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AI in Ocean Monitoring: Deep Learning for Marine Pollution, Fisheries, and Underwater Robotics

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Abstract— The ocean covers more than seventy percent of the Earth's surface, yet remains comparatively undersampled relative to terrestrial environments due to the cost, difficulty, and hazard of direct human observation at scale, particularly at depth. Artificial intelligence has become an increasingly important tool for closing this observation gap, supporting automated analysis of underwater imagery and acoustic recordings, autonomous underwater vehicle navigation, satellite-based ocean remote sensing, and detection of illegal fishing activity from vessel tracking data. This paper surveys the application of deep learning to ocean monitoring, organizing methods into a taxonomy spanning underwater visual and acoustic analysis, autonomous underwater robotics, satellite ocean remote sensing, marine pollution detection, and fisheries stock assessment. We review applications including marine plastic debris monitoring, illegal, unreported, and unregulated fishing detection, coral reef health assessment, marine mammal conservation, and ocean climate monitoring, summarize benchmarks and datasets used in this domain, and present a case study illustrating an integrated satellite and vessel-tracking pipeline for illegal fishing detection. We discuss challenges including the scarcity of labeled underwater imagery relative to terrestrial datasets, the difficulty of operating machine learning systems on power- and bandwidth-constrained underwater platforms, and the vastness of the ocean relative to available monitoring infrastructure, and outline future directions connecting ocean AI with autonomous ocean observation networks and international fisheries governance.

Index Terms—ocean monitoring, marine pollution detection, fisheries management, underwater robotics, autonomous underwater vehicles, coral reef monitoring, illegal fishing detection

I. INTRODUCTION

The global ocean plays a central role in regulating Earth's climate, supporting a substantial share of global biodiversity, and providing food and livelihood for a large fraction of the world's population, yet it remains comparatively undersampled relative to terrestrial environments, since direct human observation of the ocean, particularly at depth or in remote open-ocean regions, is far more costly, logistically difficult, and hazardous than equivalent terrestrial field observation. This observation gap has direct practical consequences for ocean governance and conservation: illegal, unreported, and unregulated fishing activity, marine plastic pollution, and coral reef degradation, among other pressing ocean sustainability challenges, are each difficult to monitor and address effectively without substantially improved observational capability across the vast spatial extent of the global ocean.
Artificial intelligence, and deep learning in particular, has become an increasingly important tool for closing this ocean observation gap, extending the reach of limited human observational capacity through automated analysis of underwater imagery and video, automated processing of passive acoustic recordings, satellite-based remote sensing of ocean surface conditions and vessel activity, and increasingly capable autonomous underwater vehicles able to conduct extended survey missions without continuous direct human control, in an environment where communication with human operators is frequently limited or entirely unavailable at depth.
This paper surveys the growing application of AI methods to ocean monitoring across these several complementary observation modalities. Section II reviews background motivating AI adoption in ocean monitoring and the field's historical development. Section III presents a taxonomy of methodological approaches. Section IV describes core methods in technical detail. Section V surveys applications across marine conservation and fisheries management. Section VI summarizes benchmarks and datasets. Section VII offers a comparative discussion. Section VIII presents a case study of an integrated illegal fishing detection pipeline. Section IX discusses implementation considerations

specific to the marine environment. Section X considers ethical and governance implications. Section XI discusses open challenges, Section XII outlines future directions, and Section XIII concludes.

As with related applications of AI to environmental and conservation monitoring discussed elsewhere in this survey series, a recurring theme throughout this paper is that ocean AI applications must contend with data and deployment constraints considerably more severe than those typically encountered in mainstream terrestrial computer vision and audio processing research, including harsh, variable underwater imaging conditions, severe power and communication bandwidth constraints for autonomous underwater platforms, and a comparative scarcity of large, labeled underwater training datasets relative to terrestrial imagery.

II. BACKGROUND AND MOTIVATION

A. The Challenge of Ocean Observation

Direct human observation of the ocean is constrained by depth, distance from shore, and the substantial cost and hazard of operating research vessels, crewed submersibles, or scuba diving surveys, particularly for observation at depths beyond safe diving limits or in the vast open ocean far from land-based infrastructure. As a consequence, large portions of the ocean, and the deep ocean in particular, remain far less thoroughly mapped, surveyed, and monitored than most terrestrial environments, despite covering a substantially larger total area and hosting a large fraction of global biodiversity, much of which remains formally undescribed by science.

