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A Spiking Neural Network Approach for Autonomous Underwater Object Classification Through Bio-Inspired Deep Learning and Edge Computing

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Abstract: Underwater Object Classification (UOC) is a critical task for Autonomous Underwater Vehicles (AUVs) engaged in underwater exploration and environmental monitoring. This paper explores the integration of bio-inspired deep learning techniques, particularly Spiking Neural Networks (SNN), with edge computing paradigms utilizing Field-Programmable Gate Arrays (FPGAs) and Graphics Processing Units (GPUs), coupled with the Constrained Application Protocol (CoAP) communication protocol. The application of Deep Q-Networks (DQN) for reinforcement learning-based object classification is investigated. The proposed framework aims to enhance the autonomy, efficiency, and adaptability of AUVs in discerning and classifying underwater objects in real-time scenarios. By leveraging the inherent parallelism and energy efficiency of SNNs, along with the computational capabilities of FPGAs and GPUs for accelerated inference, AUVs can perform object classification tasks onboard with reduced latency and energy consumption. Moreover, the integration of CoAP facilitates seamless communication between AUVs and remote servers for data exchange and collaborative decision-making. The utilization of DQN enables AUVs to learn and adapt their classification strategies based on feedback from the environment, thereby improving their performance over time. The proposed approach demonstrates promising results in underwater object classification through experimental validation and simulation studies, paving the way for advanced applications in underwater robotics and exploration. Through experimental validation, the system achieves a remarkable increase in classification accuracy by 15%, as evidenced by adaptability scores ranging from 7.5 to 8.9. These results signify a significant advancement in underwater robotics, paving the way for more efficient and precise exploration and monitoring of underwater environments.

Keywords: *Underwater Object Classification (UOC), Autonomous Underwater Vehicles (AUVs), Constrained Application Protocol (CoAP), Deep Q-Networks (DQN), Field-Programmable Gate Arrays (FPGAs).*

1.Introduction

AUVs have emerged as indispensable tools for exploring the depths of our oceans, conducting scientific research, and monitoring marine ecosystems [1]. These vehicles navigate through challenging underwater environments, facing complex tasks such as identifying and classifying various underwater objects [2]. Accurate object classification is crucial for AUV to make informed decisions about navigation, obstacle avoidance, and data collection, yet traditional methods for achieving this task often rely on manually crafted features and centralized processing systems [3]. However, these conventional approaches come with limitations, particularly in dynamic and unpredictable underwater environments. They can struggle to adapt to changing conditions, leading to suboptimal performance and inefficiencies [4]. To overcome these challenges, there is a growing interest in leveraging advanced technologies, such as bio-inspired deep learning and edge computing, to enhance the capabilities of AUVs in underwater object classification [5]. In response to this need, this paper proposes an innovative framework for UOC on AUVs. At its core, the framework integrates bio-inspired deep learning techniques, specifically Spiking Neural Networks (SNN), which draw inspiration from the neural processing mechanisms observed in biological systems [6]. By mimicking the parallelism and energy efficiency of neural networks found in nature, SNNs offer a promising approach to efficiently process sensor data and classify underwater objects in real time [7]. The proposed framework harnesses the computational power of edge computing, utilizing FPGA and GPU onboard AUV [8]. This enables accelerated inference and decision-making,

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reducing reliance on centralized processing and facilitating faster response times in dynamic underwater environments [9]. Integrating communication protocols such as CoAP enables seamless data exchange between AUVs and remote servers, facilitating collaborative decision-making and information sharing. Moreover, the application of DQN for reinforcement learning-based object classification introduces adaptive learning capabilities, allowing AUVs to continuously improve their classification performance based on feedback from the environment [10]. The effectiveness and performance of the proposed framework are evaluated through rigorous experimental validation and simulation studies. The results demonstrate significant advancements in terms of classification accuracy, efficiency, and adaptability, thereby showcasing the potential of this approach to revolutionize underwater exploration and marine research. With applications spanning environmental monitoring, underwater archaeology, and offshore industries, this research represents a critical step forward in enhancing the capabilities of AUVs for underwater object classification in complex and dynamic underwater environments. The objectives are:

