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# Development of an AI IoT-based smart system to support improved beach visitor safety

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**Abstract:** The high rate of sea accidents at Indonesian coastal tourist destinations, such as those occurring at Parangtritis and Pangandaran beaches, underscores the limitations of conventional safety systems that rely on manual surveillance. The objective of this research is to develop the Smart Beach Visitor Safety System (Smart BEVISAT), an integrated system based on artificial intelligence (AI) and the Internet of Things (IoT) to enhance beachgoer safety through preventive and reactive functions. The system development method employs the waterfall model, which includes stages of requirements analysis, design, implementation, and testing. The system is composed of three primary components: an AI surveillance camera, an IoT safety buoy, and a ground station. The AI camera utilizes advanced algorithms such as YOLOv11 for object detection, ByteTrack for tracking, and DeepLabv3+ for waterline segmentation, enabling it to monitor visitors and detect safety zone violations in real-time. In the event of an incident, the system automatically sends the victim's coordinates to the IoT Safety Buoy, an Unmanned Surface Vehicle (USV) designed to autonomously navigate to the victim's location for rapid evacuation. The implementation results show a functional prototype with measurable technical specifications, where the buoy achieves a total gross buoyancy of 205.8 kg, a net carrying capacity of approximately 190 kg, and a measured operational speed of 1.20–1.53 m/s under varying load conditions, demonstrating effective rescue capability. The development of Smart BEVISAT is expected to provide a technological solution to minimize accident risks and strengthen the maritime tourism sector in Indonesia.

**Keywords:** Artificial Intelligence, Beach Safety, Internet of Things (IoT), Line Object Detection, Unmanned Surface Vehicle (USV).

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## Introduction

Indonesia is known as a maritime country with the longest coastline in the world, stretching approximately 108,000 km [1]. This geographical condition makes the sea and coastline an important part of the social, economic and cultural life of the community. According to data from the Ministry of Maritime Affairs and Fisheries (KKP), Indonesia's maritime territory covers an area of approximately 290,000 km2 as sovereign territory, plus 2.55 million km2 of Exclusive Economic Zone (EEZ) waters [2].

This great potential is accompanied by various challenges, one of which is the high risk of marine and coastal accidents, such as the drowning of tourists and fishermen. Studies show that the effectiveness of coastal safety warning signs installed to inform beach visitors about the potential dangers on the beach as a whole is not always effective [3]. For example, on January 28, 2025, 13 students from Mojokerto were swept away by waves at Drini Beach, Gunung Kidul. Of these, 9 were rescued, 3 died, and 1 is still missing [4]. This case shows that manual warning systems are not yet able to provide optimal protection for beach visitors.

Technological developments, particularly Artificial Intelligence (AI) and the Internet of Things (IoT), have opened up new opportunities to improve safety in maritime areas and beach tourism. In this case, one example of its application is CCTV (Closed-Circuit Television) cameras that monitor visitor activities through surveillance cameras in real-time [5]. However, conventional CCTV systems are still highly dependent on human operators for monitoring, which can potentially cause delays in detection when incidents occur [6].

With technological advances, CCTV can be upgraded through the application of Computer Vision. With the support of AI and IoT, it provides comprehensive safety solutions with two main functions: preventive to prevent accidents and reactive to speed up evacuation [7]. Surveillance cameras not only record, but are also capable of detecting objects, tracking movements, and recognizing certain patterns automatically [8]. When combined with IoT, this system can connect to other devices, for example to activate warning alarms when visitors cross safe boundaries or send survivor location coordinates to automatic rescue devices [9].

To address these challenges, this study proposes the development of a Smart Beach Visitor Safety System (Smart BEVISAT). This is an integrated safety system based on Artificial Intelligence (AI) and the Internet of Things (IoT). Smart BEVISAT uses three main components, namely AI surveillance cameras, IoT safety buoys, and ground stations. The AI surveillance camera detects and tracks visitor movements in real-time and automatically sounds an alarm when someone crosses a predetermined virtual safety line. Meanwhile, the reactive function is implemented with IoT safety buoys. A hydrodynamic Unmanned Surface Vehicle (USV) can move autonomously (autopilot) to the coordinates of the victim detected by the AI system, thereby speeding up the rescue process. The entire system is supported by an independent ground station equipped with solar panels and wind turbines, ensuring 24-hour operation and wireless connectivity for remote monitoring.

