AI-Based Autonomous Underwater Submersible Machine

Santoshi Parte[1], **Mrunali Panchal** [2], **Sandhya Kaprawan**[3]

[1]*Department of Information Technology, University of Mumbai, India.*

[2]*Department of Information Technology, University of Mumbai, India.*

[3] *Professor, Department of Information Technology, University of Mumbai, Maharashtra, India.*

Abstract - *The underwater environment remains one of the least explored regions of the Earth due to several operational challenges, including high water pressure, low visibility, complex terrain, and limited accessibility. Conventional underwater exploration methods primarily depend on human divers and remotely operated vehicles (ROVs). However, these approaches are often restricted by depth limitations, safety concerns, communication constraints, and high operational costs, making long-duration and large-scale underwater missions difficult to conduct efficiently. As a result, there is a growing need for intelligent and autonomous underwater systems capable of operating with minimal human intervention. This research presents the design and development of an Artificial Intelligence (AI)-based Autonomous Underwater Submersible Machine for underwater exploration, monitoring, and navigation. The proposed system integrates advanced AI algorithms, computer vision techniques, sonar sensing, and environmental monitoring technologies to enable intelligent decision-making in underwater environments. The submersible is equipped with cameras, sonar sensors, depth sensors, and additional environmental sensors to collect real-time data regarding underwater conditions, obstacles, and surrounding objects. The collected data is processed using machine learning and deep learning models for object detection, obstacle avoidance, environmental analysis, and autonomous navigation. Image enhancement and preprocessing techniques are incorporated to improve visibility and feature extraction from underwater images affected by poor lighting and water distortion. The system is designed to perform exploration tasks efficiently while ensuring operational safety and reducing dependence on human operators.*

Keywords: **Underwater Robotics, Autonomous Navigation, Sonar Imaging, Sensor Fusion, Deep-Sea Exploration, Obstacle Avoidance, Ocean Monitoring, Swarm Robotics.**

1. INTRODUCTION

1.1 Background

The ocean covers more than 70% of the Earth's surface, yet a significant portion of it remains unexplored because of the harsh underwater environment and technological limitations [1]. Oceans are important for maintaining ecological balance, supporting marine biodiversity, regulating climate, and providing valuable natural resources. Underwater exploration plays a crucial role in marine research, environmental monitoring, defence surveillance, offshore oil and gas inspection, and disaster management [1][20]. However, underwater environments present several challenges such as high pressure, low visibility, unstable currents, and communication difficulties, making underwater exploration a complex task [3].

Recent advancements in Artificial Intelligence (AI), robotics, computer vision, and sensor technologies have enabled the development of intelligent underwater systems capable of performing autonomous underwater operations. Autonomous Underwater Vehicles (AUVs) and AI-based submersible systems can navigate underwater environments, detect obstacles, collect environmental data, and make real-time decisions with minimal human intervention [4][14]. These technologies improve operational safety, increase exploration efficiency, and reduce the risks associated with human-operated underwater missions.

The proposed AI Submersible Underwater Machine integrates AI algorithms, sonar sensing, computer vision, and environmental monitoring systems to perform intelligent underwater exploration and monitoring tasks. The system is designed to operate autonomously while collecting and analyzing underwater data efficiently. By reducing human involvement in hazardous underwater missions, the proposed system enhances safety, reliability, and long-duration underwater operation capabilities [5][14].

Underwater exploration has traditionally relied on human divers and remotely operated vehicles (ROVs)[20]. Although these methods have been widely used for underwater inspection and marine research, they have several limitations. Human divers are restricted by depth limits, oxygen availability, and operational time, making deep-sea exploration dangerous and difficult [6]. Additionally, underwater missions often require expensive equipment, skilled operators, and continuous monitoring, increasing operational costs and risks.

To overcome these challenges, researchers have focused on developing Autonomous Underwater Vehicles (AUVs) equipped with Artificial Intelligence and advanced sensing technologies. AI enables underwater systems to perform intelligent navigation, obstacle avoidance, object detection, and environmental monitoring [4][7]. Machine learning and deep learning algorithms allow underwater robots to process sonar data and underwater images for recognizing marine objects and underwater structures [2][8].

Computer vision techniques are also widely used in underwater exploration for image enhancement, underwater mapping, and target identification. However, underwater imaging faces challenges such as light absorption, scattering, blur, and color distortion [3][18]. Therefore, sonar sensing systems are integrated with computer vision methods to improve underwater perception and navigation in lowvisibility conditions [5][13]. Modern AI-powered underwater systems combine these technologies to improve the efficiency and reliability of underwater operations.

1.2 Statement of the Problem

Traditional underwater exploration methods face multiple challenges due to the limitations of human divers and conventional underwater systems. Human divers are exposed to hazardous underwater conditions such as extreme pressure, low oxygen levels, poor visibility, and dangerous marine environments [20]. In addition, manual underwater exploration is time-consuming, expensive, and unsuitable for long-duration or deep-sea missions.

Existing underwater systems also face difficulties in autonomous navigation, obstacle detection, and real-time underwater monitoring because underwater environments are highly dynamic and unpredictable. Poor underwater visibility and communication limitations reduce the effectiveness of traditional monitoring systems [3][16]. Furthermore, accurate underwater object detection and environmental monitoring remain difficult due to underwater noise, light distortion, and changing environmental conditions.

Therefore, there is a need for an intelligent and autonomous underwater system capable of operating safely and efficiently in underwater environments. The system should be able to perform obstacle detection, autonomous navigation, underwater monitoring, and real-time decision-making with minimal human intervention.

1.3 Purpose of Research

The purpose of this research is to develop an AI Submersible Underwater Machine which is able to perform operation to explore underwater and monitor the task simultaneously to check unsual things. This system integrates Artificial Intelligence, computer vision, sonar sensing, and environmental sensors to improve underwater navigation, obstacle detection, and data collection efficiency.

The research focuses on designing a reliable underwater system that can operate effectively in low visibility and hazardous underwater environments. The proposed machine will collect environmental data such as temperature, pressure, and underwater images while performing autonomous navigation and obstacle avoidance. The use of AI and machine learning techniques will help improve realtime decision-making and underwater object recognition capabilities.

Another purpose of the research is to reduce human involvement in dangerous underwater operations and improve the safety and efficiency of underwater exploration. The proposed system can be used in marine research, defense surveillance, offshore inspection, environmental monitoring, and disaster management applications [1][14]. The research also aims to contribute to the advancement of intelligent underwater robotic systems for future underwater exploration technologies.

2. LITERATURE REVIEW

Artificial Intelligence and deep learning techniques have significantly improved underwater object detection and underwater exploration systems [2][7]. Modern underwater robotic systems use Convolutional Neural Networks (CNNs), YOLO models, and transformer-based architectures for detecting underwater objects, marine species, and underwater structures. These AI-based approaches provide better accuracy and faster processing compared to traditional underwater image processing methods. However, underwater environments still create challenges such as low visibility, image distortion, and limited underwater datasets. Sonar sensing technology has become one of the most important technologies in underwater robotics because optical cameras often fail in low-light and turbid underwater environments [4][5]. Sonar-based systems are capable of detecting underwater objects, mapping underwater terrain, and assisting autonomous navigation. Deep learning techniques applied to sonar imagery improve underwater object recognition and environmental perception [2][4]. Researchers have highlighted that sonar systems improve underwater exploration efficiency, although sonar noise and real-time processing remain challenging issues [5][11].

