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Underwater Vision Technologies for Smart Fisheries: A Comprehensive Review of OpenCV-Based Optimization and Edge Computing Applications

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Abstract: With the deepening exploration of marine resources and the global emphasis on sustainable development, intelligent fishery has emerged as a critical domain for advancing ecological conservation and operational efficiency. Underwater vision technology, a cornerstone of intelligent fishery systems, encounters substantial challenges due to complex underwater environments—such as light attenuation, turbidity, biofouling, and dynamic currents—which degrade image quality and impede real-time decision-making. To address these limitations, this paper systematically reviews the integration of OpenCV-based image processing techniques with edge computing frameworks, which collectively enhance the robustness and adaptability of underwater visual systems. OpenCV's advanced algorithms, including Contrast-Limited Adaptive Histogram Equalization for low-light enhancement, geometric transformations for distortion correction, and YOLO-based object detection, have been shown to significantly improve image clarity and target recognition accuracy. Simultaneously, edge computing alleviates latency and bandwidth constraints by enabling real-time data processing on embedded devices, achieving sub-200 ms response times for critical tasks such as dissolved oxygen monitoring and fish behavior analysis. Field validations underscore performance improvements, such as 92% recognition accuracy in coral reef monitoring and 85% mean Average Precision for aquatic species detection using MobileNet-SSD models. Despite these advancements, challenges remain in extreme conditions, computational resource optimization for edge devices, and the need for interdisciplinary collaboration to integrate marine biology insights into algorithmic design. Future research directions highlight hybrid architectures combining physics-based restoration with quantized deep learning, bio-inspired optical sensors, and socio-technical frameworks to ensure equitable technology adoption.

Keywords: OpenCV, edge computing, intelligent fishery, underwater vision, image processing technology

1. Introduction

In the context of global climate change and heightened environmental awareness, intelligent fishery management has drawn increasing attention from the international community as a sustainable solution. By integrating advanced technologies such as computer vision, edge computing, and artificial intelligence, intelligent fishery aims to optimize resource utilization, enhance operational

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efficiency, and minimize ecological impacts in aquatic ecosystems. A key enabler of intelligent fishery is underwater visual technology, which plays a critical role in improving resource management, mitigating environmental effects, and promoting sustainability.

The development of intelligent fishery relies on multiple critical resources. Technologically, it leverages tools like OpenCV for real-time image processing, edge computing frameworks for decentralized data analysis, and deep learning models for species recognition. Environmentally, it reduces reliance on manual labor and combats overfishing through precision monitoring, thereby minimizing habitat disruption and fostering biodiversity conservation. For instance, automated systems can detect anomalies in fish density or disease outbreaks early, enabling targeted interventions that reduce chemical usage and waste discharge.

Despite its potentials, the application of this technology faces significant challenges due to complex underwater environments, limited lighting conditions, and high computational requirements. Underwater vision systems must address dynamic factors including light attenuation, turbidity, and biofouling, which degrade image quality and hinder real-time decision-making. Additionally, reliance on cloud-based architectures introduces latency and bandwidth limitations, especially in remote marine areas with constrained connectivity. To address these issues, this study focuses on OpenCV-based image processing techniques and edge computing applications, both of which are essential for enhancing the performance of underwater visual systems.

From a technical perspective, OpenCV provides a versatile toolkit for addressing underwater imaging challenges. Its algorithms, such as CLAHE (Contrast-Limited Adaptive Histogram Equalization) for contrast enhancement and YOLO-based models for object detection, play a pivotal role in resolving issues like color distortion and motion blur. Meanwhile, edge computing decentralizes computational tasks to local devices (e.g., NVIDIA Jetson modules), enabling real-time sensor data processing and reducing dependence on centralized cloud infrastructure. This synergy not only improves response times but also enhances energy efficiency—a crucial factor for solar-powered deployments in offshore environments.

This paper aims to comprehensively assess the potential applications of OpenCV-based image processing and edge computing in underwater visual technology for intelligent fisheries. It explores how these technologies can drive technological innovation and sustainable development. By analyzing existing research, the findings offer researchers and practitioners with a clear understanding of the current technical landscape and future directions while identifying existing limitations and potential areas for further investigation.

