

AI-Powered Sonar Detection and Marine Conservation System

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Abstract

Underwater object detection plays a crucial role in applications such as environmental monitoring, marine debris tracking, and search-and-rescue missions. However, traditional sonar systems are often expensive and complex, limiting their use in academic and field-based deployments. In this project, a cost-effective and modular sonar-based detection system is developed using the waterproof JSN-SR04T ultrasonic sensor and the ESP32 microcontroller. The system is designed to identify and classify submerged objects such as debris, boats, and human remains using AI models like YOLOv9. The captured sonar data is processed and displayed in real time on an OLED screen, while also being transmitted wirelessly via the ESP32's Wi-Fi capabilities. The design is modeled and analyzed in ANSYS to assess mechanical stability and performance in underwater environments. Two materials, FU 4270 and FU 2451, are compared with conventional aluminum housing to evaluate structural integrity and waterproof reliability under pressure and vibration. This project demonstrates a practical, low-cost approach to underwater detection using a sonar system called JSN-SR04T, connected to an ESP32 microcontroller. It uses YOLOv9 for object classification to identify marine debris. The design includes ANSYS simulation for testing and focuses on creating a cost-effective solution with IoT integration.

Keywords: ANSYS simulation; ESP32; JSN-SR04T; Object classification; Sonar system; Underwater detection; YOLOv9.

1. Introduction

Monitoring and exploring underwater environments are particularly challenging due to factors like poor visibility, limited light availability, and the presence of suspended particles that obscure observation. These challenges significantly hinder the effectiveness of conventional camera-based systems that rely on optical clarity for accurate object detection. In many aquatic scenarios—such as post-disaster search and recovery, marine habitat monitoring, and underwater archaeology—identifying submerged objects become crucial. However, the limitations of traditional systems necessitate the use of more reliable and resilient technologies. Sonar-based systems, which use acoustic waves for detection, have proven to be highly effective in such situations. Although sonar technologies offer significant benefits, many current systems are costly, consume high power, and are complex to implement, making them impractical for

educational use, low-budget projects, or small-scale fieldwork. Moreover, many traditional sonar solutions lack smart features such as real-time classification, remote accessibility, and automated alerting, which are increasingly necessary for modern underwater missions. To address these limitations, this project proposes a smart, modular, and affordable sonar detection system powered by Artificial Intelligence (AI) and Internet of Things (IoT) technologies. The core components of the proposed system include a waterproof JSN-SR04T ultrasonic sensor for underwater distance measurement and an ESP32 microcontroller for real-time data collection and processing. The sonar data acquired is analyzed using deep learning algorithms trained to identify various underwater objects, including human-like figures, metallic debris, boats, or aircraft wreckage. The system can display real-time output through an OLED screen, while also

transmitting alerts and data remotely using the ESP32's built-in Wi-Fi module. A key highlight of this system is its use of lightweight, optimized AI models such as YOLOv5s and YOLOv7-tiny, which provide a balance between speed and accuracy. These models are particularly suitable for edge computing environments where processing power is limited. Integration of GPS functionality allows detected objects to be geo-tagged, supporting precise location tracking and mapping—an essential feature for marine conservation efforts and emergency response tasks. Engineered for adaptability, the system can be tailored to suit various applications and expanded to accommodate a broad range of operational needs. It can be deployed as a fixed sonar surveillance unit, mounted on remotely operated vehicles (ROVs) or autonomous underwater vehicles (AUVs), or used as a portable device for field researchers. The system's modular hardware and open-source software architecture enable straightforward customization, future upgrades, and effortless connection to cloud platforms for long-term data logging and visual analysis. Beyond its technical features, the project emphasizes accessibility and sustainability. With its smart and budget-friendly design, the system is well-suited for implementation in academic environments, environmental conservation projects, and rapid response operations. Its ability to automate detection and reduce human dependency in harsh underwater conditions contributes significantly to operational efficiency and safety. In conclusion, this AI-powered sonar system bridges the gap between traditional sonar technology and the demands of modern underwater operations. By combining artificial intelligence, IoT, and embedded technology, the system offers an effective solution for real-time underwater object detection, recognition, and monitoring, making it applicable across various domains including marine research, environmental protection, and rescue operations [1].