Several studies have addressed water safety using AI and IoT technologies. Alotaibi [10] developed a ResNet50-based transfer learning system for swimming pool monitoring that achieved up to 99% detection accuracy. Domingo [11] demonstrated that deep learning models can predict beach attendance levels with a mean absolute error of approximately 0.03. Campo et al. [12] proposed a LoRa-based IoT wristband platform for beach resort monitoring that improved lifeguard situational awareness. However, these studies share critical limitations that leave an important gap unaddressed. First, none of them integrates both a preventive detection function and a reactive autonomous rescue function within a single unified system. The swimming pool system [10] and the beach attendance predictor [11] are purely preventive and provide no mechanism for active rescue deployment. The wristband platform [12] requires visitors to wear dedicated hardware and is not scalable to large open-beach environments. Second, none of these works addresses the unique challenges of open-sea coastal environments in developing countries, such as limited infrastructure, dynamic rip currents, and the absence of reliable power grids. Third, no existing study has proposed an energy-autonomous ground station capable of sustaining 24-hour surveillance and charging rescue devices simultaneously. This research directly addresses these gaps by developing Smart BEVISAT, the first integrated beach safety system that combines real-time AI surveillance with an autonomous IoT rescue buoy, all supported by a self-powered ground station.

The main contributions of this paper are as follows. (1) A unified preventive-reactive beach safety architecture: Smart BEVISAT is the first system to integrate AI-based safety-line crossing detection (preventive) with autonomous GPS-guided buoy deployment (reactive) in a single operational pipeline. (2) A real-time multi-algorithm AI camera subsystem: the system combines YOLOv11 for object detection, ByteTrack for multi-object tracking, OpenCV Perspective Transformation for coordinate mapping, and DeepLabv3+ for dynamic waterline segmentation, enabling accurate zone violation detection under varying coastal conditions. (3) An energy-autonomous ground station: the ground station integrates solar panels and wind turbines to operate continuously for 24 hours without external power, making the system deployable in remote coastal areas with no grid infrastructure. (4) A hydrodynamic catamaran rescue buoy: the IoT safety buoy is designed with a catamaran hull for stability in ocean waves, capable of carrying victims weighing up to 80 kg while navigating autonomously to GPS target coordinates.

The remainder of this paper is organized as follows. Section 2 describes the system development methodology, including the research design, component specifications, and experimental testing protocol. Section 3 presents the implementation results and performance measurements for each subsystem, along with a comparative discussion against related work. Section 4 concludes the paper and outlines directions for future research.

## Methodology

This research follows the Waterfall development model to guide the system engineering process, covering the stages of requirements analysis, system design, implementation, and testing. The Waterfall model was adopted because the core hardware and software requirements namely the three-component architecture (AI surveillance camera, IoT safety buoy, and ground station) were established in advance through prior prototyping work on the electric safety buoy [13]. The Waterfall model remains well suited to projects with stable, clearly defined requirements and strong demands for documentation and traceability [14]. This approach is also consistent with recent digital engineering methodologies for safety-critical AI systems, which emphasize systematic design, verification, validation, and lifecycle traceability to ensure the reliability and safety of integrated AI-enabled cyber-physical systems [15]. It is important to note that the Waterfall model describes the system-level engineering workflow, while the AI model development itself follows a standard iterative machine learning pipeline involving dataset curation, model training, validation, and fine-tuning. The overall research design is illustrated in Figure 1.