2. Edge computing and OpenCV in intelligent fisheries

2.1. The development of edge computing in smart fishery

In initial research, Zhao highlighted the efficacy of the K-means clustering algorithm in enhancing edge detection accuracy in underwater imagery [1]. This work established a crucial foundation for subsequent advancements, particularly in tackling common issues like image blurring and color distortion prevalent in underwater settings. Subsequently, Zhu et al. utilized edge computing to streamline data transmission for remote island observations [2]. By delegating data processing tasks to edge nodes within the network, the data processing efficiency was significantly boosted and the communication delays were minimized. This research emphasized the practical benefits of edge computing in marine environmental monitoring. Moreover, Zhang et al. explored the application of edge computing in intelligent aquaculture systems [3]. Through real-time monitoring and sophisticated data analysis, they achieved precise control and management of the aquaculture environment, demonstrating the profound integration of edge computing technology in smart agriculture.

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In conclusion, from early image processing methods to advanced environmental monitoring applications, the principles of edge computing have demonstrated substantial potential in improving efficiency, reducing costs, and enhancing decision support capabilities in underwater vision technology for intelligent fisheries. As technology evolves and its applications broaden, edge computing is expected to play an increasingly vital role in the future development of intelligent fisheries.

2.2. The application of edge computing in underwater

Edge computing plays a crucial role in improving underwater target recognition through real-time processing capabilities and decreased dependence on cloud infrastructure. Notable advancements involve the implementation of lightweight deep learning models, such as MobileNet-SSD, on edge devices, enabling instantaneous detection of marine species and underwater obstacles. For example, MobileNet-SSD has shown a mean Average Precision (mAP) of 85% in identifying common aquatic life [4]. Furthermore, edge computing significantly enhances the applicability of -SSD, which has demonstrated a mean Average Precision (mAP) of 85% in identifying common aquatic life [4]. Additionally, feature extraction algorithms such as SIFT (Scale-Invariant Feature Transform) and SURF (Speeded-Up Robust Features) from OpenCV are integrated, enabling the system to process turbid underwater imagery more effectively [5].

The use of NVIDIA Jetson Xavier for local processing results in a response time reduction to less than 0.5 seconds, providing a key benefit for dynamic underwater tasks like real-time tracking of fish schools in submerged settings. This functionality is powered by its integrated tensor cores, which enhance parallel computing for detection algorithms while ensuring consistent performance under hydrostatic pressures up to 100 meters [6]. Moreover, transmitting metadata (e.g., object coordinates) rather than raw video streams cuts down data transmission by as much as 80%, greatly boosting bandwidth efficiency—an essential enhancement for underwater acoustic communication systems that usually operate below 50 kbps. The sustained throughput limit of 100 Mbps guarantees dependable data exchange even in murky waters with suspended particles [7]. In coral reef monitoring initiatives, edge computing architectures have attained 92% accuracy in identifying endangered marine species in low-visibility conditions, thanks to adaptive algorithms that address turbidity changes and hydrodynamic disturbances. These features allow conservation teams to execute protective actions within 15 minutes of detection through automated pipelines from data to action, which is vital for time-critical underwater ecological responses [8]. The observed performance gains are due to edge-based preprocessing methods that include dual noise reduction: spatial filtering removes interference from sediments typically found in benthic areas, while temporal filtering eliminates temporary lighting distortions caused by surface wave refraction. Furthermore, biologically significant characteristics such as scale patterns and fin outlines are emphasized using feature saliency weighting, increasing the reliability of ecological assessments by 37% compared to cloud-based systems—a critical edge for remote underwater deployments with sporadic connectivity [8].

2.3. The research advances of image enhancement technology

The development of image enhancement techniques utilizing OpenCV within the domain of intelligent fishery underwater vision technology Is essential for improving the performance of underwater robotic vision systems. Chen and Zhang introduced an enhanced adaptive histogram equalization algorithm (CLAHE), which is specifically designed to meet the requirements of underwater bionic fish robot vision systems, tackling issues like image degradation and distortion[9]. The results of a series of experiments conducted by randomly designated ight black circular regions

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on the surface of the white-water pipe located at the bottom of the blue laboratory pool as oil leakage points revealed that the bionic fish achieved a detection rate of 73.75% for identifying these oil leakage points [9]. These experimental results confirmed the effectiveness of this approach and improves the adaptability and stability of the platform in complex underwater environments.establishing a robust foundation for future research. The improvements not only expanded the platform's functionality but also provided substantial technical support for practical image processing tasks. Additionally, Yang and Sun developed an intelligent tracking and recognition system for underwater fish targets using TensorFlow 2.0 and YOLO V4 [10]. This system adeptly manages common distortions and noise in underwater video footage while maintaining high accuracy and efficient tracking. Their findings underscore the potential benefits of combining deep learning with image enhancement techniques to enhance underwater vision system performance. Recently, Zhou proposed a deep learning-based image enhancement method to address the challenges of recognizing underwater cultural relics [11]. By creating a specialized dataset and refining the image enhancement algorithm, this approach markedly improved the recognition accuracy of underwater objects.