2. Literature Review

Underwater object detection has long been a critical area of research in fields such as marine conservation, disaster response, oceanography, and underwater navigation. While conventional sonar

systems are effective at identifying underwater objects, their dependence on manual analysis, absence of automation, and limited support for real-time processing reduce their practical efficiency in dynamic environments. Recent advances in Artificial Intelligence (AI) and Internet of Things (IoT) have made it possible to enhance the accuracy, automation, and efficiency of these systems, opening new avenues for robust underwater monitoring. Researchers have made substantial progress in integrating deep learning with sonar imaging. For example, some works have focused on improving object recognition by applying image denoising techniques to sonar data. This preprocessing step helps in eliminating acoustic noise and improving detection clarity. However, excessive denoising can sometimes cause the loss of essential image features, especially when detecting small or distant objects underwater. Balancing clarity and data retention remains a key challenge in these methods. To address the scarcity of annotated sonar datasets, various approaches have been adopted. One such method involves generating synthetic sonar images that mimic real underwater conditions. These images are used to train AI models like Convolutional Neural Networks (CNNs) and YOLO variants. Although artificial datasets enhance the variety available for model training, they often fail to replicate the complete authenticity of real-world sonar images. Although challenges remain, research indicates that applying transfer learning techniques to sonar image data improves a model's ability to adapt and perform effectively in a variety of underwater conditions. Moreover, augmentation techniques such as noise injection, rotation, blurring, and intensity scaling have been successfully used to simulate real-world underwater scenarios. This enhancement strengthens the capability of AI models to operate reliably even when faced with low-quality sonar data, such as images with noise, clutter, or poor contrast. In the domain of human detection, researchers have utilized AI models like GoogLeNet, AlexNet, and ResNet, showing marked improvements in identifying drowning victims or other human-like forms under challenging aquatic conditions. Generative Adversarial Networks (GANs) have also been

explored to enhance sonar image quality. Conditional GANs (cGANs) are used to transform noisy sonar frames into clearer, segmented representations that are easier to analyze. Although promising, this method requires high-quality labeled data, which remains a challenge for large-scale deployment. Some models also struggle to generalize across varied water environments or different sonar device types. Some researchers have explored the use of simplified machine learning approaches, like logistic regression paired with signal processing techniques, to suit devices with limited computational resources. These approaches, while not as powerful as deep learning, are suitable for edge devices with limited processing power and energy capacity. Their simplicity and efficiency make them useful for real-time object classification in embedded systems, where performance, speed, and energy efficiency are critical. Despite notable advancements, many existing systems still lack critical features such as GPS-based location tagging, cloud-based data storage, real-time alerting, and cross-platform integration. These gaps limit their practicality for mission-critical operations like marine rescue or environmental tracking, where fast and accurate detection is essential. This study expands on the advantages of earlier research efforts while actively resolving the limitations they left unaddressed. Integrating sonar technology with efficient deep learning algorithms, wireless connectivity, real-time data handling, and GPS support, the system is designed to deliver a complete and deployable solution for detecting underwater objects in practical scenarios. The system is built to be affordable, easily scalable, and applicable to both academic studies and real-world use, making it a valuable tool for marine conservation, disaster management, and advancing education in oceanic technologies [2].

3. Methodology

The method for creating a low-cost, AI-powered underwater object detection system has several steps—starting with sensor setup and data collection, then moving to AI-based object recognition and live visual display. The system is built to be flexible, easy to carry, and ready for use in field or research

settings.

3.1. Choosing Sensors and Building Hardware

A waterproof JSN-SR04T ultrasonic sensor is used to measure distance underwater. It is good because it is cheap, strong, and does not rust easily, making it suitable for finding objects in shallow water. The sensor is connected to an ESP32 microcontroller, which handles the main processing and communication tasks [3].