Several underwater navigation systems have been developed by integrating sonar, visual, inertial, and depth sensors for autonomous underwater operations [13]. Since GPS signals cannot work effectively underwater, underwater localization and mapping remain important research challenges. Sensor fusion techniques help improve underwater positioning accuracy and navigation reliability [13]. These systems are capable of performing underwater mapping and autonomous navigation in dynamic underwater environments. Accurate underwater positioning systems are essential for marine research, underwater inspection, and exploration tasks [13][22]. Researchers have explored acoustic positioning systems, inertial navigation systems, Doppler Velocity Logs (DVL), and sonar-based localization techniques for Autonomous Underwater Vehicles (AUVs). Hybrid navigation systems combining multiple positioning technologies provide better stability, reliability, and accuracy during underwater operations [13].

Artificial Intelligence-based underwater acoustic target recognition systems are increasingly used for underwater surveillance and environmental monitoring applications [4][6]. Machine learning and deep learning techniques provide efficient underwater signal analysis and target recognition capabilities [6]. AI-driven underwater systems improve object detection performance and reduce human involvement in underwater monitoring tasks. However, underwater acoustic noise and computational requirements remain major challenges in underwater target recognition systems [4][5]. AI-driven marine robotic systems are also used for monitoring coral reefs, marine ecosystems, and underwater biodiversity [19]. Intelligent underwater robots can collect environmental data, track marine species, and support underwater scientific research [19]. AI-based systems reduce the risk associated with hazardous underwater operations and support long-duration underwater monitoring tasks. Researchers have also emphasized the importance of adaptive AI models and self-supervised learning for improving underwater perception systems [7][15]. Obstacle detection and collision avoidance are essential components of autonomous underwater navigation systems [8][12]. Underwater environments contain various obstacles such as underwater rocks, marine organisms, pipelines, and underwater structures [12]. Sonar-based obstacle detection systems combined with intelligent navigation algorithms improve underwater operational safety and autonomous movement [8][12]. Forward-looking sonar sensors are widely used for detecting nearby underwater obstacles and avoiding collisions during underwater missions.

Deep learning integration has improved underwater SLAM (Simultaneous Localization and Mapping) systems and underwater perception technologies [13]. AI-based underwater navigation systems improve underwater image enhancement, object recognition, and environmental mapping[3][18]. These technologies allow underwater robots to operate autonomously while maintaining navigation accuracy in low-visibility underwater environments. However, challenges such as underwater lighting variation and computational complexity still affect system performance[3][18]. Recent advancements in underwater object detection systems demonstrate the growing importance of Artificial Intelligence and sensor fusion technologies in underwater robotics [2][7][15]. The integration of sonar sensing, machine vision, and AI algorithms improves underwater perception and autonomous decision-making capabilities. AI-based underwater systems are increasingly being used in underwater surveillance, industrial inspection, environmental monitoring, and marine exploration applications[14].

Autonomous underwater systems integrated with Artificial Intelligence, sonar sensing, and environmental monitoring technologies have shown significant potential for scientific research and underwater exploration [1][14]. Intelligent underwater machines can perform autonomous navigation, underwater data collection, and environmental analysis efficiently with minimal human intervention. These systems improve operational safety, reduce human risk, and support long-duration underwater exploration missions [14][20]. The reviewed literature indicates that Artificial Intelligence, sonar sensing, computer vision, and autonomous navigation technologies have transformed underwater robotic systems. Existing research demonstrates significant improvements in underwater monitoring, navigation, obstacle detection, and underwater object recognition using AI-based approaches[2][4][5][7][13]. However, challenges such as underwater visibility issues, sensor noise, communication limitations, and real-time processing requirements still require further research and development[3][16]. The proposed AI Submersible Underwater Machine aims to address these challenges by integrating AI algorithms, sonar sensing, computer vision, and autonomous navigation technologies to develop an efficient and reliable underwater exploration system.

3. OBJECTIVE

The primary objective of this research is to design and analyze an AI-based submersible underwater machine capable of performing autonomous underwater exploration, monitoring, and object detection using intelligent technologies. The study aims to integrate Artificial Intelligence, computer vision, and underwater robotics to improve the efficiency and accuracy of marine operations.

The specific objectives of the research are as follows:

1. To study the existing underwater exploration systems and identify their limitations in deep-sea monitoring and navigation.

2. To design an autonomous underwater machine equipped with AI-based sensors and intelligent navigation systems.
3. To implement computer vision and deep learning techniques for underwater object and marine species detection.
4. To develop an obstacle detection and avoidance mechanism for safe underwater navigation.
5. To analyze the performance of AI algorithms in underwater environmental conditions such as low visibility, pressure variations, and water disturbances.
6. To compare traditional underwater monitoring systems with AI-enabled autonomous underwater vehicles in terms of efficiency, accuracy, and adaptability.
7. To explore the potential applications of AI submersible systems in marine research, environmental monitoring, defense, rescue missions, and resource exploration.

4. METHODOLOGY

The proposed Autonomous Submersible Machine is designed as an intelligent underwater vehicle capable of sensing its environment, making decisions, navigating autonomously, and completing assigned missions without continuous human intervention. The system is equipped with multiple sensors, including sonar sensors for obstacle detection, underwater cameras for visual perception, depth and pressure sensors for measuring operating depth, and an Inertial Measurement Unit (IMU) for tracking orientation and motion. These sensors continuously collect environmental and operational data, such as sonar readings, underwater images, water pressure, temperature, depth, and vehicle movement information. The collected data is preprocessed to remove noise and improve accuracy before being integrated through sensor fusion techniques, which combine information from multiple sources to create a reliable representation of the underwater environment.

The fused sensor data is then analyzed using Artificial Intelligence (AI) and computer vision algorithms to understand the surrounding environment. This process enables the vehicle to detect obstacles, identify underwater objects, generate environmental maps, and determine safe navigation zones. Based on this environmental understanding, the localization and navigation module estimates the vehicle's current position and plans an optimal path toward the target destination. The navigation system continuously updates the planned route according to changes in environmental conditions and mission requirements. To ensure safe operation, real-time obstacle avoidance mechanisms use sonar and vision-based detection methods to identify potential hazards and automatically modify the vehicle's trajectory whenever obstacles are encountered.

An onboard AI processor serves as the decision-making unit, analyzing sensor information and mission objectives to determine appropriate actions such as route adjustments, speed control, and task prioritization. Once navigation and planning are completed, the autonomous submersible executes mission-specific tasks, including seabed mapping, environmental monitoring, underwater infrastructure inspection, marine exploration, and search-and-rescue operations. Throughout the mission, important status information and collected data are transmitted to a surface control station through acoustic communication systems whenever communication links are available. Finally, the performance of the proposed system is evaluated using metrics such as navigation accuracy, obstacle avoidance success rate, localization precision, energy efficiency, mission completion time, and data collection quality. These evaluations help assess the effectiveness, reliability, and autonomy of the submersible machine in real-world underwater environments.

