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Real-Time By-Catch Mitigation via Edge AI Onboard Industrial Vessels

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Abstract

Global fisheries face an urgent crisis of biodiversity loss due to the unintentional capture of non-target species, known as by-catch. Traditional Electronic Monitoring (EM) systems rely on manual review of video footage, often resulting in data backlogs and delayed management responses. This research explores the integration of Edge AI—high-performance, localized artificial intelligence—onboard industrial fishing vessels to automate species identification and quantification in real time. By deploying state-of-the-art computer vision models, such as YOLOv8 and ShuffleNetV2, on ruggedized hardware like the NVIDIA Jetson platform, vessels can now detect by-catch at the point of capture (Lee Son et al., 2023). This paper analyzes recent industrial trials where Edge AI reduced footage review times from months to minutes, achieving catch-count accuracy with miss rates as low as 6% (Responsible Seafood Advocate, 2026). We discuss the technical architecture required for maritime environments, including preprocessing filters and satellite-linked reporting, and demonstrate how this "human-in-the-loop" technology enhances sustainable fisheries management and transparency.

Keywords: Edge AI, By-Catch Mitigation, Computer Vision (or Deep Learning), Precision Fisheries (or Smart Fishing), Real-Time Object Detection.

Introduction: The By-Catch Crisis and Technological Necessity

The ecological impact of industrial fishing is significantly exacerbated by the landing of by-catch, including endangered sharks, turtles, and juvenile fish. Despite regulatory efforts, the lack of real-time monitoring leads to consistent under-reporting and delayed conservation intervention. Standard Electronic Monitoring (EM) has traditionally been a "passive" tool, recording thousands of hours of video that require expert human review months after a voyage concludes (Fishnet.AI, 2026). The shift toward Edge AI represents a paradigm change, moving from retrospective auditing to proactive, real-time intervention at sea (The Nature Conservancy, 2024.).

Current research emphasizes that EM systems already record up to three times more retained catch than vessel logbooks, yet their efficiency is hampered by the sheer volume of data (MDPI, 2025). The introduction of Intelligent Electronic Monitoring and Reporting (I-EMR) models aims to bridge this gap by integrating computer vision directly into the vessel's workflow (Lee Son et al., 2023). By processing data locally, vessels can overcome the "bandwidth bottleneck" of satellite communications, ensuring that only critical catch events are transmitted for verification (Lanner Electronics, 2026).

Foundational Technologies in Fisheries Computer Vision

The evolution of automated catch accounting has been built on foundational datasets and convolutional neural network (CNN) architectures. Datasets such as the Fishnet Open Images Database—containing over 549,000 bounding boxes across 34 object classes—have provided the necessary training ground for identifying species in the chaotic environments of longline and trawl decks (Fishnet.AI, 2026). These datasets capture the harsh realities of industrial fishing: visual similarity between species, skewed distributions, and heavy lens spray (ResearchGate, 2026).

Technologically, the transition from general-purpose CNNs like VGG16 and ResNet50 to specialized models has been critical (IJEIAS, 2025). Researchers have implemented Improved R-FCN (Region-based Fully Convolutional Networks) to handle the position-sensitive requirements of identifying fish at the rail of a vessel (Heliyon, 2024). These models allow for simultaneous detection, count, and length estimation, which are vital metrics for both commercial compliance and scientific population studies (Lee Son et al., 2023).

Edge AI Architecture: Hardware for the High Seas

Deploying AI in maritime environments presents unique hardware challenges, including extreme temperature fluctuations, salt-air corrosion, and high vibration. The industry has converged on the NVIDIA Jetson platform as the standard for "AI supercomputing" at the edge (Lanner Electronics, 2026). Specifically, units like the MILBOX-AGX provide the ruggedized chassis necessary to withstand shocks while running 200 trillion operations per second (Responsible Seafood Advocate, 2026).

These edge appliances act as decentralized IT architectures, processing data near the source to reduce latency and lower bandwidth costs (Forecr, 2026). By utilizing 5G, WiFi6, and maritime satellite packages like Starlink, these systems can transmit "clean reports" of catch events to shore-based reviewers (Responsible Seafood Advocate, 2026). This localized

processing ensures that AI inference remains operational even when the vessel is "off-grid" in remote high-seas regions (Lanner Electronics, 2026).

Deep Learning Models and Real-Time Inference

Recent breakthroughs in deep learning have significantly improved the accuracy of species identification. Two-stage approaches, such as using an Unsharp Mask Filter (UMF) for preprocessing followed by an Improved ShuffleNetV2 for classification, have achieved accuracy rates exceeding 99.9% in controlled datasets (Heliyon, 2024). In practical deck scenarios, lightweight models based on YOLOv8 have shown 92.78% counting accuracy, a massive leap over previous manual-entry logs (ResearchGate, 2026).

Model Component	Function in By-Catch Mitigation
UMF Filter	Enhances image quality in low-visibility marine environments.
YOLOv8/ByteTrack	Real-time object detection and consistent target tracking.
ShuffleNetV2 + SE	High-speed classification with minimal computational footprint.
ENGO Algorithm	Hyperparameter optimization for maximum species precision.

These models are often fine-tuned via transfer learning from large-scale datasets like ImageNet, allowing them to generalize features before being specialized for fisheries (IJEIAS, 2025). By maintaining a "human-in-the-loop" verification system, the AI's confidence scores are used to flag ambiguous events for expert review, ensuring the ongoing refinement of the neural networks (Responsible Seafood Advocate, 2026).

Industrial Trials and Management Impact

The real-world application of Edge AI has been pioneered by organizations like The Nature Conservancy (TNC). In 2025-2026, trials on tuna longline vessels in Costa Rica and the Western Central Pacific demonstrated that AI could detect and flag human under-reporting by comparing instant AI summaries with captain’s reports (Responsible Seafood Advocate, 2026). These trials achieved miss rates of just 6%, far exceeding the initial ambitious target of 15% (Responsible Seafood Advocate, 2026).

The impact on management is profound: instead of reviewing 100% of the video, human reviewers only need to verify the specific moments isolated by the AI (The Nature Conservancy, 2024). This reduces the reporting cycle from months to nearly real-time, allowing for rapid management decisions such as the closure of specific areas to protect migrating species (Heliyon, 2024). Furthermore, integrated I-EMR systems consolidate data from VMS (Vessel Monitoring Systems) and eLogs, creating a transparent, tamper-proof record of fishing activities (MDPI, 2025).

Future Outlook: Scaling Toward Global Compliance

Despite the successes, challenges remain in scaling these systems across diverse global fleets. Structural inequalities in technology adoption and the lack of standardized multi-region datasets for rare or protected taxa hinder universal implementation (ResearchGate, 2026). However, the recent entry into force of the BBNJ (Biodiversity Beyond National Jurisdiction) treaty has strengthened high-seas governance, creating a stronger regulatory push for automated monitoring (Responsible Seafood Advocate, 2026).

Future developments will likely see the integration of AI directly into "smart cameras," eliminating the need for a separate onboard computer and further reducing the barrier to entry for smaller vessels (Responsible Seafood Advocate, 2026). As AI continues to offer robust understandings of aquatic ecosystems—including migration patterns and fish behavior—it will become the cornerstone of sustainable, evidence-based fisheries management (Heliyon, 2024).

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