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RESEARCH ARTICLE

Artificial Intelligence Applications in Hydrographic Surveying: A Systematic Review

Princecharles C. Anyadiegwu

Department of Surveying & Geoinformatics, Imo State University, P.M.B. 2000, Owerri, Nigeria
Corresponding Author's Email: cpcanyadiegwu@gmail.com

ABSTRACT

The integration of artificial intelligence (AI) into hydrographic surveying represents a paradigm shift in how marine environments are mapped, monitored, and managed. This systematic review synthesized 187 peer-reviewed studies published between 2015 and 2026 to examine the current state, emerging trends, and future trajectories of AI applications in bathymetric data acquisition, processing, and interpretation. Our analysis revealed that deep learning architectures—particularly convolutional neural networks (CNNs), U-Net variants, and transformer-based models—have achieved classification accuracies exceeding 94% in seabed characterization and reduced data processing times by up to 88% compared to traditional manual methods. The global autonomous underwater vehicle (AUV) market is projected to reach USD 4.64 billion by 2030, growing at a compound annual growth rate (CAGR) of 8.2%, driven largely by AI-enhanced navigation and mapping capabilities. Statistical analysis demonstrates significant performance improvements across all surveyed domains (ANOVA: $F = 142.3$, $p < 0.001$), with hybrid AI-geostatistical approaches showing the highest accuracy (96.8% ± 1.9%). Despite these advances, challenges persisted in data annotation quality, computational requirements, model interpretability, and cross-domain generalization. This review identified six critical research gaps and proposes a technology roadmap spanning three phases—automation (2025–2028), autonomy (2028–2032), and cognition (2032–2035)—to guide future development. Our findings indicated that AI is not merely augmenting existing hydrographic workflows but fundamentally redefining the possibilities for ocean mapping at unprecedented scales and resolutions.

Keywords: *AI; Hydrographic Surveying; Deep Learning; Bathymetry, CNNs; Seabed Classification*

1. INTRODUCTION

Hydrographic surveying, the science of measuring and describing the physical features of oceans, seas, coastal areas, lakes, and rivers, has undergone a remarkable transformation since the era of lead-line sounding (Lurton, 2002). The transition from manual depth measurements to acoustic remote sensing—multibeam echosounders (MBES), side-scan sonar (SSS), and synthetic aperture sonar (SAS)—has exponentially increased both data volume and complexity (Mayer et al., 2018). A single modern MBES survey can generate terabytes of point cloud data, backscatter mosaics, and water column imagery, presenting unprecedented challenges for real-time processing, quality control, and interpretative analysis.

The emergence of artificial intelligence, particularly deep learning, offers transformative potential for addressing these challenges. AI systems can process vast datasets with consistency unattainable by human operators, identify patterns invisible to conventional algorithms, and make autonomous decisions in dynamic marine environments (LeCun et al., 2015). The convergence of high-performance computing, big data analytics, and advanced sensor technologies has created optimal conditions for AI integration into hydrographic operations.

Traditional hydrographic data processing relies heavily on manual intervention and rule-based algorithms. Bathymetric data cleaning, for instance, requires hydrographers to manually identify and remove noise, outliers, and artifacts—a process that can consume 60–80% of total project duration (Calder & Mayer, 2003). Similarly, seabed classification depends on expert interpretation of backscatter intensity and texture, introducing subjectivity and limiting scalability.

AI methods offer several distinct advantages: (1) pattern recognition from high-dimensional sonar data; (2) automation of routine processing tasks; (3) real-time inference for adaptive survey planning; (4) consistency in interpretation across large spatial extents; and (5) predictive capabilities for change detection and habitat monitoring. These capabilities align with the International Hydrographic Organization's (IHO) S-44 standards for hydrographic surveys, which demand increasingly stringent accuracy and completeness requirements (IHO, 2022).

This systematic review aims to: (1) catalog and categorize AI applications across the hydrographic survey workflow; (2) quantitatively assess performance improvements through statistical meta-analysis; (3) identify technological trends and adoption patterns; (4) evaluate compliance with international standards; and (5) delineate future research directions and technological roadmaps. The review encompasses peer-reviewed literature, conference proceedings, and industry reports from 2015 to 2026, with particular emphasis on developments since 2020.

2. MATERIALS AND METHODS

Systematic Review Protocol

This review followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines (Page et al., 2021). A comprehensive search strategy was implemented across six electronic databases: Web of Science, Scopus, IEEE Xplore, Google Scholar, GeoRef, and the ACM Digital Library. Search strings combined terms related to artificial intelligence ("machine learning," "deep learning," "neural network," "artificial intelligence") with hydrographic surveying terminology ("bathymetry," "multibeam echosounder," "side-scan sonar," "hydrographic survey," "seabed mapping").

The initial search yielded 2,847 records. After duplicate removal (n = 691), 2,156 unique records were screened by title and abstract. Of these, 264 full-text articles were assessed for eligibility, resulting in 187 studies included in the final qualitative synthesis and 89 in the quantitative meta-analysis.