The overall methodology of the research is divided into the following major stages:

1. Literature Identification and Selection
2. Inclusion and Exclusion Criteria
3. Data Extraction
4. Comparative Analysis Strategy

These stages were designed to ensure systematic collection, organization, analysis, and interpretation of relevant information associated with AI-enabled underwater exploration systems.

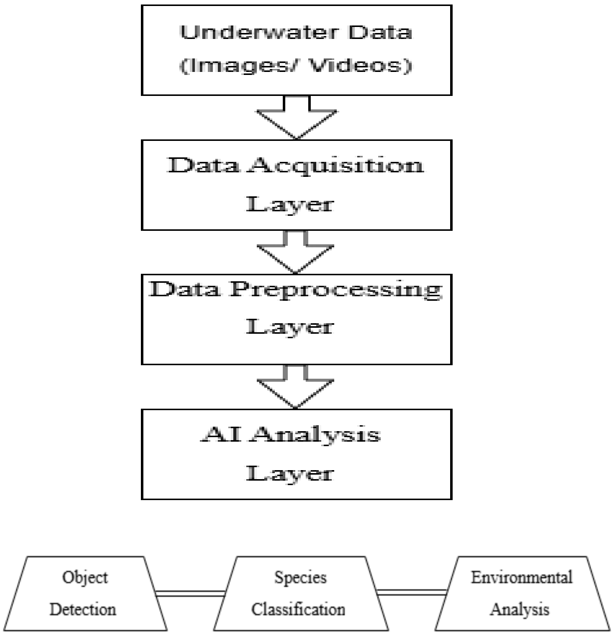
4.1 Proposed AI-Based Submersible Framework

Based on the literature review and identified research gaps, a conceptual Artificial Intelligence-based Submersible Framework is proposed for intelligent underwater exploration and monitoring. The framework focuses on the application of computer vision, deep learning, environmental analysis, and autonomous decision-making techniques to improve underwater situational awareness. The proposed framework does not involve the development of a physical underwater vehicle; instead, it investigates how AI algorithms can support underwater exploration, object detection, species classification, and navigation assistance.

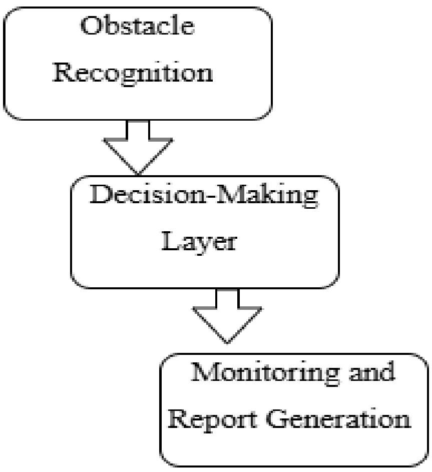
4.2 Overall System Architecture

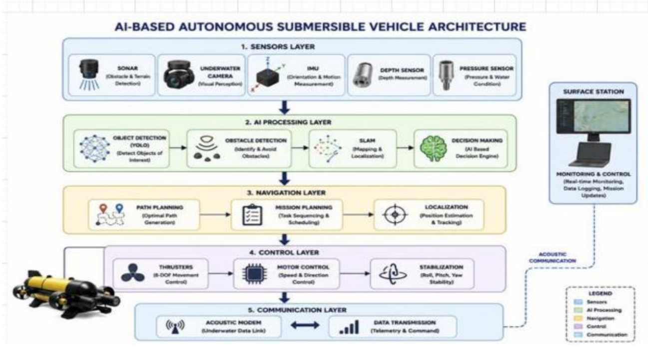
The proposed architecture consists of five major layers: Data Acquisition, Data Preprocessing, AI Analysis, Decision-Making, and Report Generation. Underwater images, video streams, sonar imagery, and environmental datasets are collected and processed through the framework. The acquired data is first enhanced and cleaned before being analyzed using deep learning models. The outputs from various AI modules are integrated to generate intelligent insights and recommendations for underwater exploration and monitoring.

Architecture Flow:



• Obstacle Recognition





4.3 Data Pre-processing and Image Enhancement Module

Underwater environments present significant challenges for visual data acquisition due to factors such as light absorption, scattering, suspended particles, water turbidity, and varying illumination conditions. As a result, underwater images and video streams often suffer from poor visibility, low contrast, color distortion, blurring, and noise, which can negatively impact the performance of Artificial Intelligence (AI) and computer vision algorithms. To address these challenges, a dedicated preprocessing and image enhancement module is incorporated into the proposed framework.

The primary objective of this module is to improve image quality and increase the visibility of important underwater features before further analysis. Various image enhancement techniques are considered, including Histogram Equalization (HE), Contrast Limited Adaptive Histogram Equalization (CLAHE), color correction algorithms, dehazing methods, noise reduction filters, and deep learning-based image restoration techniques. These approaches help restore natural colors, improve contrast, reduce image degradation, and enhance edge and texture information.
In addition to image enhancement, preprocessing operations such as image normalization, resizing, segmentation, and feature extraction are performed to prepare the data for AI-based analysis. By improving image clarity and reducing visual distortions, this module significantly enhances the accuracy and reliability of subsequent tasks such as object detection, species classification, navigation support, and environmental monitoring. The enhanced images and processed visual information are then forwarded to the AI analysis layer for further interpretation and decision-making.

4.4 AI-Based Underwater Object Detection Module

The AI-based underwater object detection module is designed to automatically identify, localize, and track objects present within underwater environments. This module plays a critical role in enabling autonomous exploration, situational awareness, obstacle avoidance, and marine ecosystem monitoring. The object detection process utilizes enhanced images and video streams generated by the preprocessing module to improve detection accuracy under challenging underwater conditions.

Advanced deep learning-based object detection architectures such as YOLO (You Only Look Once), Faster R-CNN, SSD (Single Shot Detector), and transformer-based detection models are considered for implementation. These models are capable of detecting multiple objects simultaneously while maintaining high accuracy and real-time performance. The detection framework is trained to recognize a wide variety of underwater entities, including marine species, coral reefs, underwater vegetation, rocks, shipwrecks, infrastructure components, marine debris, and potential navigation hazards.

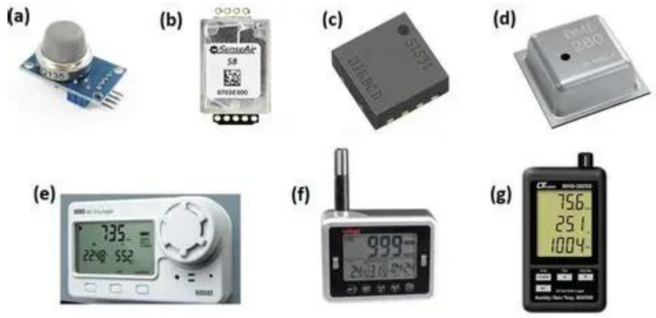
The module generates bounding boxes, confidence scores, and object labels for each detected target. This information serves as an essential input for other modules, including species classification, navigation assistance, obstacle avoidance, and environmental assessment. By automating object detection processes, the framework reduces human intervention and supports efficient underwater exploration and monitoring operations.