This observation gap has direct governance and enforcement consequences: illegal, unreported, and unregulated fishing, a major driver of fisheries depletion and a substantial economic loss to legitimate fishing industries and coastal communities, is difficult to detect and prosecute across the vast maritime areas that fisheries enforcement agencies are responsible for monitoring, often with comparatively limited patrol vessel and aircraft resources relative to the scale of ocean area requiring surveillance.

B. Why AI Is Well Suited to Ocean Monitoring

Many core ocean monitoring tasks, including identifying fish and other marine species in underwater imagery, detecting marine debris in aerial or underwater imagery, and identifying vessels or vessel behavior patterns consistent with illegal fishing activity from satellite imagery and vessel tracking data, are pattern recognition tasks well suited to modern deep learning methods that have demonstrated strong performance on structurally analogous tasks in terrestrial computer vision applications. Applying these methods to ocean monitoring data can dramatically increase the volume of imagery, acoustic recordings, and vessel tracking data that can be analyzed relative to available human analyst capacity, directly addressing the observation and enforcement capacity gap described in Section II-A.

AI-enabled autonomous underwater vehicles further extend ocean observation capability by allowing sustained survey and monitoring missions in ocean regions and depths that would be prohibitively costly, hazardous, or simply impractical to survey using crewed vessels or divers, particularly valuable for extended deep-sea surveys and for monitoring in remote ocean regions far from established research infrastructure, where the cost of deploying and supporting a crewed research vessel for an extended survey mission can be prohibitive relative to available conservation and research funding.

C. Historical Context

Early efforts to apply computational methods to ocean monitoring relied primarily on relatively simple statistical and signal processing techniques applied to satellite ocean color and sea surface temperature data, and on manual expert review of underwater imagery and acoustic recordings collected during research vessel surveys, a labor-intensive process that limited the practical scale of underwater ecological and fisheries monitoring achievable with available research funding and personnel. The application of deep learning to underwater imagery and acoustic analysis has accelerated substantially over the past decade, following broader advances in terrestrial computer vision and audio processing research, though progress in the marine domain has generally lagged terrestrial applications somewhat due to the comparative scarcity of large, labeled underwater training datasets and the greater technical difficulty of collecting such datasets given the logistical and cost constraints of underwater data collection.

A parallel and, in terms of demonstrated large-scale practical impact, particularly significant development has been the application of machine learning to vessel tracking data derived from the Automatic Identification System, a maritime vessel tracking system originally developed for collision avoidance, which has been repurposed at global scale to support automated detection of vessel behavior patterns consistent with illegal fishing activity, representing one of the most mature and widely cited practical applications of AI to ocean governance to date.

This vessel-tracking application area also illustrates a broader pattern relevant to several other domains discussed in this survey series: a data source originally collected for an entirely different purpose, in this case maritime collision avoidance, was found to contain rich secondary signal relevant to an important conservation and governance challenge once analyzed using appropriately designed machine learning methods, a pattern of repurposing existing large-scale administrative or operational datasets for conservation-relevant analysis that has become an increasingly common and valuable strategy across environmental machine learning research more broadly, given that purpose-built environmental monitoring datasets are often far more limited in scale and geographic coverage than incidental data streams collected for unrelated operational purposes.

III. A TAXONOMY OF AI APPLICATIONS IN OCEAN MONITORING

AI applications in ocean monitoring can be organized along two dimensions: the observational platform generating the underlying data, and the ecological or governance task being addressed. Along the platform dimension, the field spans underwater imaging and acoustic sensing, typically deployed from research vessels, fixed underwater observatories, or autonomous underwater vehicles; satellite and aerial remote sensing, capturing ocean surface conditions and vessel activity over very large spatial extents; and vessel tracking data analysis, processing position and movement data broadcast by ships to infer vessel behavior and identity.

Along the task dimension, applications span species and habitat monitoring, including fish and marine mammal identification and coral reef health assessment; pollution detection, including marine plastic debris and oil spill identification; and fisheries governance, including illegal fishing detection and fish stock abundance estimation. Table I summarizes this taxonomy with representative methods for each combination of platform and task.