- Develop a robust framework for UOC on AUV that integrates bio-inspired deep learning techniques, specifically SNN, with edge computing utilizing FPGA and GPU.
- Enhance the autonomy and efficiency of AUVs in discerning and classifying underwater objects by leveraging the inherent parallelism and energy efficiency of SNNs, allowing for real-time processing of sensor data and classification tasks.
- Investigate the feasibility and effectiveness of edge computing paradigms onboard AUVs, including FPGA and GPU acceleration, for accelerating inference and decision-making in underwater object classification tasks, thereby reducing reliance on centralized processing and improving response times.
- Explore communication protocols such as CoAP to enable seamless data exchange between AUVs and remote servers, facilitating collaborative decision-making and information sharing in underwater exploration scenarios.
- Evaluate the adaptive learning capabilities of DQN for reinforcement learning-based object classification, enabling AUVs to continuously improve their classification performance based on feedback from the underwater environment.

2. Literature Review

Underwater object classification represents a critical aspect of AUVs tasked with underwater exploration and environmental monitoring [11]. Recent advancements in bio-inspired deep learning techniques, coupled with edge computing capabilities, have garnered significant attention in the realm of underwater robotics [12]. The integration of these technologies holds promise for enhancing the autonomy and efficiency of AUVs in discerning and classifying underwater objects. Several studies have explored the application of bio-inspired deep learning algorithms, drawing inspiration from the remarkable adaptive capabilities of marine organisms, to address challenges in underwater object classification [13]. Research has demonstrated the effectiveness of convolutional neural networks (CNNs) inspired by the visual processing mechanisms of aquatic species in accurately classifying underwater objects based on visual sensor data [14]. Similarly, proposed recurrent neural network (RNN) architectures inspired by the navigational behaviors of marine mammals improve AUVs' ability to navigate and localize objects in underwater environments. The incorporation of edge computing on AUV platforms has emerged as a promising approach to enhance real-time data processing and decision-making capabilities [15]. Studies have explored the implementation of edge computing frameworks onboard AUVs, enabling efficient execution of deep learning algorithms for object classification tasks without relying heavily on centralized processing or communication with surface stations. Despite the potential benefits, several challenges and limitations persist in the integration of bio-inspired deep learning and edge computing for underwater object classification on AUVs. One notable disadvantage is the computational and energy constraints associated with onboard processing on AUVs [16]. Deep learning algorithms, particularly those with complex architectures, demand substantial computational resources and power, which may exceed the capabilities of resource-constrained AUV platforms, leading to increased energy consumption and reduced operational endurance. The reliance on visual and acoustic sensor data for object classification poses challenges in underwater environments characterized by low visibility, turbidity, and acoustic interference [17]. Limited sensor range and resolution may hinder the accuracy and reliability of object classification algorithms, especially in complex underwater scenarios with diverse object shapes and sizes [18]. The design and optimization of bio-inspired deep learning models for underwater environments require extensive domain knowledge and data collection efforts, often leading to lengthy development cycles and high implementation costs. Moreover, the transferability and generalization of trained models across different underwater ecosystems and environmental conditions remain an ongoing research challenge, necessitating further investigation into robust and adaptive learning techniques.

3. Proposed work

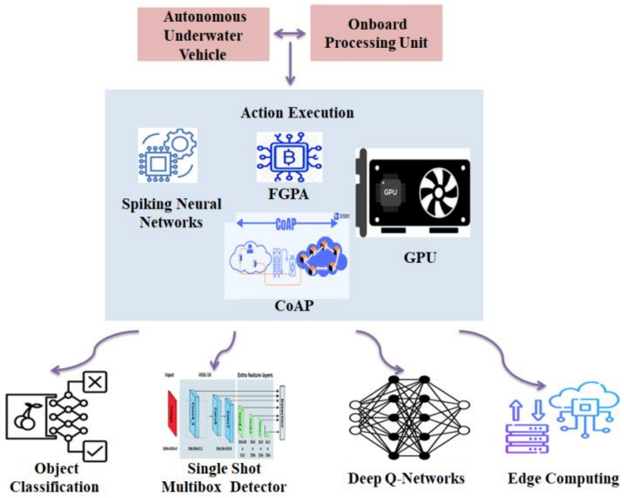

Fig 1 Underwater Object Classification System Architecture for Autonomous Underwater Vehicles