4.5 Marine Species Classification Module

Following the successful detection of underwater organisms and objects, the marine species classification module is responsible for identifying and categorizing detected marine life into specific species or biological groups. Accurate species classification is essential for marine biodiversity assessment, ecological monitoring, conservation planning, and scientific research.

The classification process relies on deep learning-based image classification techniques capable of extracting complex visual features from underwater imagery. Various state-of-the-art architectures, including ResNet, EfficientNet, Vision Transformers (ViT), MobileNet, and DenseNet, are investigated due to their proven performance in image recognition tasks. These models analyze visual characteristics such as shape, texture, color patterns, body structure, and distinguishing biological features to accurately classify marine organisms.

The module can be applied to identify fish species, coral species, crustaceans, marine mammals, and other underwater organisms. The generated classification results contribute to environmental monitoring programs by providing valuable information regarding species distribution, biodiversity changes, habitat conditions, and ecosystem health. Furthermore, the integration of AI-based classification techniques significantly reduces the time and effort required for manual species identification.



4.6 Intelligent Navigation and Obstacle Recognition Module

Safe and efficient underwater navigation is a fundamental requirement for autonomous underwater exploration systems. The Intelligent Navigation and Obstacle Recognition Module is designed to support route planning, environmental awareness, and collision avoidance through the integration of computer vision, sonar sensing, environmental observations, and AI-based decision-making techniques.

The module continuously analyzes incoming sensor data to identify obstacles, evaluate environmental conditions, and determine safe navigation pathways. Information obtained from underwater cameras, sonar systems, and environmental sensors is combined using sensor fusion techniques to generate a comprehensive representation of the surrounding environment. Potential hazards such as rocks, coral formations, underwater structures, marine debris, and other moving or stationary obstacles are identified and classified.

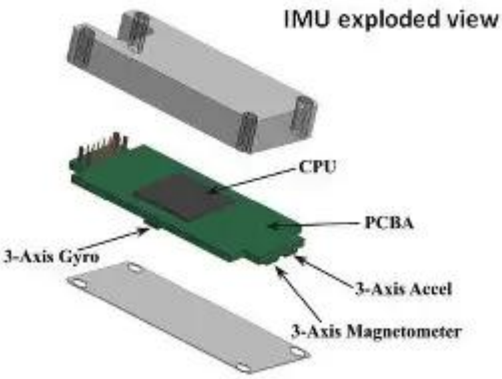
Artificial Intelligence techniques including Reinforcement Learning (RL), Deep Q Networks (DQN), Deep Reinforcement Learning (DRL), Simultaneous Localization and Mapping (SLAM), and path-planning algorithms are investigated to support intelligent navigation. These methods enable the system to learn optimal navigation strategies, adapt to changing underwater conditions, and dynamically update routes when obstacles are encountered. The module aims to improve navigation accuracy, reduce collision risks, and enhance the overall autonomy of underwater exploration systems.

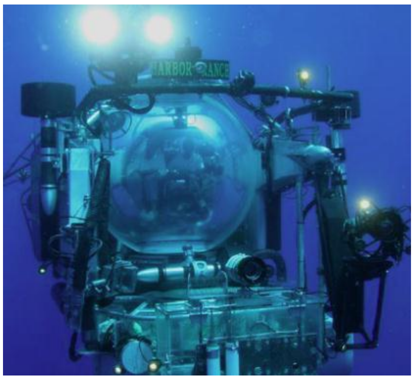
4.7 Environmental Monitoring and Analysis Module

The Environmental Monitoring and Analysis Module focuses on collecting, interpreting, and analyzing marine environmental data to support ecosystem assessment, scientific research, and conservation initiatives. Oceans and underwater ecosystems are highly dynamic environments influenced by numerous physical, chemical, and biological factors. Continuous monitoring of these parameters is essential for understanding environmental changes and maintaining marine sustainability.

The module processes environmental data collected from onboard sensors, including water temperature, salinity, pH levels, dissolved oxygen concentration, turbidity, conductivity, and pressure measurements. Machine learning and data analytics techniques are employed to identify environmental patterns, detect anomalies, predict ecological changes, and generate meaningful insights from collected data.

The analysis results can be used for various applications, including pollution monitoring, climate change assessment, marine habitat evaluation, coral reef health monitoring, and ecosystem conservation. By integrating AI-driven environmental analysis, the proposed framework enhances the capability of underwater exploration systems to support scientific research and environmental management efforts while providing real-time situational awareness of marine conditions.





4.8 AI-Based Decision-Making Framework

The AI-Based Decision-Making Framework serves as the central intelligence layer of the proposed underwater exploration system. This module integrates outputs generated from object detection, species classification, navigation support, obstacle recognition, and environmental analysis modules to produce comprehensive situational awareness and intelligent operational recommendations.

Information fusion techniques are employed to combine heterogeneous data obtained from multiple sensors and AI subsystems. The integrated information is analyzed using machine learning and decision-support algorithms to evaluate environmental conditions, identify potential risks, prioritize exploration objectives, and recommend appropriate actions. The framework can generate intelligent outputs such as exploration strategies, navigation recommendations, obstacle avoidance decisions, biodiversity reports, environmental assessments, and risk evaluation summaries.

The decision-making framework enhances the autonomy and adaptability of underwater exploration systems by enabling data-driven responses to complex underwater scenarios. Furthermore, the integration of multiple AI modules improves operational efficiency, reduces dependence on human intervention, and demonstrates the potential of Artificial Intelligence to support future autonomous underwater exploration, monitoring, and marine research applications.

Sr. No.	Comparative Parameter	Description of Parameter	Evaluation Criteria	Purpose of Analysis
1	Autonomous Navigation	Ability of the underwater machine to navigate independently without human intervention	Path planning accuracy, localization, route optimization, navigation stability	To evaluate autonomous movement capability in underwater environments
2	Obstacle Detection and Avoidance	Capability to detect and avoid underwater obstacles during operation	Detection range, response time, collision avoidance accuracy	To ensure operational safety and uninterrupted navigation
3	Underwater Object Detection	Identification and recognition of underwater objects and marine species	Detection accuracy, image clarity, recognition efficiency	To analyze effectiveness of computer vision systems
4	Artificial Intelligence Algorithms	AI techniques used for intelligent decisionmaking and automation	Machine learning models, deep learning techniques, neural networks	To determine efficiency of AIbased underwater operations
5	Computer Vision Performance	Performance of image processing systems in underwater conditions	Image enhancement, feature extraction, object classification	To evaluate underwater visual analysis capability
6	Sensor Integration	Types and efficiency of sensors integrated into the underwater machine	Sonar accuracy, camera performance, IMU precision, sensor fusion	To assess environmental sensing and monitoring capability
7	Environmental Adaptability	Ability of the system to function in harsh underwater conditions	Low-light performance, pressure tolerance, water turbulence handling	To analyze operational reliability in marine environments
8	Communication System	Underwater communication and data transmission efficiency	Communication range, latency, signal reliability	To evaluate underwater connectivity and remote monitoring
9	Real-Time Processing	Capability to process underwater data instantly and respond accordingly	Processing speed, real-time AI inference, response efficiency	To assess real-time operational intelligence
10	Energy Efficiency	Power consumption and battery optimization during underwater operations	Battery life, power management, operational duration	To determine longduration exploration capability
11	Localization and Positioning	Accuracy of underwater positioning and tracking systems	GPS alternatives, acoustic positioning, tracking precision	To ensure accurate underwater positioning
12	Marine Data Collection	Efficiency in collecting environmental and marine ecosystem data	Data quality, monitoring accuracy, storage efficiency	To analyze research and monitoring effectiveness