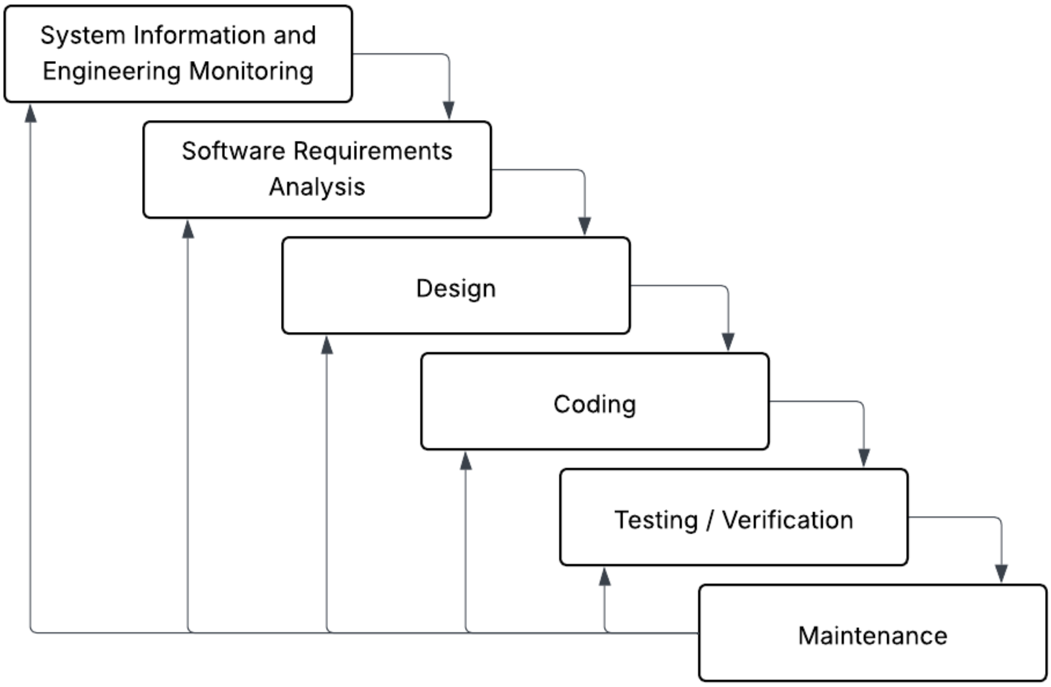


**Figure 1.** Waterfall method flow

### *Software Requirements Analysis*

This stage established the functional and non-functional requirements of Smart BEVISAT. Based on accident records from Indonesia's major beaches (129 incidents at Parangtritis and 39 at Pangandaran throughout 2023), two core system functions were identified: a preventive function to detect safety-zone violations and alert lifeguards in real time, and a reactive function to deploy an autonomous rescue buoy to victim coordinates. These requirements were translated into three product components: the AI Surveillance Camera, the IoT Safety Buoy, and the Ground Station.

### *Design*

Once all system requirements have been defined, the next step is to design the system architecture and detailed product blueprint. The design process includes:

### *Software Design*

The AI pipeline was architected around YOLOv11 for real-time human detection, ByteTrack for multi-object tracking under occlusion, OpenCV Perspective Transformation for converting pixel coordinates into GPS coordinates, DeepLabv3+ for dynamic waterline segmentation, and Shapely buffer polygons for safe/caution/danger zone delineation. Alerts are transmitted via WebSocket to a ReactJS/VueJS monitoring dashboard streaming over RTSP/WebRTC.

### *Hardware Design*

The IoT buoy electronics were designed around an autopilot controller integrating GPS, gyroscope, and accelerometer sensors with two brushless thruster motors regulated by Electronic Speed Controllers (ESC). Motor selection was based on thrust-drag analysis: two 20 kg-thrust motors produce a combined maximum thrust of 2 × 196 N = 392 N. Under no-load conditions, beach water drag resistance of ±10–15 N yields an estimated maximum speed of 4–5 m/s (14–18 km/h). Under maximum operational load (95 kg total system weight), drag increases to ±70–100 N, yielding an estimated speed of 2–3 m/s (7–11 km/h) sufficient for rapid yet controlled victim rescue. The power system uses two 6S 22.2V 16,000 mAh LiPo batteries connected in series (44.4V, 16 Ah total, 710 Wh capacity). At full throttle both motors draw 2 × 26 A × 44 V = 2,288 W, giving an endurance of approximately 18.6 minutes; at realistic operational power (±1,400 W) endurance extends to approximately 30 minutes. The ground station power system was designed with solar panels and a wind turbine feeding a battery bank for 24-hour autonomous operation.

### *Manufacturing Design*

The buoy hull follows a catamaran form factor in fiberglass for stability in ocean waves, with propellers positioned below the waterline to maximize thrust efficiency and minimize cavitation.