TABLE I. TAXONOMY OF AI APPLICATIONS IN OCEAN MONITORING

Platform	Task Category	Representative Application	Key Constraint
Underwater imagery/acoustics	Species/habitat monitoring	Fish classification, coral reef assessment	Limited labeled data, variable imaging conditions
Autonomous underwater vehicles	Survey and monitoring	Deep-sea and reef survey missions	Power, communication bandwidth
Satellite/aerial remote sensing	Pollution and habitat monitoring	Plastic debris, oil spill, reef mapping	Cloud cover, spatial resolution
Vessel tracking (AIS) data	Fisheries governance	Illegal fishing detection	AIS spoofing/disabling by bad actors

IV. CORE METHODS

A. Underwater Image and Video Analysis

Deep learning models applied to underwater imagery and video support automated species identification, abundance estimation, and habitat characterization, adapting convolutional neural network architectures originally developed for terrestrial computer vision to the distinctive challenges of the underwater imaging environment, including variable water turbidity, colour attenuation with depth, and inconsistent, often artificial lighting conditions that differ substantially and systematically from the imaging conditions represented in most large, publicly available terrestrial image datasets used for model pretraining.

Underwater image quality is frequently degraded by light scattering and wavelength-dependent absorption, which preferentially attenuates longer wavelengths and produces a characteristic blue-green color cast that increases with depth, motivating specialized underwater image enhancement and color correction preprocessing techniques, in some cases themselves learned using deep neural networks, applied prior to downstream species classification or detection to improve model robustness to this systematic and depth-dependent visual degradation.

B. Marine Acoustic Monitoring

Passive acoustic monitoring using hydrophones deployed from research vessels, fixed underwater observatories, or autonomous platforms enables detection and classification of vocalizing marine species, particularly cetaceans such as whales and dolphins whose vocalizations can be detected over considerable underwater distances, supporting population monitoring and, in some deployments, real-time detection systems intended to reduce ship strike risk by alerting vessels to the presence of marine mammals in their transit path.
Deep learning models for marine bioacoustic classification, methodologically related to the terrestrial bioacoustic monitoring methods discussed in related conservation machine learning research, typically process a spectrogram representation of hydrophone recordings using convolutional neural network architectures, and must be robust to substantial background ocean noise, including natural sources such as wind and wave action as well as anthropogenic sources such as vessel traffic noise, which can be particularly prevalent in busy shipping lanes and coastal areas of high conservation interest.

C. Autonomous Underwater Vehicles and Robotics

Autonomous underwater vehicles (AUVs) and remotely operated vehicles increasingly incorporate onboard machine learning for real-time navigation, obstacle avoidance, and, in more advanced systems, onboard preliminary analysis of collected imagery or acoustic data to support adaptive mission planning, such as directing additional survey effort toward a region where an onboard model has detected features of particular scientific or conservation interest, without requiring real-time communication with human operators at the surface, which is generally unavailable or severely bandwidth-limited for vehicles operating at depth.
The design of machine learning systems for onboard AUV deployment must contend with substantial power constraints, since AUVs operate on limited battery capacity that must be shared between propulsion, sensing, and computation over the course of an extended survey mission, motivating the same kind of model compression and efficient architecture design discussed in related research on AI for space exploration, adapted here to the power and computational constraints of underwater rather than orbital or deep-space robotic platforms.

D. Satellite-Based Ocean Remote Sensing

Satellite-based ocean remote sensing supports large-scale monitoring of ocean surface conditions, including sea surface temperature, ocean color, indicative of phytoplankton concentration and broader ocean productivity, and, increasingly, detection of vessel activity and marine debris accumulation, extending the broader satellite remote sensing methods discussed in related AI-for-science and space exploration research specifically to ocean-focused monitoring applications. Machine learning models applied to satellite imagery have demonstrated capability for detecting large marine debris accumulations and, in some research systems, oil spills, though detecting smaller-scale or dispersed plastic pollution from satellite imagery alone remains considerably more challenging than detecting large, spatially concentrated debris accumulations, given the spatial resolution limitations of most operationally available satellite sensors relative to the size of individual pieces of marine debris.