13	System Reliability	Stability and consistency of underwater machine performance	Error rate, fault tolerance, operational consistency	To evaluate long-term operational dependability
14	Autonomous Decision-Making	Ability of AI system to make independent operational decisions	Adaptive learning, intelligent control systems	To assess smart underwater automation capability
15	Scalability and Flexibility	Capability to upgrade and adapt the system for various applications	Modular design, software adaptability, integration capability	To evaluate future expansion potential
16	Safety Mechanisms	Safety features integrated into the underwater system	Hazard detection, emergency response systems	To reduce risks during underwater missions
17	Cost Effectiveness	Financial feasibility of developing and deploying the underwater system	Development cost, maintenance cost, operational efficiency	To evaluate economic practicality
18	Computational Efficiency	Efficiency of AI algorithms and onboard processing systems	Memory usage, processor performance, algorithm optimization	To analyze technical efficiency of AI implementation
19	Exploration Depth Capability	Ability to operate at different underwater depths	Pressure resistance, structural durability	To evaluate deep-sea exploration capability
20	Overall System Performance	Combined evaluation of all technological components	Accuracy, adaptability, efficiency, reliability	To determine overall effectiveness of the AI underwater machine

The comparative analysis strategy was developed to evaluate various AI-based underwater robotic systems and Autonomous Underwater Vehicles (AUVs). Each selected research study was analyzed using the above parameters to identify the strengths, weaknesses, and technological advancements in underwater exploration systems.

The comparison mainly focused on:

- AI and deep learning performance
- Navigation efficiency
- Obstacle detection capability
- Sensor integration
- Environmental adaptability
- Real-time monitoring capability
- Autonomous functionality

5. DISCUSSION

5.1 Trends in Performance Described for AI Models

The evolution from CNN-based detection to sophisticated YOLO architectures represents a fundamental shift in deep learning approaches to underwater object detection. Early CNN-based methods achieved detection accuracy ranging from 65-75% on standard underwater benchmarks, primarily limited by two-stage detection pipelines that were computationally expensive and inadequately adapted to small object detection challenges prevalent in underwater imagery [27]. The introduction of single-stage detectors, beginning with YOLO and SSD, immediately demonstrated performance improvements, with YOLOv3 achieving 72-78% mAP on underwater datasets while operating at 30+ frames per second on embedded hardware a critical capability for real-time marine applications.

Subsequent YOLO iterations (v5, v7, v8) have shown consistent performance improvements. More advanced variants incorporating architectural innovations such as UWS-YOLO with orthogonal channel attention and YOLO-DAFS with enhanced feature extraction demonstrate that systematic domain-specific engineering continues to yield meaningful improvements. These trends indicate that raw model capacity and general architectural principles have been substantially exploited; further improvements increasingly depend on underwater-specific adaptations and careful optimization for deployment constraints.

Real-time performance improvements have been equally significant. The shift from GPU-dependent inference (requiring expensive onboard GPUs or remote cloud processing) to efficient inference on lightweight embedded systems (NVIDIA Jetson Nano, Raspberry Pi, specialized marine robotics computers) has been transformative [32]. YOLOv5 and v8 models achieve 40-80 frames per second on Jetson Nano sufficient for real-time video processing while consuming only 2-5 watts of power, compared to 10-15 watts for more computationally intensive architectures. This represents not merely an incremental improvement but a qualitative shift enabling practical deployment in power-constrained underwater systems.

Edge AI growth has accelerated dramatically, driven by specialized hardware accelerators (Coral Edge TPU, NVIDIA Jetson Orin Nano) and optimized inference frameworks (TensorFlow Lite, ONNX Runtime, MediaPipe). The availability of model compression techniques quantization (int8, int4), pruning, knowledge distillation enables deployment of sophisticated detection networks on microcontrollers with only kilobytes of RAM. This democratization of AI capability extends real-time detection capabilities to platforms previously considered too resource-constrained for deep learning inference.

5.2 Influence of Dataset Size, Diversity, and Quality

A critical insight emerging from systematic analysis of the literature is the profound influence of dataset characteristics on model performance and generalization. Studies employing large, diverse underwater datasets (>5000 images across multiple water types, lighting conditions, and species) consistently achieve superior performance and better generalization to novel environments compared to studies using smaller, more homogeneous datasets. The UTDAC2020 benchmark dataset, comprising 8000+ annotated underwater images across diverse scenarios, has become the de facto standard for comparative evaluation; models achieving 80%+ mAP on this challenging benchmark are considered strong performers in the field.

However, data scarcity remains a pervasive challenge. Most specialized underwater applications (coral health assessment, specific fish species detection, jellyfish monitoring) must operate with datasets of only 500-2000 annotated images orders of magnitude smaller than terrestrial benchmarks like COCO (>300,000 images) or ImageNet (>1M images). This data paucity fundamentally constrains model capacity and necessitates heavy reliance on transfer learning rather than training from scratch.

Underwater image degradation characteristics critically influence dataset utility and model learning. Images captured in clear tropical waters with good natural lighting bear minimal resemblance to images from turbid temperate waters or deep-sea environments with artificial illumination. The color cast characterized by loss of red channel information is highly variable and depends on water depth, sediment concentration, and ambient light spectrum. Models trained exclusively on clear-water imagery often catastrophically fail when deployed in turbid conditions, while models trained on only synthetic data suffer from sim-to-real domain gap. The most successful approaches employ diverse datasets intentionally capturing this environmental variability or employ domain adaptation techniques to bridge the gap.
The impact of data annotation quality and labeling accuracy cannot be overstated. Underwater target bounding boxes are often ambiguous due to poor visibility, occlusion by marine vegetation, and target deformation. Studies comparing datasets with high inter-rater agreement (>90%) to those with lower agreement (70-80%) show that labeling quality differences can dwarf the impact of dataset size differences [33]. This suggests that investment in careful, expert-reviewed dataset curation may yield greater performance benefits than simple dataset expansion through automated or crowd-sourced annotation.