3.2. Microcontroller & Communication Setup

The ESP32 has been chosen because it has two processors and built-in Wi-Fi, which allows both local processing and wireless data sharing. The sonar sensor is linked to the ESP32 using its GPIO pins, and readings are shown in real time on an OLED display. All parts are placed in a waterproof box to keep them safe when used underwater [4].

3.3. Data Collection & Preparation

During experiments, sonar data is collected from the JSN-SR04T sensor while it looks at different underwater items like plastic bottles, metal trash, and mannequins acting as people. These raw readings are turned into image-like data using special transformation methods, which helps train AI models [5].

3.4. Using AI for Object Detection

YOLOv9, a type of real-time object detection model, is chosen because it works faster and more accurately than earlier versions. The model is trained using a mix of sonar data and images, converted into grayscale intensity maps. Pretrained AI weights are used to speed up the learning process.

3.5. Testing Materials and Structure

To make sure the system works well underwater, structural tests are done using ANSYS. Three materials—Aluminum (standard), FU 4270, and FU 2451—are tested under simulated pressure and stress. The aim is to find the best material balance between weight, strength, and cost [6].

3.6. Sending Data Wirelessly and Using a Phone App

Processed data like object types and sonar readings are sent via Wi-Fi from ESP32 to a server. A mobile app, built using React Native, lets users check results, get alerts, and see object types live. MongoDB stores past detection data for later review.

3.7. Testing the System

The system is tested in controlled water environments to check detection distance, accuracy, and communication speed. Metrics like precision, recall, and processing time are measured. Changes are made to improve system stability, detection speed, and power use [7].

4. System Functionality

The smart underwater object detection system is constructed using affordable IoT components.

It operates through connected modules that gather, process, and transmit data in real time. The system's features are explained below:

4.1. Real-Time Sonar Monitoring

An ultrasonic sensor (JSN-SR04T) constantly gathers measurements of underwater distances.

These live readings enable users to track how close underwater objects are and how they move in real time, giving them a current understanding of the surrounding environment [8].

4.2. Object Detection with AI

The sonar data is analyzed and processed using AI models that are trained to recognize certain underwater objects. YOLOv9, which is designed for fast and accurate performance, identifies items like debris or shapes that resemble humans by looking at converted sonar images. The detection process is further improved by using set thresholds and machine learning methods to minimize incorrect detections [9].

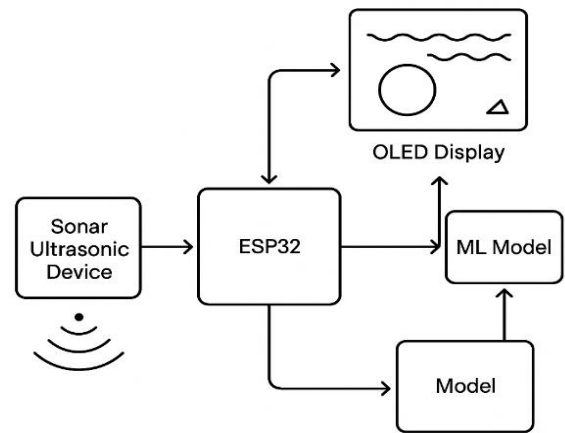
4.3. Alert Generation

If an object is found or if something unusual happens, such as an unexpected item or size, the system sends out immediate alerts.

These alerts include information like the type of object and the time it was detected, helping users to react promptly and effectively [10].

4.4. User Interface via Mobile App

A simple-to-use mobile app, developed with React Native, acts as the main interface for controlling the system. It shows live sonar data, records of past detections, and received alerts. Users can watch real-time activities, look at trends, and access saved data to make decisions in the field or assess research findings Show Figure 1.