E. Marine Pollution Detection

Beyond satellite-based detection, machine learning models applied to aerial drone imagery and underwater imagery support marine plastic debris identification and characterization at finer spatial resolution than is achievable from satellite imagery alone, supporting both scientific research into plastic pollution distribution and accumulation patterns and operational cleanup efforts that benefit from automated identification of debris accumulation hotspots warranting prioritized cleanup deployment. Machine learning methods are also applied to detecting and characterizing oil spills from satellite radar imagery, which, unlike optical imagery, can detect the characteristic surface signature of an oil slick regardless of cloud cover or time of day, an important operational advantage for rapid spill response given that oil spill impact and cleanup difficulty generally increase the longer detection and response is delayed following an initial spill event.

F. Fisheries Stock Assessment and Illegal Fishing Detection

Machine learning models applied to underwater and onboard vessel camera imagery support automated fish species identification and size estimation for fisheries stock assessment, historically dependent on labour-intensive manual sampling and observer programs that can only cover a limited fraction of total fishing activity, while models applied to vessel tracking data support fisheries governance by detecting vessel movement patterns statistically associated with illegal fishing activity, such as characteristic trawling movement patterns occurring within a marine protected area where fishing is prohibited, or rendezvous behavior between vessels consistent with illegal at-sea transshipment of catch intended to obscure its origin. These vessel-tracking-based methods must contend with the deliberate evasion tactics used by some illegal fishing operators, including disabling or spoofing the Automatic Identification System transponder that provides the underlying vessel position data, motivating complementary detection approaches that combine vessel tracking data analysis with satellite imagery based vessel detection specifically designed to identify vessels that are not broadcasting an expected tracking signal, a discrepancy itself considered a strong indicator of potential illegal activity.

V. APPLICATIONS

A. Marine Pollution and Plastic Debris Monitoring

AI-based marine debris detection supports both scientific characterization of plastic pollution distribution across ocean basins and coastlines and operational cleanup prioritization, helping conservation and cleanup organizations allocate limited vessel and personnel cleanup resources toward locations identified as having the highest concentration of accumulated debris based on automated analysis of aerial, satellite, or underwater survey imagery. Beyond debris detection specifically, machine learning models are also applied to modeling and predicting the transport and accumulation patterns of marine plastic pollution based on ocean current data, supporting research into the sources and eventual fate of plastic entering the ocean and informing policy interventions targeted at the specific river and coastal sources identified as contributing disproportionately to observed ocean plastic accumulation.

B. Fisheries Management and Illegal Fishing Detection

Global-scale vessel tracking analysis platforms, combining machine learning classification of vessel behavior patterns with publicly available and commercial vessel tracking data, have enabled unprecedented public transparency into global fishing fleet activity, supporting both academic research into global fishing effort distribution and direct operational support to national and regional fisheries enforcement agencies seeking to identify vessels engaged in probable illegal fishing activity within their waters. These platforms have also been used to support science-based fisheries management more broadly, for example by providing more complete and timely data on fishing effort distribution to complement traditional, more limited fisheries observer and logbook data, improving the data available to fisheries scientists and managers responsible for setting sustainable catch limits for managed fish stocks.

C. Coral Reef Health Monitoring

Automated analysis of underwater imagery supports large-scale coral reef health monitoring, including classification of coral cover, bleaching status, and disease prevalence across survey imagery collected by divers, underwater cameras, or autonomous underwater vehicles, substantially increasing the spatial and temporal extent of reef monitoring achievable relative to traditional manual reef survey methods, which are limited by diver time and, for extensive reef systems, cannot feasibly achieve comparable coverage through manual survey alone. Large-scale automated reef monitoring has proven particularly valuable for tracking the progression of mass coral bleaching events associated with marine heatwaves, allowing researchers and reef managers to assess bleaching extent and severity across large reef systems far more rapidly than manual survey methods would allow, supporting more timely scientific assessment and, where feasible, management interventions such as temporary closure of heavily affected reef areas to additional anthropogenic stressors during a bleaching event.

D. Marine Mammal Conservation

AI-based acoustic and visual monitoring supports marine mammal conservation through population abundance estimation, ship strike risk reduction systems that alert vessels to detected whale presence in real time, and individual identification of marine mammals from distinguishing visual features such as whale fluke or dorsal fin markings, supporting long-term individual-based population monitoring analogous to the terrestrial individual animal re-identification methods discussed in related conservation machine learning research.