In summary, the integration of traditional image enhancement algorithms (e.g., CLAHE) based on OpenCV with deep learning techniques (e.g., YOLO V4 and customized datasets) has significantly enhanced the performance of underwater vision systems. These approaches effectively address challenges such as image degradation, noise interference, and low target recognition accuracy, providing robust technical support for applications like intelligent fishery monitoring, underwater robot navigation, and cultural heritage preservation. Moving forward, further integration of traditional image processing methods and deep learning frameworks is expected to advance underwater vision technologies toward greater adaptability, intelligence, and generalization across diverse scenarios.

2.4. OpenCV vs conventional image recognition

OpenCV surpasses traditional image recognition methods across multiple dimensions. OpenCV's 2500+ pre-built optimized functions (e.g., Haar cascades for object detection [12]) demonstrate its algorithm diversity advantage over traditional image recognition methods. Seamless machine learning integration with frameworks like TensorFlow/PyTorch enables hybrid pipelines to achieve 95% accuracy in fish disease detection [13]. Computational efficiency can be further boosted through GPU/NPU hardware acceleration (10–20x faster processing via CUDA/OpenVINO) and memory-optimized algorithms like ORB (40% reduced memory usage) [14-15], and community-driven adaptability. Community-driven adaptability mainly include an open-source ecosystem that is constantly updated for challenges like underwater distortion correction, and cross-platform compatibility from embedded systems (Raspberry Pi) to cloud servers [16-17]. As indicated in Table 1, the results robustly substantiate that OpenCV exhibits shorter construction time, higher accuracy of underwater recognition, and lower hardware costs compared with traditional methods. It surpasses traditional methods in the above respects and is more compatible with the configuration of smart agriculture.

Table 1: Comparative analysis of OpenCV versus conventional techniques

Aspect	Conventional Methods	OpenCV
Development Time	Weeks for custom algorithm coding	Hours via pre-built functions [12]
Accuracy	70–80% for basic thresholding	90–95% with ML integration [13]
Hardware Cost	High (dedicated FPGA setups)	Low (runs on $35 Raspberry Pi) [17]

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3. The application prospects of OpenCV and edge computing in intelligent fisheries

3.1. The construction of an intelligent breeding monitoring and supervision system

The integration of OpenCV and edge computing enables the development of intelligent breeding monitoring systems that enhance precision and sustainability in fisheries. This system comprises three key components: real-time environmental perception, edge-AI decision-making and centralized supervision platform.

OpenCV-based vision analysis integrated with multi-sensor fusion systems enhances underwater aquaculture monitoring through real-time environmental sensing to detect fish density, and behavioral anomalies (e.g., disease-indicating erratic swimming), and combines with YOLOv4 to estimate biomass (over 90% accuracy in clear water [18]).

In the context of aquaculture systems, edge computing frameworks based on Edge-AI Decision-Making improve localized control and priority-driven data processing. These frameworks integrate optimized OpenCV models on edge devices like the NVIDIA Jetson Nano to enable swift responses. For instance, aerators are activated when dissolved oxygen levels fall below critical thresholds (e.g., 4 mg/L) [19], and feeding schedules are adjusted based on real-time fish behavior analysis [19-20].

In addition, the multi-tiered processing architecture in Hierarchical Data Management enhances operational efficiency. Time-sensitive alerts, such as the occurrence of pH irregularities or oxygen shortages, achieve sub-200 ms latency for immediate local resolution. Non-critical data, including growth metrics, are asynchronously aggregated and stored in cloud storage [21]. This dual-mode approach ensures a balance between immediate responsiveness and efficient resource management, aligning with the scalability needs of smart aquaculture infrastructure.

Integrated aquaculture management platforms combine a cloud-based visual dashboard that aggregates multi-node edge data—The system provides real-time farm status visualization through water quality heatmaps and behavior-annotated video streams [22]. Additionally, blockchain-integrated traceability systems securely archive operational logs and compliance records on Hyperledger Fabric chains, ensuring auditable transparency for certification procedures [23].

As demonstrated in Table 2, the combination of OpenCV with edge computing clearly surpasses conventional methods by providing enhanced real-time responsiveness, improved recognition precision, reduced construction expenses, and increased adaptability for future expansions.