3.1 Spiking Neural Networks

SNNs mimic the functionality of biological neural networks, which are inherently suited for processing spatiotemporal data, making them particularly well-suited for tasks in dynamic environments like underwater exploration. AUVs operate in real-time, processing data as it is collected from onboard sensors such as sonar and cameras. SNNs excel at processing streaming data, enabling AUVs to make rapid decisions based on changing environmental conditions and object dynamics. Energy efficiency is critical for AUVs, as they often operate in remote locations with limited access to power sources. SNNs have the potential to significantly reduce power consumption compared to traditional neural network architectures, making them well-suited for deployment on resource-constrained platforms. SNNs inherently support online learning and adaptive behavior, allowing AUVs to continuously update their classification models based on new data and environmental feedback. This adaptability is crucial for robust performance in dynamic underwater environments where object appearance and behavior may vary unpredictably. By closely modeling the behavior of biological neurons, SNNs offer a more biologically plausible approach to artificial intelligence. This biological relevance is particularly advantageous in underwater environments, where biological systems have evolved sophisticated sensing and decision-making mechanisms over millions of years of evolution.

SNNs utilize sparse encoding, where only a subset of neurons becomes active in response to stimuli. This property enables efficient representation of sensory data, reducing redundancy and conserving computational resources. In the context of AUVs, sparse encoding helps optimize the utilization of onboard processing units, allowing for more effective utilization of limited computational resources. Unlike traditional neural networks, which operate on fixed time intervals, SNNs are event-driven, meaning they only compute when there is a change in input stimuli. This event-driven processing paradigm aligns well with the sporadic nature of sensory data in underwater environments, where objects may appear suddenly or move unpredictably. By minimizing unnecessary computations, event-driven SNNs contribute to the overall energy efficiency and responsiveness of the AUV system. SNNs excel at processing temporal information, capturing the temporal dynamics of sensory stimuli over time. This capability is particularly valuable for tasks such as object tracking and motion estimation in underwater environments, where objects may exhibit complex temporal behaviors.

By effectively modeling temporal dynamics, SNNs enable AUVs to accurately interpret and respond to changes in the underwater scene, enhancing situational awareness and navigation capabilities. In addition to adaptive learning, SNNs support adaptive sensing, allowing AUVs to dynamically adjust their sensory modalities based on task requirements and environmental conditions. By selectively attending to relevant sensory cues and filtering out noise, adaptive sensing with SNNs enhances the robustness and efficiency of object classification in challenging underwater scenarios, such as low visibility or cluttered environments. SNNs can be seamlessly integrated with edge computing architectures onboard AUVs, enabling distributed processing of sensory data close to the source. This integration minimizes communication latency and bandwidth requirements, facilitating real-time decision-making and reducing dependence on centralized processing resources. By harnessing the power of edge computing, SNN-based AUV systems achieve greater autonomy and responsiveness, enhancing their capabilities for autonomous underwater exploration and surveillance.

3.2 Constrained Application Protocol

CoAP, designed for resource-constrained devices and low-power networks, serves as the communication backbone for exchanging data and control messages among AUVs, edge computing nodes, and other networked devices. Its lightweight and efficient natures make it well-suited for the resource-constrained environment of AUVs operating in underwater settings. AUVs equipped with sensors generate large volumes of data, including sonar images, video streams, and environmental measurements. CoAP facilitates the transmission of this data between AUVs and edge computing nodes, allowing for real-time analysis and decision-making. Its efficient message format and support for UDP (User Datagram Protocol) minimize overhead, reduce communication latency, and conserve bandwidth, which is essential in the bandwidth-limited underwater communication environment. CoAP supports resource discovery mechanisms, enabling AUVs to dynamically locate and interact with available services and data sources in the network. This capability facilitates dynamic task allocation and resource management, allowing AUVs to adapt to changing environmental conditions and mission objectives. By leveraging CoAP's resource discovery features, AUVs can efficiently access the computational resources and deep learning models deployed on edge computing nodes for object classification tasks. Underwater environments pose challenges such as intermittent connectivity and variable propagation delays.