5.3 Role of Transfer Learning and Data Augmentation

Transfer learning has become the dominant paradigm for underwater deep learning applications, with the overwhelming majority of recent papers employing pre-trained ImageNet weights as initialization rather than training from scratch. Systematic studies demonstrate that fine-tuning pre-trained models on 1000-2000 underwater images achieves comparable performance to training from scratch on 10,000+ underwater images **[5]**. This reduction in required labeled data represents the primary value proposition of transfer learning for underwater applications.

The effectiveness of transfer learning varies substantially depending on the degree of feature similarity between source (ImageNet) and target (underwater) domains. Tasks involving generic detection of physical objects (fish, debris, structures) benefit substantially from transfer learning, with typical performance boosts of 15-25% compared to scratch training on small datasets. Conversely, tasks requiring discrimination of fine-grained features show more modest transfer learning benefits (5-10%), suggesting that task-specific feature learning remains necessary despite pre-training.

Data augmentation strategies have become increasingly sophisticated, moving beyond basic geometric transformations. While horizontal/vertical flipping, rotation, and brightness adjustment remain standard, contemporary approaches incorporate physics-based augmentations simulating realistic underwater degradation (color cast, scattering, attenuation), cutout/mixup techniques that create synthetic training examples by combining multiple images, and synthetic image generation through GANs trained to transform clear images into realistic underwater versions. These advanced augmentation strategies have been shown to improve model robustness across diverse underwater conditions.

Curriculum learning where models are trained progressively on increasingly difficult scenarios represents an emerging augmentation paradigm showing promise for underwater applications. By starting with clean, well-lit images and gradually introducing degradation, occlusion, and challenging viewing angles, models learn more robust features and achieve faster convergence.

5.4 Interpretability and Practical Applicability

While deep learning models achieve impressive accuracy metrics in laboratory settings, their deployment in real-world marine systems requires consideration of interpretability and practical applicability. Black-box nature of neural networks poses challenges for safety-critical applications (collision avoidance, autonomous navigation in populated areas), where system failures could result in property damage or environmental harm. Explainable AI (XAI) techniques particularly Grad-CAM, LIME, and SHAP have been applied to visualize which image regions influence detection decisions, providing partial transparency into model reasoning **[34]**. However, even with visualization tools, understanding failure modes and systematic biases remains challenging.

Real-world deployment introduces practical challenges not fully captured in laboratory evaluations. Environmental variability including diurnal cycles affecting water clarity, seasonal species migration patterns, weather-induced turbidity changes requires models to generalize across conditions not represented in training data. Field trials demonstrate that models achieving 85%+ accuracy on benchmark datasets often exhibit 10-20% performance degradation in actual deployment scenarios. This generalization challenge suggests that test-time adaptation strategies where models update parameters based on deployment-specific data—may be necessary for sustained performance.

Power consumption remains a critical constraint often underappreciated in academic publications. While inference latency is routinely reported, power consumption receives less attention despite its criticality for battery-powered underwater systems. A model requiring 10 watts of continuous inference power can only operate for hours before battery exhaustion, making the system impractical for mission-duration deployments spanning days or weeks. Recent advances in model compression and specialized hardware accelerators have substantially improved power efficiency, with state-of-the-art methods achieving 2-5 watts for real-time object detection, but energy remains a binding constraint.

5.5 Limitations and Future Challenges

Several fundamental limitations constrain current underwater AI systems and point toward necessary future research directions. Communication bandwidth limitations remain severe, with acoustic underwater communication typically achieving only 10-100 kilobits per second compared to megabits per second in terrestrial wireless systems. This constraint forces all substantial data processing to occur locally on the AUV, precluding real-time cloud-assisted detection or remote operator decision-making. Multi-sensor fusion over acoustic links requires careful data compression and adaptive communication strategies.

Sensor failure robustness represents another critical challenge inadequately addressed in the literature. Underwater systems inevitably experience sensor faults (camera fouling, acoustic noise, pressure sensor drift), yet most published systems assume sensor reliability. Fault-tolerant architectures employing sensor redundancy and graceful degradation strategies are necessary but rarely implemented or evaluated.

The lack of standardized underwater benchmark datasets and evaluation protocols hinders reproducible research and fair algorithm comparison. While terrestrial computer vision benefits from standard benchmarks (COCO, Pascal VOC, ImageNet), underwater research employs numerous non-public or limited-scale datasets, making cross-study performance comparison difficult. Creation of large-scale, standardized underwater datasets comparable to terrestrial benchmarks would substantially accelerate field progress.

Sim-to-real domain gap persists as a fundamental challenge despite substantial research. Models trained exclusively on synthetic or laboratory imagery often perform poorly in natural underwater environments. While sim-to-real transfer learning techniques show promise, they remain less effective for underwater applications than for terrestrial robotics, potentially due to greater environmental variability.

CONCLUSION

This comprehensive literature review has synthesized recent advances in AI-driven underwater robotics and object detection, revealing a field in rapid maturation characterized by systematic performance improvements, expanding practical deployment, and emerging integration with edge computing and IoT sensor networks. Deep learning architectures particularly sophisticated YOLO variants enhanced through underwater-specific optimizations have achieved detection accuracy levels (80-87% mAP on challenging benchmarks) and inference speeds (40-80 FPS on embedded hardware) sufficient for practical real-time marine applications. The transformation from GPU-dependent cloud processing to lightweight edge inference represents a qualitative shift enabling autonomous decision-making in communication-constrained underwater environments.

Transfer learning and data augmentation strategies have substantially mitigated the dataset scarcity challenge inherent to underwater applications, enabling effective model training on corpora of only 1000-2000 annotated images through careful exploitation of pre-trained knowledge. The synthesis of deep learning with underwater image enhancement techniques has addressed fundamental visual degradation challenges, enabling detection even in heavily compromised visibility conditions. Integration with IoT sensor networks and multi-modal fusion architectures has extended single-modality detection to comprehensive environmental understanding combining camera, sonar, temperature, and other sensor streams [31].

Despite these advances, substantial gaps remain between reported laboratory performance and real-world operational capabilities. Generalization to novel environments, robustness to sensor failures, power consumption optimization, and interpretability for safety-critical applications require sustained research attention. The field would benefit substantially from larger-scale, standardized underwater datasets enabling reproducible benchmarking and fair algorithm comparison.

FUTURE SCOPE

Several promising research directions emerge from current limitations and technological trajectories:

Swarm Underwater Robotics and Collaborative Intelligence: Multi-robot underwater systems promise synergistic advantages including distributed sensing coverage, redundancy for fault tolerance, and emergent capabilities impossible for individual vehicles. Deep reinforcement learning and decentralized control algorithms enable autonomous coordination without reliance on centralized communication or planning. This represents a frontier combining multi-agent reinforcement learning with underwater-specific constraints.

Advanced Reinforcement Learning for Autonomous Navigation: Beyond classical obstacle avoidance, next-generation RL algorithms (PPO, SAC, TD3) trained on realistic physics simulations promise more robust and adaptable navigation strategies [49]. Physics-informed neural networks (PINNs) that encode hydrodynamic constraints directly into learning architectures may substantially improve performance and generalization.