Table 2: The advantages of the combination of OpenCV and edge computing

Aspect	Traditional Monitoring	OpenCV + Edge Computing
Real-Time Response	Delayed (5–10 min for manual data entry)	Immediate (<1 s for edge-based triggers)
Accuracy	Subjective human judgment (~75% accuracy)	Algorithm-driven (>90% accuracy) [18]
Cost Efficiency	High labor costs ($15k/year per farm)	Reduced OPEX via automation (ROI 140% [24])
Scalability	Limited to small-scale operations	Supports 100+ nodes per gateway [21]

3.2. The superiority of the novel underwater visual system

As illustrated in Table 3, the integration of OpenCV and edge computing achieves superior accuracy in underwater recognition compared to conventional techniques. This approach demonstrates a significant performance advantage and is better aligned with the development needs of smart aquaculture systems. The enhanced precision offered by this combined methodology not only

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outpaces traditional methods but also provides greater support for the advancement and optimization of intelligent aquatic farming technologies.

Table 3: Comparative study of underwater recognition accuracy

Condition	Accuracy (OpenCV + Edge)	Accuracy (Traditional)
Clear water	92% [18]	78% [25]
Turbid water (NTU >10)	65% [26]	42% [25]

Underwater vision systems addressing operational challenges implement OpenCV's CLAHE algorithm for low-light adaptation (effective above 1 lux environments) while investigating hybrid infrared-RetinaNet solutions for extreme darkness [27], coupled with graphene oxide nanocoating on camera lenses that extends biofouling-resistant operation from 7 to 45 days in saline conditions [28], enabling reliable long-term aquatic monitoring.

The adoption of edge computing in aquaculture systems demonstrates cost-effectiveness through modular edge vision nodes with 800 initial investment vs. 1,200 for cloud-dependent architectures [24], achieving 140% 3-year ROI through bandwidth/labor savings, while concurrently reducing energy demands via solar-powered operation (8-12 W consumption vs. 20-30 W for full-cloud systems [29]).

4. The challenges and prospect

4.1. The limitations of the present research

Image degradation in underwater environments remains a critical challenge, primarily caused by the interplay of light attenuation, scattering effects, and suspended particulate matter. Water selectively absorbs longer wavelengths (e.g., red and orange light), leading to color distortion and reduced contrast, while scattering from suspended particles or microorganisms further degrades image clarity by introducing haze-like artifacts.

Additionally, dynamic lighting conditions and biofouling on optical sensors exacerbate these issues, resulting in blurred edges and noisy imagery that hinder accurate feature extraction and object recognition [28]. Although existing image enhancement techniques, such as CLAHE and deep learning-based methods, mitigate these effects to some extent, their performance varies significantly under extreme conditions (e.g., turbid waters with NTU >10 or near-total darkness), necessitating further empirical validation and scenario-specific optimization [26].

Underwater robotic vision systems also require precise geometric transformations to correct distortions caused by refraction at water-air interfaces and irregular camera angles. Current algorithms, while effective in controlled settings, struggle to maintain robustness in dynamic underwater environments characterized by fluctuating currents, uneven terrain, or rapid target movements. For instance, real-time geometric corrections for fish school tracking demand computationally intensive calculations, which strain the limited resources of embedded edge devices like the NVIDIA Jetson Nano [17]. Although lightweight models such as MobileNet-SSD improve efficiency, their accuracy declines in cluttered scenes, highlighting a trade-off between computational efficiency and algorithmic precision [16,26].

Moreover, the current research predominantly relies on theoretical analyses and laboratory-based validations, with a notable lack of empirical studies in real-world fishery environments. For example, while edge computing frameworks and OpenCV-based systems are reported to achieve high accuracy in controlled experiments (e.g., 92% in coral reef monitoring [8]), their long-term reliability and scalability in operational aquaculture settings remain under-documented. Field trials addressing

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practical challenges, such as biofouling-induced sensor degradation or power constraints in remote marine areas, are scarce, limiting the generalizability of proposed solutions [29].

Furthermore, critical non-technical dimensions essential for holistic technology adoption are often overlooked. Economic feasibility analyses—such as cost-benefit comparisons between edge computing and cloud-dependent architectures, remain underexplored despite claims of reduced operational expenses (ROI 140% [24]). Similarly, socio-environmental factors, including the impact of automated systems on small-scale fisheries or compliance with regional sustainability guidelines (e.g., FAO Technical Paper No. 638 [29]), are absent from the discourse.