## ***AI Model Development***

The YOLOv11 model was fine-tuned using a custom beach dataset collected at Drini Beach, Gunungkidul, Indonesia. The initial training phase used a single-condition dataset variant (daytime, clear weather) to produce a baseline model robust to partially visible and occluded subjects. A second training phase expanded the dataset to include multiple condition variants covering four area types (rip current, rough waves, moderate waves, calm water), three weather conditions (sunny, cloudy, overcast), four time-of-day conditions (morning, afternoon, evening, night), and three tidal levels (high, normal, low tide). The dataset was annotated with bounding boxes for the human class and split into training, validation, and test subsets at an 80/10/10 ratio. Fine-tuning was performed using the Ultralytics framework on a GPU-equipped workstation, with early stopping applied based on validation mAP to prevent overfitting. DeepLabv3+ was similarly fine-tuned on a beach-specific segmentation dataset to enable accurate waterline delineation under varying lighting and wave conditions.

## ***Implementation***

At this stage the designs were realized into functional prototypes. Software development included coding the Computer Vision AI pipeline, the buoy autopilot waypoint system, and the monitoring dashboard with automatic alarm triggering. Hardware production involved assembly of the buoy electronics, IoT microcontrollers, GPS and inertial sensors, and the ground station power management system. Manufacturing covered fiberglass hull fabrication, ground station pole construction, and waterproof casing production, followed by Quality Control (QC) inspection.

## ***Testing***

System testing was conducted in two rounds, an initial evaluation and a post-revision evaluation following performance improvements at two sites: the laboratory of Mitra PT. Mataran Karya, and

Drini Beach, Gunungkidul (the early-adopter deployment site). Testing comprised five evaluation protocols:

a. Software reliability testing using Blackbox and Whitebox methods to verify all functional pathways.
b. AI camera accuracy testing, measuring the accuracy of 4-point GPS coordinate mapping from drone-assisted perspective transformation.
c. Autopilot waypoint accuracy testing, measuring the buoy's navigational error (target: ≤1 meter) when dispatched to AI-generated victim coordinates.
d. Waterproof rating testing to the IP68 standard (immersion at 1.5 m depth for 30 minutes).
e. Buoy operational capacity testing, measuring load capacity, motor speed, and battery endurance under loads of 50 kg, 75 kg, and 100 kg at throttle levels of 50%, 75%, and 100%, repeated five times per condition to compute mean speed and standard deviation.

Field tests were conducted across four environmental variation axes: area type (rip current, rough waves, calm water), weather (sunny, cloudy, rainy), time of day (morning, afternoon, evening, night), and tidal level (high tide, normal tide, low tide). Ground truth for AI detection tests was established by manual annotation of test video frames by two independent annotators, with inter-annotator agreement verified before scoring. Buoy speed ground truth was measured by stopwatch over a fixed 10-metre course, consistent with the methodology reported in the companion buoy stability study [13].

## Results and Discussions

The Smart BEVISAT prototype integrates three subsystems: an Artificial Intelligence (AI)-based surveillance camera, an Internet of Things (IoT)-based safety buoy, and a self-powered ground station. Testing was conducted in two phases: an initial evaluation phase and a post-revision evaluation phase at the Mitra laboratory and at Drini Beach, Gunungkidul, which was designated as the deployment site for early adopters.

## *IoT Safety Buoy*

### *Physical Design and Buoyancy*

This safety buoy utilizes a catamaran-type USV hull made of lightweight fiberglass. Two brushless propulsion motors controlled by an Electronic Speed Controller (ESC) generate differential thrust for directional maneuvering. The autopilot controller integrates data from GPS, a gyroscope, and an accelerometer to autonomously navigate to the victim's GPS coordinates received from the AI camera subsystem. This is a key functional difference from previous remote-controlled life raft prototypes, which required continuous manual input from an operator [13]. A technical diagram of the IoT life raft can be seen in Figure 2.