Edge AI and Neuromorphic Computing: Specialized neural network architectures optimized for power efficiency spiking neural networks, neuromorphic processors (Intel Loihi) offer orders-of-magnitude improvements in energy efficiency, potentially enabling multi-day deployments on current battery technologies. These architectures fundamentally depart from conventional deep learning but show exceptional promise for resource-constrained underwater platforms.

5G/6G Underwater Communication Infrastructure: Emerging underwater communication technologies promise substantially increased bandwidth, enabling new applications including remote operator teleoperation, cloud-assisted inference, and real-time swarm coordination. Integration of advanced communication with edge intelligence represents a critical frontier for future underwater systems.

Physics-Informed Learning and Hybrid Models: Combining classical underwater physics models with learned neural network components promises models that generalize better across environmental conditions while remaining interpretable. These hybrid approaches leverage domain knowledge while maintaining flexibility **[29]**.

Autonomous Marine Rescue and Environmental Monitoring: Integration of AI-driven detection with autonomous intervention (collecting trash, monitoring endangered species, assessing pollution) represents a compelling application combining vision intelligence with mechanical intervention capability [36].

REFERENCES

[1] National Oceanic and Atmospheric Administration (NOAA), "Why Explore the Ocean?," NOAA Ocean Exploration, USA.

[2] Y. Steiniger, D. Kraus, and T. Meisen, "Survey on Deep Learning Based Computer Vision for Sonar Imagery," Engineering Applications of Artificial Intelligence, vol. 114, 2022.

[3] S. P. González-Sabbagh and A. Robles-Kelly, "A Survey on Underwater Computer Vision," ACM Computing Surveys, vol. 56, no. 3, 2023.
[4] D. Neupane and J. Seok, "A Review on Deep Learning-Based Approaches for Automatic Sonar Target Recognition," Electronics, vol. 9, no. 11, pp. 1–28, 2020.
[5] M. Aubard, P. Checchin, and L. Trassoudaine, "Sonar-based Deep Learning in Underwater Robotics: Overview, Robustness and Challenges," arXiv preprint arXiv:2412.11840, 2024.
[6] B. Teng and H. Zhao, "Underwater Target Recognition Methods Based on the Framework of Deep Learning: A Survey," International Journal of Advanced Robotic Systems, vol. 17, no. 6, 2020.
[7] P. Sun, Y. Wang, and H. Zhang, "A Review of Underwater Object Detection Methods Based on Deep Learning," Journal of Marine Science and Engineering, vol. 14, no. 2, 2026.
[8] T. Zhou, Y. Li, and X. Wang, "Automatic Detection of Underwater Small Targets Using ForwardLooking Sonar Images," IEEE Transactions on Geoscience and Remote Sensing, vol. 60, pp. 1–13, 2022.
[9] S. P. González-Sabbagh and A. Robles-Kelly, "Survey on Underwater Computer Vision Techniques and Applications," ACM Computing Surveys, vol. 55, no. 9, pp. 1–36, 2023.
[10] G. Labbe-Morissette and S. Gauthier, "A Machine Vision Meta-Algorithm for Automated Recognition of Underwater Objects Using Sidescan Sonar Imagery," arXiv preprint arXiv:1909.07763, 2019.
[11] M. Aubard, P. Checchin, and L. Trassoudaine, "Deep Learning Approaches in Underwater Robotics Using Sonar Systems," arXiv preprint arXiv:2412.11840, 2024.
[12] X. Cao, L. Ren, and C. Sun, "Research on Obstacle Detection and Avoidance of Autonomous Underwater Vehicle Based on Forward-Looking Sonar," IEEE Access, vol. 11, pp. 45872– 45884, 2023.
[13] S. Rahman, A. Quattrini Li, and I. Rekleitis, "SVIn2: An Underwater SLAM System using Sonar, Visual, Inertial, and Depth Sensor," arXiv preprint arXiv:1810.03200, 2018.
[14] H. Almazrouei, M. Hassan, and K. El-Mougy, "AI-Powered Autonomous Underwater Systems for Marine Exploration and Monitoring," arXiv preprint, 2024.
[15] M. Aubard et al., "Sonar-based Deep Learning in Underwater Robotics: Overview, Robustness and Challenges," arXiv preprint, 2024.
[16] J. Heidemann et al., "Research Challenges and Applications for Underwater Sensor Networking," IEEE Wireless Communications, vol. 16, no. 4, pp. 12–18, 2009.
[17] M. Ayaz, I. Baig, A. Abdullah, and I. Faye, "A Survey on Routing Techniques in Underwater Wireless Sensor Networks," Journal of Network and Computer Applications, vol. 34, no. 6, pp. 1908–1927, 2011.
[18] C. Li, J. Guo, R. Cong, Y. Pang, and B. Wang, "Underwater Image Enhancement by Dehazing with Minimum Information Loss and Histogram Distribution Prior," IEEE Transactions on Image Processing, vol. 25, no. 12, pp. 5664–5677, 2016.
[19] Y. Salman, M. Jalal, and H. Kim, "Deep Learning-Based Fish Species Classification in Underwater Images," Fisheries Research, vol. 245, 2022.
[20] G. Antonelli, "Underwater Robots," Springer Handbook of Robotics, Springer, pp. 987– 1008, 2016.
[21] Y. Kantaros and M. Zavlanos, "Distributed Communication-Aware Coverage Control by Mobile Sensor Networks," Automatica, vol. 63, pp. 209–220, 2016.
[22] H. Li, R. Sutton, and C. Yang, "Reinforcement Learning for Autonomous Underwater Vehicle Navigation," Ocean Engineering, vol. 235, 2021.
[23] N. Javaid et al., "Underwater Wireless Sensor Networks: A Review of Recent Issues and Challenges," Wireless Communications and Mobile Computing, vol. 2016, pp. 1–20, 2016.
[24] A. Khan, M. Reisslein, and S. R. Hassan, "Security and Privacy in Underwater Wireless Sensor Networks," IEEE Communications Surveys & Tutorials, vol. 23, no. 1, pp. 74–112, 2021.
[25] X. Sun and N. Ansari, "EdgeIoT: Mobile Edge Computing for the Internet of Things," IEEE Communications Magazine, vol. 54, no. 12, pp. 22–29, 2016.
[26] C. Y. Yu and W. J. Zhao, "SimpleEnhanceNet: A Deep Learning-Based Underwater Image Enhancement Method," in Proceedings of the 2025 IEEE International Conference on Smart AI-Technology Communication and Integration, 2025, doi: 10.1109/ISCAIT69154.2026.11477232.
[27] V. Ingale, M. Kumar, and A. Verma, "Advances in Deep Learning-Based Underwater Image Enhancement: From CNNs to Transformers and Diffusion Models," in Proceedings of the 2025 IEEE International Conference on Computational Intelligence and Communication Networks, 2025, doi: 10.1109/CICN67655.2025.11368209.
[28] A. Begum and M. R. Ahmed, "Underwater Object Detection Using Deep Learning," International Journal of Scientific Research and Engineering Analysis and Technology, vol. 20, no. 5, 2025, doi: 10.59256/ijsreat.20250504006.
[29] J. S. Walia, K. Haridass, and L. K. Pavithra, "Deep Learning Innovations for Underwater Waste Detection: An In-Depth Analysis," IEEE Access, vol. 13, 2025, doi: https://doi.org/10.1109/access.2025.3569344.
[30] L. Zhao, X. Ren, L. Fu, Q. Yun, and J. Yang, "UWS-YOLO: Advancing Underwater Sonar Object Detection via Transfer Learning and Orthogonal-