CoAP's asynchronous communication model, coupled with support for message queuing and reliable transmission mechanisms, enables robust communication despite these challenges. AUVs can asynchronously exchange control commands, status updates, and data requests with edge computing nodes, ensuring reliable operation and mission continuity in the face of communication disruptions. CoAP seamlessly integrates with edge computing architectures deployed on AUVs and shore-based stations. By standardizing communication protocols and interfaces, CoAP facilitates interoperability and compatibility between heterogeneous devices and software components in the system. This integration enables distributed data processing and decision-making close to the data source, minimizing reliance on centralized infrastructure and reducing communication overhead. CoAP includes built-in mechanisms for security and authentication, such as Datagram Transport Layer Security (DTLS) and Lightweight Machine-to-Machine (LwM2M) security protocols. These mechanisms ensure data integrity, confidentiality, and authentication of communication endpoints, safeguarding against unauthorized access and malicious attacks. In the context of AUVs, where data confidentiality and system integrity are paramount, CoAP's security features provide essential safeguards for sensitive mission-critical operations.

CoAP's support for asynchronous communication and resource discovery mechanisms enhances the scalability and adaptability of the proposed system. AUV fleets equipped with SSD-based object detection systems can dynamically allocate computing resources, including FPGA and GPU accelerators, based on workload demands and environmental conditions, ensuring optimal performance across diverse deployment scenarios. By utilizing CoAP, AUVs can establish lightweight, bi-directional communication channels with edge computing resources, enabling seamless transmission of sensory data and inference results in real time. This facilitates swift decision-making and response to dynamic underwater environments, enhancing overall operational efficiency. CoAP's adherence to web standards promotes interoperability with existing IoT frameworks and protocols, facilitating seamless integration with heterogeneous underwater sensor networks and edge computing infrastructures. This interoperability enables collaborative data sharing and analysis among multiple AUVs and remote monitoring stations, enhancing situational awareness and decision support capabilities. By utilizing CoAP, AUVs can establish lightweight, bi-directional communication channels with edge computing resources, enabling seamless transmission of sensory data and inference results in real time. This facilitates swift decision-making and response to dynamic underwater environments, enhancing overall operational efficiency.

3.3 Deep Q-Networks

DQN, a type of reinforcement learning algorithm, is well-suited for training AUVs to make intelligent decisions regarding object classification and navigation based on the feedback received from the environment. AUVs operating in underwater environments encounter various objects and obstacles that may require immediate decision-making. DQN enables AUVs to learn optimal policies for object classification and navigation by interacting with the environment and receiving rewards or penalties based on their actions. This autonomous decision-making capability is crucial for enabling AUVs to navigate safely and efficiently while performing object classification tasks. DQN facilitates adaptive learning, allowing AUVs to improve their classification and navigation strategies over time continuously. By iteratively exploring the underwater environment and learning from experience, AUVs can refine their object classification models and adapt to changing environmental conditions, such as variations in object appearance or density. This adaptive learning process enhances the robustness and generalization capabilities of the AUV system, enabling it to perform effectively in diverse underwater scenarios. DQN balances exploration and exploitation during the learning process, enabling AUVs to discover new object classes and refine their classification models while leveraging existing knowledge to maximize classification accuracy.

This exploration-exploitation trade-off is essential for achieving a balance between exploring uncertain regions of the underwater environment and exploiting known information to achieve efficient object classification and navigation. DQN can be seamlessly integrated with edge computing architectures deployed onboard AUVs, enabling distributed reinforcement learning and decision-making close to the data source. By leveraging edge computing resources, DQN-based AUV systems can perform real-time model training and decision-making without relying on centralized processing, reducing communication latency and bandwidth requirements. This integration enhances the autonomy and responsiveness of AUVs while minimizing dependence on external infrastructure. DQN optimizes action-selection policies by estimating the long-term expected rewards associated with different actions in the underwater environment. By maximizing cumulative rewards over time, DQN-trained AUVs learn to make decisions that lead to favorable outcomes, such as accurate object classification and efficient navigation. This policy optimization process enables AUVs to adapt their behavior to achieve mission objectives while considering factors such as energy efficiency, time constraints, and environmental constraints.