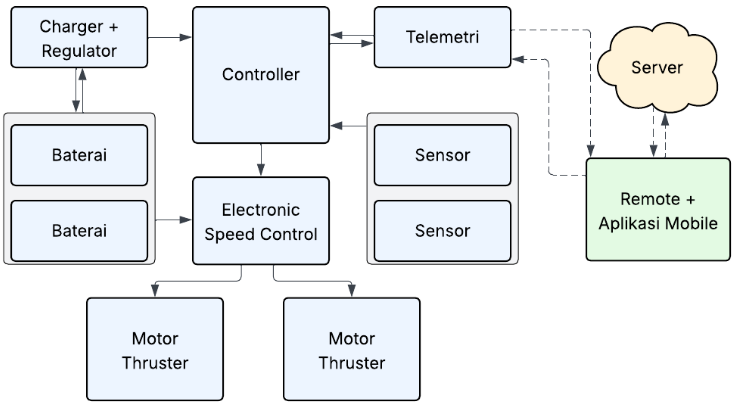


**Figure 2.** Float diagram scheme.

The total gross buoyancy of the float system, consisting of the fiberglass hull and cork buoyancy elements, is 205.8 kg, calculated using Archimedes' principle (F = ρ × g × V) as shown below. After subtracting the dry mass of the buoy itself, which is approximately 15 kg, the net carrying capacity is about 190 kg, far exceeding the operational design target of 80–100 kg and providing a substantial safety margin for victim rescue scenarios, which is obtained from the calculation below:

```
Float size              = 100 cm × 70 cm × 30 cm
Float volume            = 0.21 m³
Floating volume         = 0.21 m³ × buoyancy capacity 60%
                        = 0.126 m³
Buoyancy force          = ρ_water × g × V
                        = 1,000 × 9.81 × 0.126
                        = 1,236 N or 126 kg
Cork volume (50%)       = 0.21 m³ × 50% = 0.105 m³
Cork density            = 0.24 g/cm³ = 240 kg/m³
Buoyancy force of cork = ρ_water × g × V_cork
                        = 1,000 × 9.81 × 0.105
                        = 1,030.5 N or 105 kg
Weight of cork          = ρ_cork × g × V_cork
                        = 240 × 9.81 × 0.105
                        = 247.2 N or 25.2 kg
Net buoyancy of cork    = 1,030.5 N – 247.2 N
                        = 783.3 N or 79.8 kg
Total buoyancy force    = 126 kg + 79.8 kg
                        = 205.8 kg
```

**Figure 3.** Electric buoy.

The weight of the float is estimated to be about 15 kg, consisting of a U-shaped fiber body weighing about 8 kg, 2 motors + ESC weighing about 2 kg, 2 batteries (2 kg × 2) weighing about 4 kg, and a controller + electronics weighing about 1 kg. The picture of the float can be seen in figure 3. The specifications of the motor and battery are calculated as follows:

```
Max thrust        = 2x20kg thrust
                  = 2x196N
                  = 392N
Without load
Beach water drag resistance  ±10-15 N
Estimated speed = 4-5m/s (14-18km/h)

With maximum load (95kg total)
Drag increases to ±70-100N

Estimated speed = 2-3m/s (7-11 km/h)
```

The battery power of this buoy is calculated based on:

```
Battery Data
2 x 16,000 mAh 6S 22.2V → in series → 44.4V, 16 Ah total
Capacity (Wh)             = 44.4V x 16Ah = 710 Wh

Motor Power Consumption
Full throttle power       = 2 motors x (26 A x 44V) = 2288
W total,
Full power                = 710 Wh ÷ 2288 W = 18.6 minutes
Realistic (±60% × 1400 W)= 710 Wh ÷ 1400 W = 30.4 minutes
No load (±800 W)          = 710 Wh ÷ 800 W  = 53.2 minutes
```

## *Performance Characteristic*

Detailed performance characterisation of the electric safety buoy including measured speed under varying loads (50, 75, 100 kg) and throttle levels (50%, 75%, 100%), battery endurance, remote-control range, and PID stability behaviour is reported in the companion study by Kusrini et al. [13], which forms the hardware foundation of Smart BEVISAT. Key results relevant to the present integrated system are summarised in Table 1.