Snake Convolution Mechanisms," Journal of Marine Science and Engineering, vol. 13, no. 10, 2025, doi: 10.3390/jmse13101847.
[31] H. Zhu, X. Luo, Z. Zhai, J. Li, F. Li, and X. Zhu, "UNet-Based YOLO for Underwater Object Detection," in Proceedings of the 2024 IEEE Conference on Digital Image and Image Applications, 2024, doi: 10.1109/DIIA62678.2024.10871910.
[32] S. Luo, C. Dong, G. Dong, R. Chen, B. Zheng, M. Xiang, P. Zhang, and Z. Li, "YOLO-DAFS: A Composite-Enhanced Underwater Object Detection Algorithm," Journal of Marine Science and Engineering, vol. 13, no. 5, 2025, doi: 10.3390/jmse13050947
[33] N. Deluxni, P. Sudhakaran, M. Alsafyani, and A. Yousef, "Underwater Debris Segmentation Using Improved YOLOv12s With Recursive Efficient Layer Aggregation and FlashAttention for Autonomous Underwater Vehicle," IEEE Access, 2025, doi: 10.1109/ACCESS.2025.3636283.
[34] A. Tarekegn, F. Cheikh, M. Ullah, E. T. Sollesnes, C. Alexandru, S. Azar, E. Erol, and G. Suciu, "Underwater Object Detection using Image Enhancement and Deep Learning Models," in Proceedings of the 2023 IEEE European Conference on Visual Information Processing, 2023, doi: 10.1109/EUVIP58404.2023.10323047.
[35] A. D. Wanekar, N. P. B. Mannam, and P. Rajalakshmi, "Novel Approach to Underwater Object Detection Using Sonar Sensors for Autonomous Underwater Vehicles (AUVs)," in Proceedings of the 2023 IEEE International Conference on Offshore and Subsea Operations, 2023, doi: 10.1109/i-COSTE60462.2023.10500768.
[36] V. Pagire, A. C. Phadke, and J. Hemant, "A deep learning approach for underwater fish detection," Journal of Information Science and Technology, vol. 12,2024,doi:https://doi.org/10.62110/sciencein.jist.2024. v12.765.
[37] M. Elmezain, L. S. Saoud, A. Sultan, M. Heshmat, L. D. Seneviratne, and I. Hussain, "Advancing Underwater Vision: A Survey of Deep Learning Models for Underwater Object Recognition and Tracking," IEEE Access, 2025, doi: 10.1109/ACCESS.2025.3534098.
[38] M. F. Ercan, N. I. Muhammad, and M. R. N. B. Sirhan, "Underwater target detection using deep learning," in Proceedings of the 2022 IEEE Tencon Conference, 2022,doi:https://doi.org/10.1109/tencon55691.2022. 9977994.
[39] X. Cao, L. Ren, and C. Sun, "Research on Obstacle Detection and Avoidance of Autonomous Underwater Vehicle Based on Forward-Looking Sonar," IEEE Transactions on Neural Networks and Learning Systems, vol. 33, no. 3, 2022, doi: 10.1109/TNNLS.2022.3156907.
[40] L. Tang, H. Xu, W. Han, D. Tan, and L. Gao, "Research on Collaborative Object Detection and Recognition of Autonomous Underwater Vehicle Based on YOLO Algorithm," in Proceedings of the 2021 IEEE Chinese Control and Decision Conference, 2021, doi: 10.1109/CCDC52312.2021.9601610.
[41] M. R. Trinadh, M. Deepika, M. Manojna, K. Lavanya, H. P. Deep, and K. R. Sri, "Object Detection in Underwater Using Deep Learning Techniques," International Journal for Research in Applied Science & Engineering Technology, vol. 11, no. 5, 2023, doi: 10.22214/ijraset.2023.50919.
[42] . M. Topple and J. A. Fawcett, "MiNet: Efficient Deep Learning Automatic Target Recognition for Small Autonomous Vehicles," IEEE Geoscience and Remote Sensing Letters, vol. 17, no. 7, 2020, doi: https://doi.org/10.1109/lgrs.2020.2993652.
[43] J. Watanabe, Y. Shao, and N. Miura, "Underwater and airborne monitoring of marine ecosystems and debris," Journal of Applied Remote Sensing, vol. 13, 2019, doi: https://doi.org/10.1117/1.jrs.13.044509.
[44] U. Jain, N. S. Boob, M. Bhavana, Y. Kumar, A. Sehgal, and A. R. J, "Machine Learning Algorithms for Autonomous Underwater Vehicle (AUV) Navigation," in Proceedings of the 2025 IEEE International Conference on Communication, Circuits, Computing and Control, 2025, doi: 10.1109/ICCCIT62592.2025.10927905.
[45] Y. Yuan, H. Wang, H. Zhang, C. Lin, D. Yu, and C. Li, "AUV Obstacle Avoidance Planning Based on Deep Reinforcement Learning," Journal of Marine Science and Engineering, vol. 9, no. 11, 2021, doi: https://doi.org/10.3390/jmse9111166.
[46] H. Zhi, Z. Zhou, H. Wu, Z. Chen, S. Tian, Y. Zhang, and Y. Ruan, "Oscillatory Forward-Looking Sonar Based 3D Reconstruction Method for Autonomous Underwater Vehicle Obstacle Avoidance," Journal of Marine Science and Engineering, vol. 13, no. 5, 2025, doi: 10.3390/jmse13050943.
[47] S. Holly, A. Wendt, and M. Lechner, "Profiling Energy Consumption of Deep Neural Networks on NVIDIA Jetson Nano," in Proceedings of the 2020 IEEE International Green Computing Conference, 2020, doi: 10.1109/IGSC51522.2020.9290876.
[48] O. Natan, W. Suryanto, A. Dharmawan, R. H. Sari, and Z. Hakim, "ORCA: AI-powered Autonomous Underwater Vehicle for Subaquatic Exploration," IIUM Engineering Journal, vol. 27, no. 1, 2026, doi: 10.31436/iiumej.v27i1.3716.
[49] A. D. Wanekar, N. P. B. Mannam, and P. Rajalakshmi, "Novel Approach to Underwater Object Detection Using Sonar Sensors for Autonomous Underwater Vehicles (AUVs)," in Proceedings of the 2023 IEEE International Conference on Offshore and Subsea Operations, 2023, doi: 10.1109/i-COSTE60462.2023.10500768.