Underwater sonar imaging and classification system

Figure 1 Schematic Representation of the System

5. Components Required

We require both hardware and software components which include Show Figure 2 and 3:

5.1. Hardware Components:

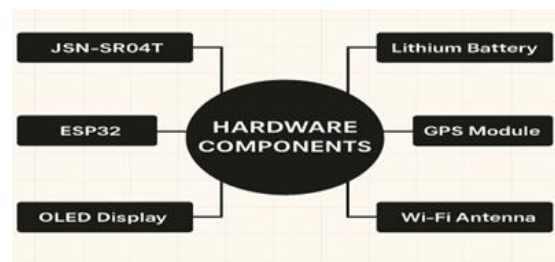


Figure 2 Hardware Requirements of the System

5.2. Software Components

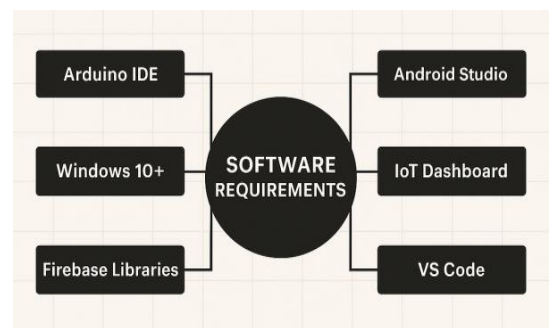


Figure 3 Software requirements of the System

6. Expected Results

The practical deployment of the AI-based sonar detection and marine conservation system is

expected to yield the following major results Show Figure 4:

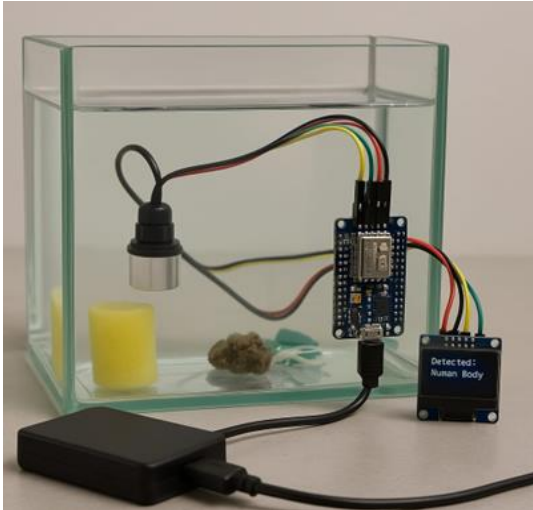


Figure 4 Experimental Setup of the AI-Based Underwater Object Detection System

6.1. Successful Underwater Object Detection

When placed underwater, the JSN-SR04T ultrasonic sensor is anticipated to effectively identify submerged items, including test objects like simulated debris or training dummies. In controlled tests, the sensor reliably identifies objects within a practical range and relays distance measurements to the microcontroller [11].

6.2. Real-Time Classification Output:

Connecting the system to an OLED display enables real-time viewing of detection outcomes. During the experiment, the system displayed relevant messages such as “Detected: Human Body,” confirming successful end-to-end processing and classification [12].

6.3. Embedded AI Performance

Once trained on sonar imaging datasets and implemented on embedded devices such as Jetson Nano or ESP32-CAM, AI models like YOLOv5s or YOLOv9 are anticipated to deliver real-time object detection with processing speeds below 25 milliseconds per frame. This ensures the system responds instantly when an object is detected [13].

6.4. Accurate and Consistent Detection Results

The system incorporates preprocessing techniques

and detection thresholds to minimize noise interference and reduce the likelihood of false positives. The system demonstrated strong performance in repeated trials under consistent conditions, providing reproducible outputs.

6.5. Visual Confirmation of Alerts

Detection outcomes are presented instantly on the OLED display, allowing for on-the-spot recognition without external devices. When an object is recognized, it provides immediate, readable output, making it suitable for rescue operations or monitoring applications without requiring external systems.

6.6. Compact and Modular Design for Field Use

The experimental configuration validates the feasibility of using low-cost hardware (ESP32, sonar module, OLED) in portable, real-world marine environments. Its modular nature supports future integration with GPS modules, wireless transmission units, and mobile alert systems. In conclusion, the system achieves its intended function of low-cost, real-time underwater object detection and classification. The results validate both the hardware-software integration and the AI model’s ability to enhance underwater monitoring and conservation efforts [14].