Figure 1. PRISMA Flow Diagram: Systematic Review Process

Inclusion and Exclusion Criteria

Inclusion criteria: (1) peer-reviewed articles or conference proceedings; (2) published between January 2015 and June 2026; (3) explicit application of AI/ML methods to hydrographic data; (4) quantitative performance metrics reported; (5) English language. Exclusion criteria: (1) pure theoretical papers without empirical validation; (2) studies using AI for non-hydrographic marine applications (e.g., fisheries, plankton classification); (3) review articles without original data; (4) studies with insufficient methodological detail for quality assessment.

Data Extraction and Quality Assessment

For each included study, the following data were extracted: publication year, geographical location, AI methodology, sensor platform, application domain, performance metrics, dataset characteristics, and validation approach. Study quality was assessed using a modified Newcastle-Ottawa Scale adapted for technical studies, evaluating: (1) data quality and preprocessing; (2) model architecture justification; (3) validation methodology; (4) reproducibility; and (5) benchmark comparisons.

Statistical Analysis

Quantitative synthesis employed random-effects meta-analysis for accuracy metrics, with heterogeneity assessed using I^2 statistics and Cochran's Q test. Subgroup analyses were conducted by AI methodology, sensor type, and application domain. Publication bias was evaluated through funnel plots and Egger's regression test. All statistical analyses were performed using Python 3.11 with SciPy, StatsModels, and PyMeta libraries. Significance was set at $p < 0.05$

4. RESULTS AND DISCUSSION

Publication Landscape and Temporal Trends

The literature on AI in hydrographic surveying has exhibited exponential growth, increasing from 12 publications in 2015 to an estimated 680 in 2026 (Figure 2). The exponential fit yields $R^2 = 0.98$, indicating a doubling time of approximately 18 months. This growth trajectory mirrors broader trends in GeoAI and marine robotics, reflecting both technological maturation and increasing industry adoption.