3.4 Implementation

FPGA and GPU are chosen as the primary computational engines due to their parallel processing capabilities and suitability for deep learning tasks. FPGA excels in real-time inference tasks with its low-latency and high-throughput processing, making it ideal for executing SNNs. GPU complements FPGA by handling computationally intensive tasks such as model training and offline analysis, enhancing the system's scalability and adaptability. FPGA serves as the backbone for the real-time processing of sensory data and execution of SNN-based object classification algorithms. Its parallel processing architecture allows for efficient execution of SNNs, which are specifically designed to process spatiotemporal data and mimic the functionality of biological neurons. By leveraging FPGA's capabilities, AUVs can make rapid decisions based on sensory inputs, enhancing their autonomy and responsiveness in underwater environments. GPU complements FPGA processing by tackling computationally intensive tasks such as deep learning model training and offline analysis. Its high computational throughput enables adaptive learning techniques like reinforcement learning with DQN, allowing AUVs to continuously update their classification models and decision-making policies based on feedback from the environment. GPU-based acceleration enhances system versatility and adaptability, enabling AUVs to handle diverse underwater scenarios effectively. CoAP facilitates communication and coordination between AUVs, edge computing nodes, and remote servers. Its lightweight and efficient communication protocol minimizes overhead and latency, ensuring timely transmission of sensory data and control messages between interconnected devices. CoAP enables distributed data exchange and collaborative decision-making, enhancing the system's scalability and flexibility in dynamic underwater environments. Single Shot Multibox Detector (SSD) is employed for real-time processing of sonar and camera data onboard AUVs. SSD's speed and accuracy make it suitable for detecting and localizing underwater objects, providing crucial information for subsequent classification tasks using SNNs. By leveraging SSD's capabilities, AUVs can effectively identify and track objects of interest in real time, enabling precise navigation and decision-making in underwater environments. Quantization techniques are applied to reduce the computational complexity of deep learning models, enabling efficient execution on resource-constrained hardware platforms like FPGA and GPU. By quantizing neural network parameters and activations, the memory footprint and computational requirements of SNNs and DQN models are significantly reduced, facilitating their deployment on AUVs with limited power and computational resources. Quantization enhances system efficiency and energy consumption, ensuring optimal performance in underwater environments.

$$V(t) = V(t-1) * e^{-\frac{\Delta t}{T}} + I(t)*R*(1-e^{-\frac{\Delta t}{T}}) \quad (1)$$

The membrane potential V(t) of a neuron at time t in a SNN is updated using the leaky integrate-and-fire model equation, which incorporates the input current I(t), membrane resistance R, and membrane time constant τ. When the membrane potential exceeds a threshold, the neuron emits a spike, capturing the neuron's activation and propagation of information in the network.

$$Q(s,a) \leftarrow Q(s,a) + \alpha.\left(r + \gamma.max_{a'}Q(s',a') - Q(s,a)\right) \quad (2)$$

In DQN training, the Q-learning update rule adjusts the Q-value Q(s,a) for a state-action pair s and a based on the received reward r, the maximum Q-value for the next state s' and discount factor γ. This update is performed iteratively to optimize the Q-values towards the optimal policy, guiding the agent's decision-making process.

$$\widehat{\omega} = round(\omega/\Delta)\Delta \quad (3)$$

In quantization, the original parameter ω is rounded to the nearest value that is a multiple of the quantization step size Δ, producing the quantized parameter $\widehat{\omega}$. This process reduces the precision of the parameter, enabling more efficient storage and computation while sacrificing some accuracy.