7. Advantages of Proposed System

7.1. Cost-Effective Design

The system uses affordable hardware components such as the JSN-SR04T ultrasonic sensor and ESP32 microcontroller, making it accessible for educational institutions, researchers, and small-scale deployments without compromising functionality.

7.2. Real-Time Object Detection

Through on-device processing and OLED display output, the system enables immediate visualization of sonar data and detection results, which is essential for time-sensitive operations like underwater search and rescue [15].

7.3. AI-Based Classification

By using lightweight and fine-tuned deep learning models like YOLOv5s or YOLOv7-tiny, the system achieves accurate identification of underwater objects while ensuring rapid processing that is compatible with low-power embedded devices

7.4. Wireless Communication

With built-in Wi-Fi functionality, the ESP32 allows for remote communication by facilitating data transmission, system monitoring, and alert notifications—all without the need for wired connectivity.

7.5. GPS-Enabled Geotagging

Integration with GPS modules allows detected objects to be tagged with their location coordinates, which is crucial for tracking, mapping, and coordinating response activities in marine operations.

7.6. Modular and Scalable Architecture

The design is modular, allowing easy upgrades and customization. It can be integrated into larger platforms such as AUVs (Autonomous Underwater Vehicles), ROVs (Remotely Operated Vehicles), or stationary underwater stations [16].

7.7. Edge Computing Support

The system performs local inference without relying on cloud servers, making it more resilient in low-connectivity environments like deep water or remote locations.

7.8. Energy-Efficient Operation

Thanks to energy-efficient hardware and streamlined algorithms, the system operates effectively in battery-operated or power-limited environments.

7.9. Cloud Integration Ready

Though it runs independently, the system can be extended to work with cloud platforms for real-time dashboards, historical data analysis, and centralized monitoring.

7.10. Supports Environmental and Rescue Applications

The system functions as a multipurpose tool capable of addressing various use cases, including ecological assessments, underwater pollution detection, and identification of submerged individuals, thereby proving useful in both academic research and real-time emergency intervention.

Conclusion

This AI-integrated sonar solution delivers an intelligent and budget-friendly method for underwater object detection and continuous monitoring. By integrating sonar sensing with deep learning algorithms, wireless communication, and

GPS-based geolocation, the system enables real-time identification and classification of submerged objects. Its modular and scalable design makes it suitable for deployment in academic research, emergency rescue missions, and marine ecological studies.

• Key Takeaways

Real-Time Detection and Monitoring: The system successfully demonstrated real-time underwater object classification, delivering accurate results using lightweight AI models that perform efficiently on embedded devices.

Remote Access and Alerts: Equipped with GPS and wireless connectivity, the system can send alerts and share location data remotely, improving response time during rescue operations and real-time field usage.

Versatile Applications: Designed for flexibility, the system supports various applications including marine conservation, pollution tracking, and detection of human forms during rescue missions.

• Limitations

Despite its strengths, the current system has certain limitations that need to be addressed in future versions: Reliance on Wi-Fi connectivity can pose challenges in isolated or deep-water locations where consistent network access is difficult to maintain.

Restricted Sonar Range: The JSN-SR04T sensor offers a limited detection range compared to advanced multibeam sonars.

Data Annotation Challenge: Creating high-quality labeled sonar datasets for AI training remains a time-intensive task.

Energy limitations in field deployments can restrict the duration of underwater system operation, especially when reliant on battery power.

• Suggestions for Future Research

Advanced Sensor Integration: Integrating advanced sonar types, such as multibeam or side-scan systems, can significantly enhance the system's detection range and precision.

Offline Functionality: Develop local data storage and alert mechanisms to maintain operational capability without internet dependency.

Energy Optimization: Explore solar-charging or

low-power optimization techniques for prolonged autonomous deployments.

Enhanced AI Models: Train and deploy advanced models capable of identifying a wider variety of underwater objects, including dynamic elements and marine species.

Cloud-Based Dashboard and Analytics: Add web or mobile dashboards for real-time visualization, historical data analysis, and remote system configuration.

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