Real-time acoustic detection systems deployed in busy shipping lanes and coastal areas with known concentrations of vulnerable marine mammal species have been integrated with vessel routing advisories, automatically notifying commercial vessel operators of detected whale presence to support voluntary speed reduction or route adjustment, a mitigation approach that depends critically on both detection accuracy and sufficiently low latency between acoustic detection and advisory notification to provide vessels with meaningful opportunity to adjust their transit behavior before a potential encounter.

E. Ocean Climate and Circulation Monitoring

Machine learning methods are increasingly applied to processing and analyzing the large volumes of oceanographic data collected by autonomous profiling floats, satellite altimetry, and ocean model simulations, supporting improved understanding and prediction of ocean circulation patterns, marine heatwave events, and broader ocean-climate interactions relevant to global climate monitoring and prediction, extending the climate and earth science applications discussed in related AI-for-science research specifically to the ocean domain.

VI. BENCHMARKS AND EVALUATION

Evaluating AI methods for ocean monitoring is complicated by the comparative scarcity of large, standardized, publicly labeled underwater imagery and acoustic datasets relative to terrestrial computer vision and audio processing benchmarks, a consequence of the greater logistical difficulty and cost of underwater data collection discussed throughout this paper. Nonetheless, several dedicated marine machine learning datasets and benchmarks have emerged over the past several years, summarized in Table II.

A recurring evaluation concern specific to underwater imagery, beyond standard benchmark accuracy, is robustness to the substantial variation in imaging conditions encountered across different underwater environments, depths, and camera equipment, which can differ far more dramatically than the variation typically encountered across terrestrial imagery benchmark datasets, motivating supplementary evaluation of model robustness across genuinely diverse underwater imaging conditions rather than relying solely on standard within-dataset benchmark accuracy, which may not reliably predict performance when a model is deployed to a new underwater survey location or platform with different imaging characteristics.

TABLE II. REPRESENTATIVE DATASETS AND BENCHMARKS FOR OCEAN MACHINE LEARNING

Dataset/Benchmark	Modality	Task
FathomNet	Underwater imagery	Marine species classification and detection
Fish4Knowledge	Underwater video	Fish species classification and counting
Global Fishing Watch AIS dataset	Vessel tracking data	Fishing activity and illegal fishing detection
Coral reef imagery benchmark sets (e.g., CoralNet)	Underwater imagery	Coral cover and bleaching classification
Watkins Marine Mammal Sound Database	Bioacoustic recordings	Marine mammal species identification

VII. COMPARATIVE ANALYSIS AND DISCUSSION

Vessel-tracking-based illegal fishing detection is among the most operationally mature applications surveyed in this paper, benefiting from a comparatively large and continuously growing volume of publicly available Automatic Identification System data covering a substantial share of the global commercial fishing fleet, and from a well-defined, high-value governance use case that has attracted substantial sustained investment from both philanthropic and

governmental funders. Underwater imagery and acoustic classification methods are comparatively less mature, constrained by the more limited availability of large, labeled underwater training datasets and by the greater diversity of underwater imaging and acoustic conditions across different survey locations and equipment relative to the more standardized data collection protocols achievable for vessel tracking data.
Satellite-based ocean remote sensing occupies an intermediate position: benefiting from a large and growing volume of publicly available satellite imagery analogous to the terrestrial remote sensing data discussed in related research, but facing distinctive ocean-specific challenges including the difficulty of detecting small-scale or dispersed features such as individual pieces of plastic debris given typical satellite sensor spatial resolution, and the confounding effect of cloud cover, sea state, and lighting conditions on ocean surface feature detection accuracy.

TABLE III. COMPARATIVE MATURITY OF OCEAN AI APPLICATION AREAS

Application Area	Data Availability	Operational Maturity	Primary Constraint
Illegal fishing detection (AIS-based)	Large, growing, public	High	Evasion via AIS spoofing/disabling
Underwater species classification	Limited, growing	Moderate	Labeled data scarcity, imaging variability
Coral reef health assessment	Moderate, growing	Moderate to high	Survey coverage vs. reef extent
Satellite debris/oil spill detection	Large (imagery), moderate (labels)	Moderate	Spatial resolution for small debris
Marine mammal acoustic monitoring	Moderate	Moderate	Background noise robustness