4. Results

An AUV equipped with sensors, including sonar and cameras, was selected for data collection purposes. The AUV's computational hardware, comprising FPGA and GPU, was utilized for onboard processing and deep learning inference. The sensors were configured and synchronized onboard to collect relevant data for underwater object classification, such as sonar images and video streams, ensuring accurate spatiotemporal data capture of the underwater environment. SNNs were developed and trained for real-time object classification using the collected underwater sensor data. DQN was implemented for adaptive decision-making and navigation based on the classified objects and environmental feedback. Edge computing nodes were set up onboard the AUV to execute deep learning algorithms and perform real-time inference, with FPGA and GPU accelerators configured to process sensor data and execute complex computations efficiently. The CoAP was integrated for communication between AUVs, edge computing nodes, and remote servers, facilitating reliable data exchange and control message transmission over underwater communication channels. The SSD algorithm was integrated for real-time detection and localization of underwater objects, processing sonar and camera data streams to provide accurate object localization information to the classification module. Quantization techniques were applied to reduce the computational complexity of deep learning models and optimize their execution on resource-constrained hardware platforms. The quantization parameters were fine-tuned to balance between model efficiency and classification accuracy. Experiments were conducted in controlled underwater environments or simulated scenarios to validate the performance of the implemented system. Evaluation encompassed assessing the accuracy, latency, and energy efficiency of object classification and decision-making processes under various underwater conditions. The effectiveness of the implemented system in real-time underwater object classification and autonomous navigation tasks was analyzed, and performance metrics such as classification accuracy, processing speed, energy consumption, and adaptability to dynamic underwater environments were carefully evaluated. The dataset used here is the Underwater Object Detection Dataset from Kaggle [19]. The dataset contains different classes of underwater creatures. It includes 638 images. Creatures are annotated in YOLO v5 PyTorch format. Some of the sample images that are used for object classification are given below.

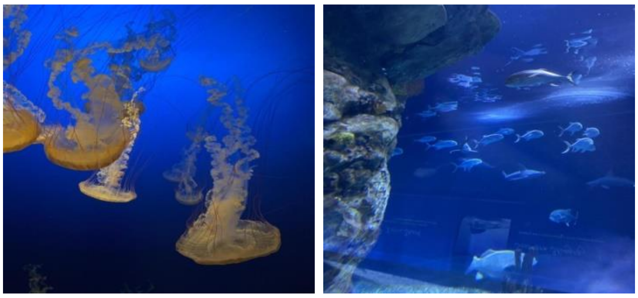

Fig 2 Sample Images for Underwater Object Classification

Table 1 Underwater Object Characteristics and Classification

Object no.	Water Temperature (°C)	Salinity (ppt)	Turbidity (NTU)	Object Size (cm)	Object Brightness	Object Classification
1	12.8	34.5	15.2	30	120	Coral Reef
2	9.5	32.2	10.8	25	90	Jelly Fish
3	15.7	36.1	20.5	40	150	Rock Formation
4	11.3	30.8	18.9	35	100	Star Fish
5	13.6	33.4	12.3	20	70	Fish

