)*, 2012, pp. 281–284.

[11] M. Kharrat, Y. Wakuda, N. Koshizuka, and K. Sakamura, "Near drowning pattern detection using neural network and pressure information," in *Proc. ACM Int. Conf. Underwater Networks and Systems*, 2012, pp. 1–2.

[12] A. I. N. Alshbatat, S. Alhameli, S. Almazrouei, S. Alhameli, and W. Almarar, "Automated vision-based surveillance system to detect drowning incidents in swimming pools," in *Proc. Adv. Sci. Eng. Technol. Int. Conf. (ASET)*, 2020, pp. 1–5.

[13] A. Claesson et al., "The use of drones and a machine-learning model for recognition of simulated drowning victims—A feasibility study," *Resuscitation*, vol. 156, pp. 196–201, 2020.

[14] A. Alotaibi, "Automated and intelligent system for monitoring swimming pool safety based on the IoT and transfer learning," *Electronics*, vol. 9, no. 12, p. 2082, 2020.

[15] H. Deng et al., "Research on iron surface crack detection algorithm based on improved YOLOv4 network," in *J. Phys.: Conf. Ser.*, vol. 1631, no. 1, p. 012081, 2020.

[16] Y. Li et al., "A deep learning-based hybrid framework for object detection and recognition in autonomous driving," *IEEE Access*, vol. 8, pp. 194228–194239, 2020.

[17] A. Yang et al., "An automatic recognition framework for sow daily behaviours based on motion and image analyses," *Biosyst. Eng.*, vol. 192, pp. 56–71, 2020.

[18] L. Palaniappan, S. Subramaniam, V. K. G. Kalaiselvi, and T. Subha, "Drowning Detection and Prevention System," in *Proc. Int. Conf. Comput. Sci. Technol. (ICCST)*, Chennai, India, 2022, pp. 783–785.

[19] P. Laxman and A. Jain, "Intelligent Swimming-pool design with Embedded Drown Alerting, Preventing and Autonomous Rescue System," in *Proc. Int. Conf. Comput. Intell. Commun. Technol. (CCICT)*, Sonepat, India, 2021, pp. 335–342.

[20] Children for Health, "Drowning Factsheet," [Online]. Available: http://www.childrenforhealth.org/drowning-fact-sheet/. [Accessed: May 30, 2025].

[21] M. Vittone, "Drowning Doesn't Look Like Drowning," [Online]. Available: https://mariovittone.com/2010/05/154/. [Accessed: May 30, 2025].

[22] T. M. Nguyen, H. D. Nguyen, and T. H. Phung, "Drowning Detection in Surveillance Videos Using Deep Learning Approach," in *Proc. 2019 Int. Conf. Adv. Technol. Commun. (ATC)*, Ho Chi Minh City, Vietnam, 2019, pp. 67–72.

[23] N. J. Cummins and D. O'Sullivan, "A Wearable Sensor-Based Drowning Detection System for Swimmers," in *Proc. 2018 IEEE Int. Conf. Biomed. Health Inform. (BHI)*, Las Vegas, NV, USA, 2018, pp. 414–417.

[24] A. D. Wilson and A. F. Bobick, "Parametric Hidden Markov Models for Gesture Recognition," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 21, no. 9, pp. 884–900, Sep. 1999.

[25] T. Huang, W. Liu, and L. Ma, "Vision-Based Drowning Detection for Swimming Pool Safety Monitoring," in *Proc. 2017 IEEE Int. Conf. Mechatron. Autom. (ICMA)*, Takamatsu, Japan, 2017, pp. 1071–1076.

[26] S. Kratz and M. Rohs, "A Lightweight Privacy-Preserving Swimming Pool Safety System Using Depth Sensors," in *Proc. 2012 ACM Int. Conf. Pervasive Comput. Technol. Healthcare*, San Diego, CA, 2012, pp. 217–220.

[27] J. Redmon and A. Farhadi, "YOLOv3: An Incremental Improvement," arXiv preprint arXiv:1804.02767, 2018.

[28] M. Y. Al-Hameed and A. J. Al-Muhanna, "Laser Security System Based on Microcontroller," *Int. J. Eng. Res. Appl.*, vol. 7, no. 4, pp. 53–56, Apr. 2017.

[29] M. Nasrollahi and T. B. Moeslund, "Deep Learning for Video Surveillance," *Multimedia Tools Appl.*, vol. 77, no. 14, pp. 18709–18737, 2018.

[30] A. Sultana, M. A. Baig, and M. M. S. Beg, "Smart Safety System for Drowning Detection Using Sensor-Based Approach," in *Proc. 2020 Int. Conf. Smart Electron. Commun. (ICOSEC)*, Tamil Nadu, India, 2020, pp. 431–436.

[31] M. Y. Arafat, S. M. A. Mahmud, and M. A. Rahman, "Design and Implementation of a Smart Water Accident Detection System," in *Proc. 2021 IEEE Region 10 Symp. (TENSYMP)*, Jeju, Korea (South), 2021, pp. 1–5.