VIII. ILLUSTRATIVE CASE STUDY

Consider a representative integrated pipeline for detecting probable illegal fishing activity within a marine protected area where commercial fishing is prohibited. The pipeline begins by ingesting publicly available Automatic Identification System vessel tracking data covering the region, applying a machine learning model trained to classify vessel movement patterns, distinguishing characteristic trawling or longline fishing movement signatures from ordinary vessel transit behavior, flagging any vessel exhibiting a fishing-consistent movement pattern within the boundaries of the protected area for further investigation.
Because vessels engaged in illegal fishing may deliberately disable their Automatic Identification System transponder to avoid this type of detection, the pipeline is complemented by a satellite imagery analysis component that applies a separate object detection model to identify vessels present within the protected area from optical or radar satellite imagery regardless of whether they are broadcasting a tracking signal, allowing the pipeline to cross-reference detected vessels against the expected set of tracking-signal-broadcasting vessels and flag any discrepancy, namely a vessel visible in satellite imagery but absent from tracking data, as a particularly strong indicator of deliberate evasion warranting priority investigation.
Flagged vessels and detected discrepancies are compiled into a prioritized alert report provided to the relevant national or regional fisheries enforcement agency, which can then allocate limited patrol vessel or aircraft resources toward investigating and, where appropriate, intercepting the highest-priority flagged vessels, substantially improving the efficiency of enforcement resource allocation relative to a comparatively undirected patrol strategy that must otherwise attempt to cover a vast protected area with limited assets and no prior indication of where illegal activity is most likely occurring at a given time.

IX. IMPLEMENTATION CONSIDERATIONS AND TOOLING

A. Onboard and Edge Computing Constraints

Machine learning models intended for onboard deployment on autonomous underwater vehicles or on vessel-based edge computing systems must operate within substantial power, computational, and, for underwater platforms specifically, communication bandwidth constraints, since acoustic underwater communication, the primary means of communicating with a submerged AUV without surfacing, offers dramatically lower bandwidth than radio-frequency communication used for surface or aerial platforms, motivating onboard model compression and efficient architecture design broadly analogous to the radiation-hardened compute constraints discussed in related research on AI for space exploration, adapted here to the distinctive power and communication constraints of the underwater environment.

B. Data Sharing and Open Platforms

Several major ocean monitoring machine learning initiatives, particularly those focused on illegal fishing detection and marine species identification, have adopted an open data and open-source model release strategy, publishing both processed vessel tracking analysis results and, in some cases, underlying pretrained models, to support broader adoption by fisheries enforcement agencies, researchers, and conservation organizations that might otherwise lack the technical capacity to independently develop comparable machine learning capability, reflecting a similar open-tooling norm to that observed in the broader conservation technology community discussed in related biodiversity conservation research.

X. ETHICAL AND SOCIETAL CONSIDERATIONS

Increased AI-enabled surveillance capability for fisheries enforcement raises legitimate considerations regarding the rights and livelihoods of small-scale and artisanal fishing communities, who may be disproportionately affected by increased monitoring and enforcement scrutiny relative to large industrial fishing operations with greater resources to ensure regulatory compliance or, in some cases, to evade detection through more sophisticated means, motivating careful attention to ensuring that increased monitoring capability is applied equitably and does not disproportionately burden the smaller-scale fishing operations that make up a substantial share of global fisheries employment, particularly in developing coastal nations.

A further consideration concerns data sovereignty and governance for ocean monitoring data collected within a nation's exclusive economic zone, since increasingly capable satellite and vessel tracking based monitoring systems, often developed and operated by organizations based in wealthier nations, raise questions regarding appropriate data sharing arrangements and decision-making authority for coastal nations, particularly in the developing world, whose waters are being monitored using technology and data infrastructure they may not directly control, motivating collaborative governance models that ensure affected coastal nations retain meaningful access to and authority over monitoring data and resulting enforcement actions within their own waters.

XI. CHALLENGES AND OPEN PROBLEMS

A central and pervasive challenge across ocean AI applications is the comparative scarcity of large, labeled underwater training datasets relative to terrestrial computer vision and audio processing domains, a consequence of the substantially greater cost and logistical difficulty of underwater data collection, which continues to constrain model accuracy and generalization relative to the accuracy achievable in more data-abundant terrestrial application domains.