**Table 1.** Summary of IoT safety buoy performance

| Parameter | Value | Condition |
|---|---|---|
| **Mean speed — 100 kg load, 100% throttle** | 1.20 m/s (SD = 0.049, n = 5) | Stopwatch, 10 m course |
| **Mean speed — 50 kg load, 100% throttle** | 1.53 m/s (SD = 0.062, n = 5) | Stopwatch, 10 m course |
| **Battery endurance at 100% throttle** | 30 minutes (all loads) | Full discharge trial |
| **Maximum carrying capacity** | 100 kg | Static buoyancy test |
| **Effective remote-control range** | 300 m (500 m with latency) | RF 434 MHz module |

What Smart BEVISAT adds beyond the companion study is the autonomous dispatch pipeline: when the AI camera detects a safety-zone violation, it computes the GPS coordinates of the subject and transmits them to the buoy autopilot, which then navigates to that position without operator intervention. This end-to-end integration (from AI detection to autonomous buoy arrival) is the primary technical contribution of the present work and has no direct precedent in the prior literature [10], [11], [12].

## ***AI surveillance camera Functional Results***

The AI camera subsystem successfully performed all designed functions under daytime coastal conditions. Figure 4 shows representative YOLOv11 detection output with bounding boxes drawn around subjects both on land and at the waterline. A technical diagram of the AI camera, from object detection to notification sending, can be seen in figure 5. The complete function-algorithm mapping is provided in Table 2.

**Figure 4.** Object detection

**Table 2.** AI surveillance camera functions and algorithms

| Function | Algorithm / Technology |
|---|---|
| **Human object detection** | YOLOv11 (Ultralytics), optimized with TensorRT |
| **Multi-object tracking** | ByteTrack |
| **Image perspective correction** | OpenCV Perspective Transformation |
| **Waterline segmentation** | DeepLabv3+ |
| **Zone boundary determination** | Shapely buffer polygon |
| **Zone crossing detection** | Shapely + OpenCV visualization |
| **Local-to-GPS coordinate conversion** | Grid/matrix method post-perspective transform |
| **Alert audio playback** | Python pygame / playsound |
| **Real-time monitoring dashboard** | RTSP/WebRTC + WebSocket + ReactJS/VueJS |