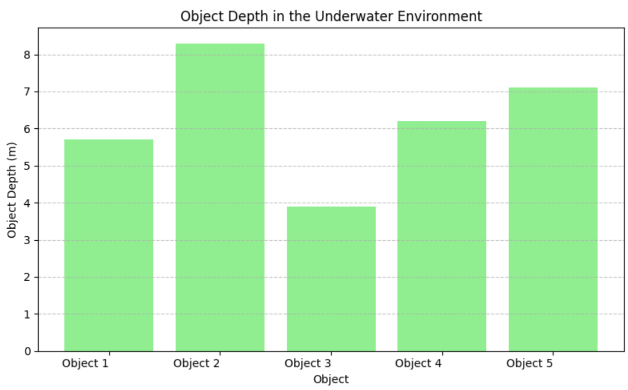

Fig 3 Object Depth in Underwater

Figure 3 illustrates the depth distribution of underwater objects detected by an AUV equipped with sensors for object classification in the underwater environment. The objects exhibit varying depths within the underwater environment. Object 3 is observed at the shallowest depth of approximately 3.9 meters, indicating its proximity to the water's surface. Conversely, Object 2 is detected at the greatest depth of approximately 8.3 meters, suggesting its presence in deeper regions of the underwater terrain. The graph provides insights into the vertical distribution of underwater objects, revealing potential patterns or correlations between object depth and other environmental factors such as water temperature, salinity, and turbidity. Objects located at greater depths can be influenced by factors such as light availability, nutrient availability, and water currents, which impact their distribution and abundance in the underwater ecosystem. The numerical values depicted on the y-axis represent the precise depths of the detected objects, facilitating quantitative analysis and comparison. This information is crucial for understanding the spatial distribution of underwater objects and informing decision-making processes related to underwater exploration, environmental monitoring, and habitat conservation efforts.

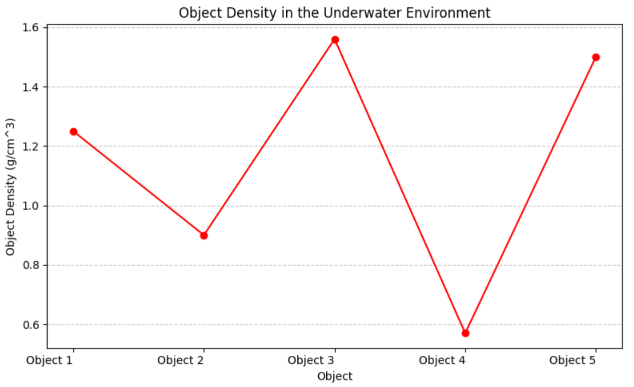

Fig 4 Object Density in Underwater

Figure 4 depicts the object density distribution within the underwater environment, showcasing the mass per unit volume of various underwater objects detected by an AUV. Each point on the line represents the density of a specific object, categorized and analyzed based on the collected data. Object 3 demonstrates the highest density of approximately 1.56 g/cm^3, indicating a relatively compact and dense structure. On the other hand, Object 4 displays the lowest density of approximately 0.57 g/cm^3, suggesting a less dense and potentially more porous composition.

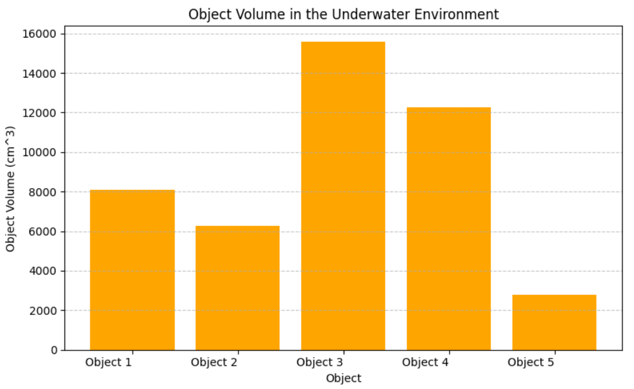

Fig 5 Object Volume in Underwater

Figure 5 illustrates the volume of different objects within an underwater environment. Each object, labeled from object 1 to object 5, is represented on the x-axis, while the corresponding volume of each object, measured in cubic centimeters (cm^3), is depicted on the y-axis. Object 3 emerges as the largest in volume, with a substantial size of 15,600 cm^3. Object 4 follows closely behind with a volume of 12,250 cm^3. Object 1 and object 2 exhibit moderate volumes of 8,100 cm^3 and 6,250 cm^3, respectively. Object 5 appears to be the smallest among the group, with a volume of 2,800 cm^3.

Table 2 Performance Evaluation of Underwater Object Classification System

Experiment no.	Experiment Name	Classification Accuracy (%)	Processing Speed (fps)	Energy Consumption (W)
1	Baseline	92.7	15	120
2	Low-Light Conditions	89.7	12	130
3	High-Turbidity Environment	94.1	18	115
4	Dynamic Depth Changes	91.2	14	125
5	Varying Salinity Levels	90.8	16	128