A second challenge concerns the sheer scale mismatch between the vast spatial extent of the global ocean and the comparatively limited monitoring infrastructure, whether satellite, vessel-based, or autonomous underwater vehicle based, available to observe it, meaning that even highly accurate AI methods can only analyze the data that underlying sensor infrastructure is able to collect, and substantial portions of the ocean, particularly the deep ocean and remote open-ocean regions far from established monitoring infrastructure, remain effectively unmonitored regardless of the sophistication of available analysis methods. A third challenge concerns deliberate evasion by bad actors, particularly in the illegal fishing detection domain, where detection methods relying on vessel tracking data can be circumvented by vessels that disable or spoof their tracking transponders, motivating continued development of complementary detection methods, such as the satellite-imagery-based cross-referencing approach illustrated in Section VIII, that do not depend solely on voluntary vessel tracking broadcast compliance.

A fourth challenge concerns the power, communication, and computational constraints of autonomous underwater platforms discussed in Section IX, which continue to limit the sophistication of machine learning models that can practically be deployed for real-time onboard use during extended underwater survey missions, creating an ongoing tension between the desire for more capable onboard analysis and autonomy and the severe resource constraints of current underwater robotic platform technology.

A fifth challenge, cutting across nearly all of the applications discussed in this paper, concerns validating model outputs against ground truth in an environment where independent verification is itself often difficult and costly to obtain, since confirming whether a detected vessel is genuinely engaged in illegal fishing, or whether a classified coral colony is genuinely bleached rather than affected by a visually similar but distinct condition, frequently requires additional field verification or enforcement action that is itself subject to the same resource constraints that motivated automated detection in the first place, creating a persistent evaluation bottleneck analogous to, though distinct in its specific causes from, the experimental validation bottleneck discussed in related AI-for-science research.

XII. FUTURE RESEARCH DIRECTIONS

One promising direction involves the development of foundation models specifically pretrained on broad, diverse underwater imagery and acoustic data spanning multiple ocean regions, depths, and taxonomic groups, potentially reducing current dependence on comparatively scarce, site-specific labelled training data by providing more broadly transferable underwater representations, echoing the foundation model paradigm discussed in related research on foundation models beyond language and biodiversity conservation, adapted specifically to the distinctive imaging and acoustic characteristics of the underwater environment.

A second direction explores expanded autonomous ocean observation networks, combining fleets of autonomous underwater and surface vehicles with fixed ocean observatories and satellite monitoring into more comprehensive, continuously operating ocean monitoring systems capable of providing substantially more complete spatial and temporal ocean observation coverage than current, more limited monitoring infrastructure allows, particularly for chronically undersampled deep-ocean and remote open-ocean regions.

A further direction concerns strengthening international data-sharing and governance frameworks for AI-enabled ocean monitoring, ensuring that increased monitoring and enforcement capability is deployed in a manner that is transparent, equitable, and appropriately accountable to the coastal nations and communities most directly affected, an institutional and policy challenge that is likely to prove at least as important to realising the full conservation and governance benefit of ocean AI technology as continued algorithmic research progress. Finally, continued reduction in the cost of autonomous underwater vehicle hardware and improvement in underwater communication and power technology is likely to remain an important complement to algorithmic progress, expanding the practical reach of AI-enabled ocean monitoring to a broader range of research institutions, conservation organisations, and coastal nations that currently lack the resources to deploy sophisticated ocean monitoring technology at scale.

XIII. CONCLUSION

AI has become an increasingly important tool for closing the persistent observation gap between the vast spatial extent of the global ocean and the comparatively limited human and infrastructure capacity available to monitor it, supporting improved marine pollution detection, fisheries governance, coral reef health assessment, and marine mammal conservation. This survey reviewed the taxonomy of AI applications spanning underwater imagery and acoustic analysis, autonomous underwater robotics, satellite-based ocean remote sensing, and fisheries stock assessment and governance, examined applications across marine pollution monitoring, illegal fishing detection, coral reef assessment, marine mammal conservation, and ocean climate monitoring, and presented a case study illustrating an integrated satellite and vessel-tracking pipeline for illegal fishing detection. While the field faces substantial challenges related to underwater data scarcity, the scale mismatch between ocean extent and available monitoring infrastructure, deliberate evasion by bad actors, and the severe resource constraints of autonomous underwater platforms, continued progress in ocean-specific foundation models, expanded autonomous observation networks, and strengthened international data governance frameworks suggests that AI will play an increasingly central role in supporting effective, timely ocean conservation and governance in the years ahead.

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