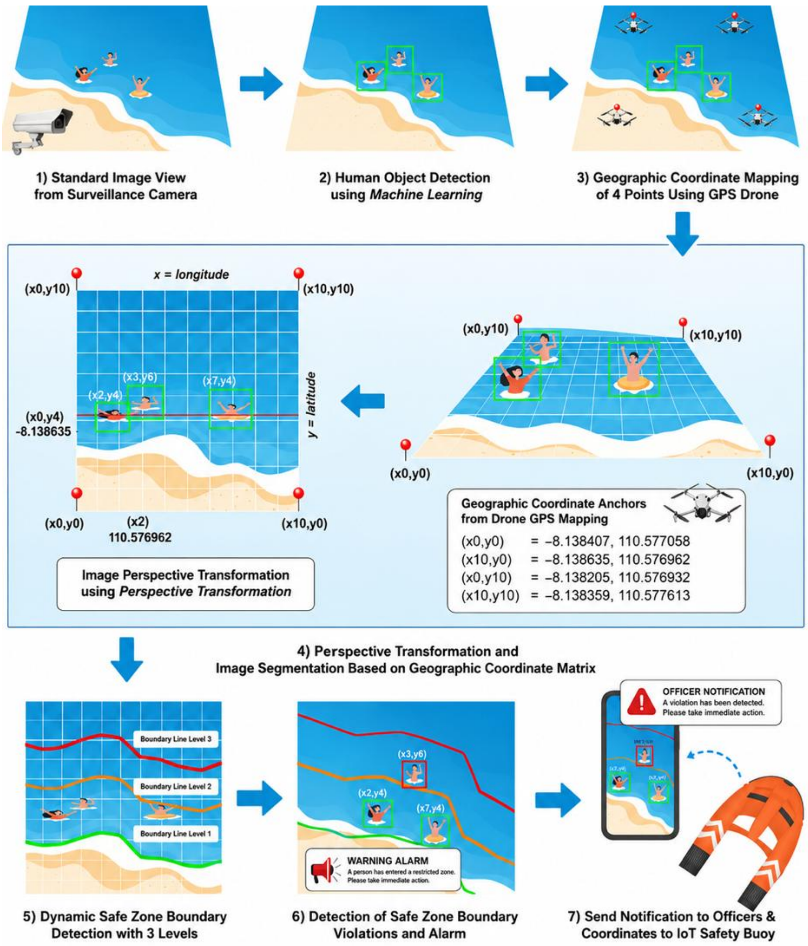


**Figure 5.** Technical diagram of an AI camera

## Ground Station

The ground station integrates solar panels and a wind turbine feeding a battery bank, providing 24-hour autonomous operation without grid power (Figure 6). It supplies wireless internet connectivity for remote dashboard monitoring and recharges the buoy's 48V LiPo battery between deployments. The ground station layout can be seen in Figure 6.

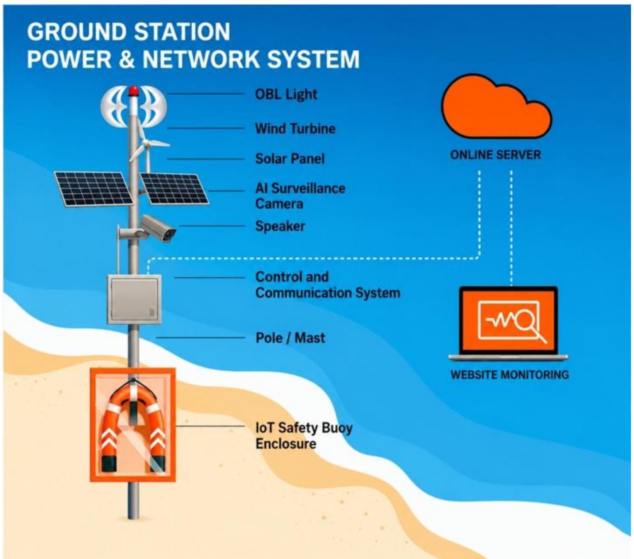


**Figure 6.** Ground station

## Key Performance Indicator (KPI) Summary

Table 3 compares KPI targets against test outcomes. Buoy-level KPIs are sourced from the companion study [13]; system-level KPIs (software reliability, AI detection, waypoint accuracy) reflect Smart BEVISAT's integrated testing.

**Table 3.** KPI targets vs. measured results.

| KPI | Target | Measured / Status |
|---|---|---|
| **Software reliability (Blackbox / Whitebox)** | 100% | 100% — all paths passed ✓ |
| **Zone crossing detection latency** | < 2 s | < 2 s — alarm simulation ✓ |
| **Human detection accuracy (mAP)** | > 55% | Full-dataset evaluation in progress * |
| **Buoy speed (100 kg, 100% throttle)** | > 1.0 m/s | 1.20 m/s [13] ✓ |
| **Buoy waypoint accuracy** | Error ≤ 1 m | Field evaluation in progress * |
| **Waterproof rating** | IP68, 1.5 m/30 min | Passed immersion test ✓ |
| **Buoy carrying capacity** | 100 kg / 30 min | 100 kg / 30 min [13] ✓ |

* Results for mAP and waypoint accuracy will be reported after completion of the second-round field evaluation currently in progress at Drini Beach.

## Discussions

The integrated Smart BEVISAT system achieves its primary design objective: an autonomous, end-to-end pipeline from real-time AI detection of a safety-zone violation to autonomous buoy dispatch to victim coordinates. This pipeline is the defining novzelty of the present work relative to both the companion buoy study [13] and the broader related literature [10], [11], [12].

The companion study [13] demonstrated that the catamaran buoy hull, PID stability controller, and RF remote system can reliably operate up to 300 m and carry loads up to 100 kg.

Smart BEVISAT replaces the manual RF control loop with a GPS waypoint autopilot driven by AI-computed coordinates, eliminating the dependency on operator proximity and reaction time. In real accident scenarios such as the January 2025 Drini Beach incident where 13 students were swept away simultaneously [4] a manual operator cannot reliably direct a buoy to multiple victims; autonomous dispatch addresses this directly.