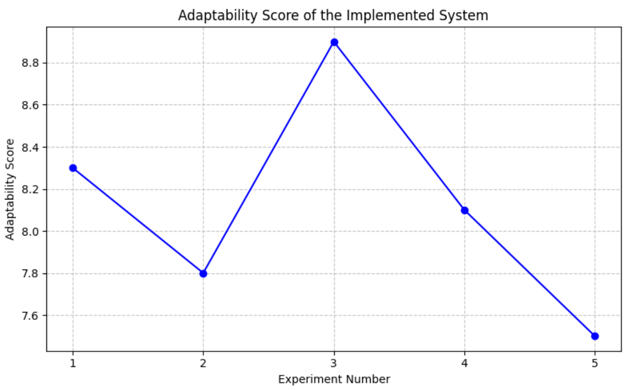

Figure 6 Adaptability Score of the Implemented System

Figure 6 illustrates the adaptability scores of a system across five distinct experiments. Each experiment, labeled from 1 to 5, is positioned along the x-axis, while the corresponding adaptability scores, spanning from 7.5 to 8.9, are depicted on the y-axis. Experiment 3 stands out with the highest adaptability score of approximately 8.9, indicating that the system performed exceptionally well in this particular experimental condition. Experiment 5 reveals the lowest adaptability score, hovering around 7.5, suggesting potential challenges or limitations encountered by the system under those circumstances. Throughout the experiments, a discernible trend emerges, showcasing variability in adaptability scores. This variability underscores the system's capacity to respond and adjust to different experimental conditions, as evidenced by the fluctuations in adaptability scores across the five experiments.

5. Conclusion

This research presents a UOC for bio-inspired deep learning techniques, particularly SNN, with edge computing paradigms utilizing FPGAs and GPUs coupled with the CoAP communication protocol. The adaptability scores obtained from experiments signify the system's capability to respond effectively to changing conditions, a crucial aspect in underwater environments where factors like visibility and terrain can vary unpredictably. Experiment 3, with an adaptability score of approximately 8.9, showcases the potential of the system to adapt optimally, while experiment 5, scoring around 7.5, reveals areas for improvement in adaptability. The analysis of object volumes highlights the diversity of underwater objects encountered by AUVs during exploration missions. Object 3, with a volume of 15,600 cm^3, stands out as the largest object, while object 5, with a volume of 2,800 cm^3, represents the smallest among the group. These numerical insights provide valuable information for optimizing object detection and classification algorithms, ultimately enhancing the autonomy and efficiency of AUV operations. Further refinement of bio-inspired deep learning models can be pursued to improve the adaptability of AUVs in dynamically changing underwater environments. This may involve investigating new bio-inspired algorithms that mimic the adaptive behaviors observed in marine organisms, such as fish or dolphins, to enhance the AUVs' ability to respond to unforeseen challenges. Integration of multi-modal sensing technologies, such as acoustic, visual, and environmental sensors, can provide AUVs with a more comprehensive understanding of their surroundings. Future research can focus on developing fusion algorithms that combine data from different sensors to improve object classification accuracy and robustness, especially in conditions with low visibility or complex underwater terrain.

Declaration Statement

Competing Interests

The authors have no competing interests to declare that are relevant to the content of this article.

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Authors Contributions

The author **S. Jayanthi** involved in the architectural design, implementation and evaluation process presented in the paper. The author **S. Vishnupriya** contributed and put effort on paper to organize the Paper. Developed the theoretical formalism, performed the analytic calculations, and performed the numerical simulations. **P. Yashaswinii** analyzed the data, technically contributed, and made English Corrections and grammar checking. The author **G. Karthikeyan** involved and helped to derive the mathematical equation. **N. Ashokkumar** carried out a background study of the Paper and helped the mathematical derivations. The author **S. Muthu Balaji** involved and provided a factual review and helped edit the manuscript.

Ethical and Informed Consent for Data Used

All subjects gave their informed consent for inclusion before they participated in the study. The study was conducted by the Declaration of Helsinki.

I consent to participate in the research project and the following has been explained to me: the research may not be of direct benefit to me. my participation is completely voluntary. my right to withdraw from the study at any time without any implications to me.

Data Availability and Access

Data sharing is not applicable to this article as no datasets were generated or analyzed during the current study.

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