Additionally, current research frameworks demonstrate constrained generalization capabilities, predominantly validated in controlled environments like aquaculture tanks or coral reefs [8,18], with limited adaptation to heterogeneous marine ecosystems. While hybrid methodologies merging OpenCV techniques and deep learning exhibit potential for scenario-specific tasks, the absence of unified evaluation standards for cross-environment adaptability impedes their scalability in complex fishery operations. This gap is further compounded by the literature's disproportionate emphasis on computational advancements, overlooking critical interdisciplinary dimensions such as marine species' behavioral adaptations for algorithm refinement or oceanographic turbidity modeling to improve ecological validity. Addressing these limitations necessitates collaborative efforts across optical physics, marine ecology, and embedded systems engineering to develop adaptive solutions that reconcile technical innovation with biological and environmental realities. Additionally, recent advancements in bio-inspired optical sensors or hybrid edge-cloud architectures are underrepresented, potentially limiting the innovation trajectory of future research [28].

These limitations underscore the need for interdisciplinary collaboration to develop holistic solutions that integrate optical physics, marine biology, embedded system design, and socio-economic considerations.

4.2. Outlook

Future research in intelligent fishery underwater vision systems should adopt an integrated approach that systematically addresses technical, environmental, and socio-economic challenges. Advancing hybrid architectures combining physics-based image restoration (e.g., wavelength compensation) with quantized deep learning models could help overcome current limitations in extreme underwater conditions. By dynamically adjusting parameters through edge-compatible turbidity sensors, these systems could maintain robustness in turbid waters (NTU >10) while leveraging neuromorphic processors and spiking neural networks to reduce power consumption below 300mW - a critical threshold for solar-powered deployments. Concurrently, large-scale field validation across diverse aquaculture environments, from open-ocean cages to mangrove ecosystems, must be accelerated through partnerships with fisheries authorities. Such collaborations would enable stress-testing against real-world challenges like biofouling and tidal fluctuations while establishing standardized metrics balancing computational efficiency (FPS/Watt) with ecological impact.

Building on these advancements, cross-disciplinary integration with marine biology offers transformative potential. Fish schooling pattern datasets could refine motion prediction algorithms, while coral symbiosis studies might inform biofouling-resistant hardware designs. The development of mantis shrimp-inspired polarization vision sensors demonstrates how biomimicry could enhance image clarity in murky waters through multispectral polarization imaging, potentially achieving over 50% detection accuracy improvements. Meanwhile, sustainable implementation demands parallel progress in socio-technical frameworks. Cost-optimized modular systems designed for community maintenance, aligned with FAO sustainability guidelines, could democratize access while preventing technological displacement in small-scale fisheries. Pilot deployments in Southeast Asian aquaculture

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hubs should prioritize co-design processes with local fishers, iteratively improving human-machine interfaces while collecting longitudinal data on automation's socio-economic impacts.

Ultimately, this interconnected strategy - weaving algorithmic innovation with ecological insights and community-centric design - requires synchronized development across three axes: adaptive vision architectures resilient to environmental variability, biologically informed evaluation protocols, and equitable technology dissemination models. By maintaining tight feedback loops between laboratory prototypes and real-world deployments through continuous sensor data collection and stakeholder engagement, the field could transition from isolated technical achievements to holistic solutions that genuinely advance sustainable aquaculture practices.

5. Conclusion

This paper systematically explores the integration of OpenCV-based image processing and edge computing in intelligent fishery underwater vision systems. By leveraging OpenCV's advanced techniques—such as CLAHE for contrast enhancement, geometric transformation corrections for distortion mitigation, and YOLO-based object detection—these systems significantly improve image clarity and operational reliability in complex underwater environments. The synergy with edge computing further addresses critical limitations like latency and bandwidth constraints, enabling real-time data processing for applications such as remote aquaculture monitoring and fish behavior analysis. The incorporation of edge computing further mitigates key challenges such as latency and bandwidth constraints, enabling real-time data processing for applications like remote aquaculture monitoring and fish behavior analysis.

However, challenges remain in ensuring model generalization across diverse environmental conditions, optimizing computational efficiency in embedded edge devices, and improving the effectiveness of image enhancement algorithms under extreme conditions such as turbid waters or low-light environments. While edge computing reduces reliance on cloud infrastructure, its long-term energy efficiency—especially for solar-powered underwater devices—requires further optimization. Additionally, interdisciplinary collaboration is essential for developing solutions tailored to fisheries' specific needs, such as incorporating biological insights into algorithm design for species-specific identification.

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