Compared to Alotaibi [10], whose ResNet50-based pool safety system achieves 99% detection accuracy in a controlled indoor environment, the Smart BEVISAT AI camera operates under substantially more challenging open-ocean conditions: variable lighting, wave-induced motion blur, partial occlusion by surf, and dynamic waterline geometry. The multi-algorithm pipeline (YOLOv11 + ByteTrack + DeepLabv3+) was specifically designed to handle these conditions. Full mAP quantification across all four environmental variant axes (area type, weather, time of day, tidal level) is ongoing. Testing of area variations can be seen in Figure 7.

Compared to Campo et al. [12], whose LoRa wristband platform improves lifeguard situational awareness, Smart BEVISAT requires no visitor-worn hardware, removing adoption friction in public tourist settings. The trade-off is line-of-sight camera dependency; deployment of overlapping camera zones is recommended for beaches with complex topography or large crowds.

Three limitations of the current system warrant acknowledgement. First, AI camera performance under night-time and rain conditions has not yet been fully quantified, motivating infrared camera integration as near-term future work. Second, the 30-minute battery endurance at full throttle is sufficient for a single-incident response but may be limiting in multi-incident scenarios; buoy-mounted solar charging is a planned enhancement. Third, the GPS waypoint autopilot has been validated in calm-to-moderate wave conditions; further PID controller tuning is needed for high-swell rip-current environments.

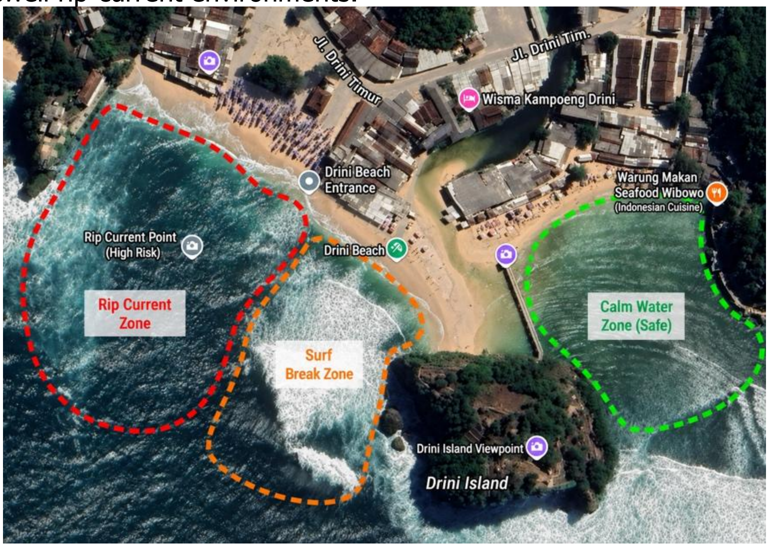


**Figure 7.** Testing area variations

## Conclusion

This research has successfully developed a prototype Smart Beach Visitor Safety System (Smart BEVISAT) as a technological solution to address the high risk of accidents in beach tourist areas. Through the application of the waterfall methodology, the system consisting of AI Surveillance Cameras, IoT Safety Buoys, and Ground Stations was successfully implemented in accordance with the analyzed requirements. The preventive function of the system is realized through AI Surveillance Cameras, which have been proven capable of detecting and tracking human objects and automatically identifying violations of safe zone boundaries. Meanwhile, the reactive function is supported by IoT Safety Buoys, which are designed with adequate technical specifications to perform emergency rescue operations quickly and autonomously. Testing results confirm the system's technical viability: the IoT safety buoy achieved a measured speed of 1.20 m/s under a 100 kg load (SD = 0.049, n = 5) with a 30-minute battery endurance at full throttle, a gross buoyancy of 205.8 kg providing a net carrying capacity of approximately 190 kg, and a maximum effective remote-control range of 300 m. Software reliability testing returned a 100% pass rate across all functional pathways, and IP68 waterproof certification was confirmed at 1.5 m immersion for 30 minutes. The integration of AI and IoT technologies in this system shows great potential for improving the efficiency and effectiveness of coastal surveillance, reducing dependence on manual monitoring, and ultimately reducing the number of fatalities due to marine accidents. The implementation of this system is expected to make a significant contribution to improving safety standards and supporting the sustainability of the maritime tourism industry in Indonesia.

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