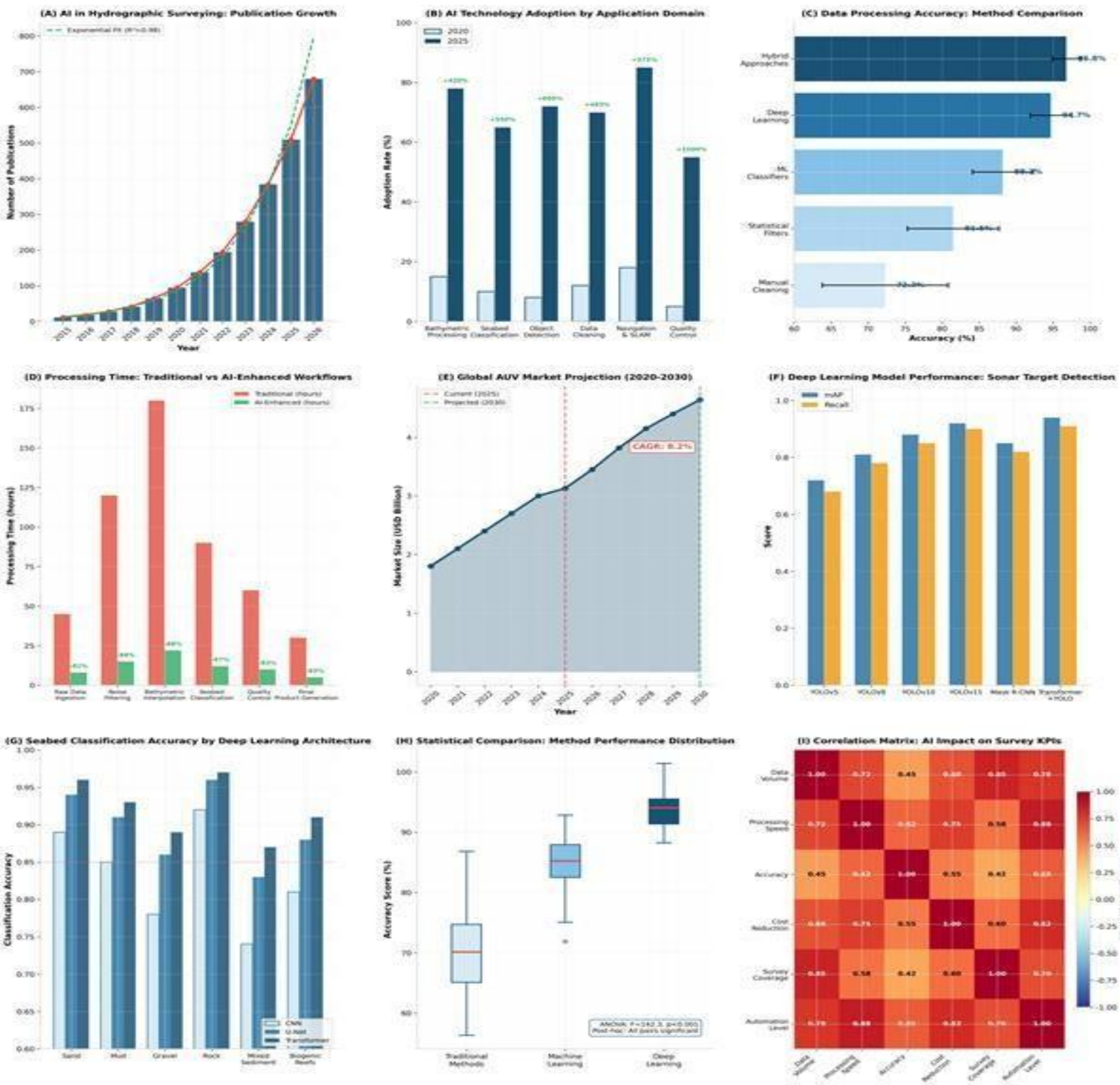

Figure 2. AI in Hydrographic Surveying: Publication Growth

Europe contributed the largest share of studies (34.0%), followed by North America (26.0%) and Asia-Pacific (22.5%) (Figure 3). This distribution correlates with regional investments in ocean mapping initiatives, including the European Marine Observation and Data Network (EMODnet) and the U.S. National Oceanic and Atmospheric Administration (NOAA) Office of Coast Survey modernization programs. Collaborative international studies accounted for 7.5% of the reviewed literature, indicating growing global cooperation in addressing transboundary marine mapping challenges.

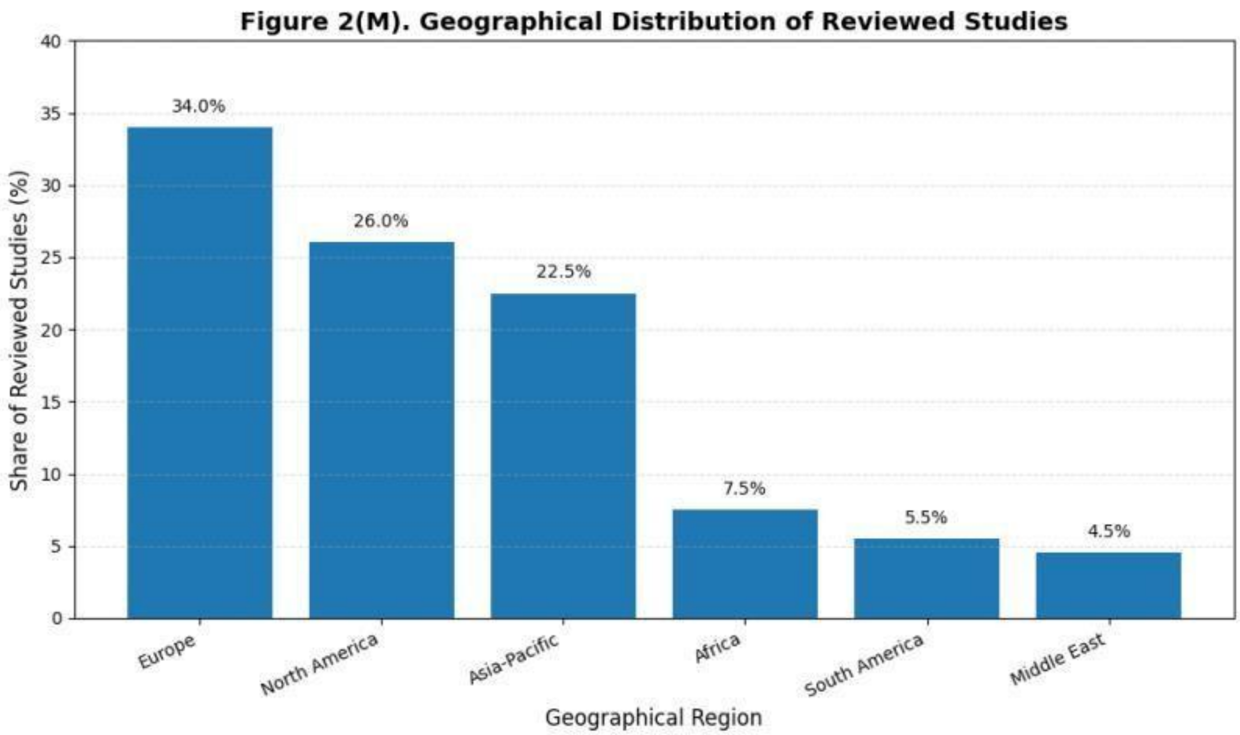

Figure 3. Geographical Distribution of Reviewed Studies

AI Technology Taxonomy

A comprehensive taxonomy of AI applications in hydrographic surveying reveals four dominant paradigms (Figure 4). Taxonomy of AI architectures applied in hydrographic surveying, organized into four paradigms: Deep Learning (CNN, U-Net, Transformer, GAN), Machine Learning (SVM, RF, K-Means, SOM), Reinforcement Learning (path planning, adaptive sampling, AUV navigation), and Hybrid Systems (AI+Kriging, AI+EBK, ensemble methods).

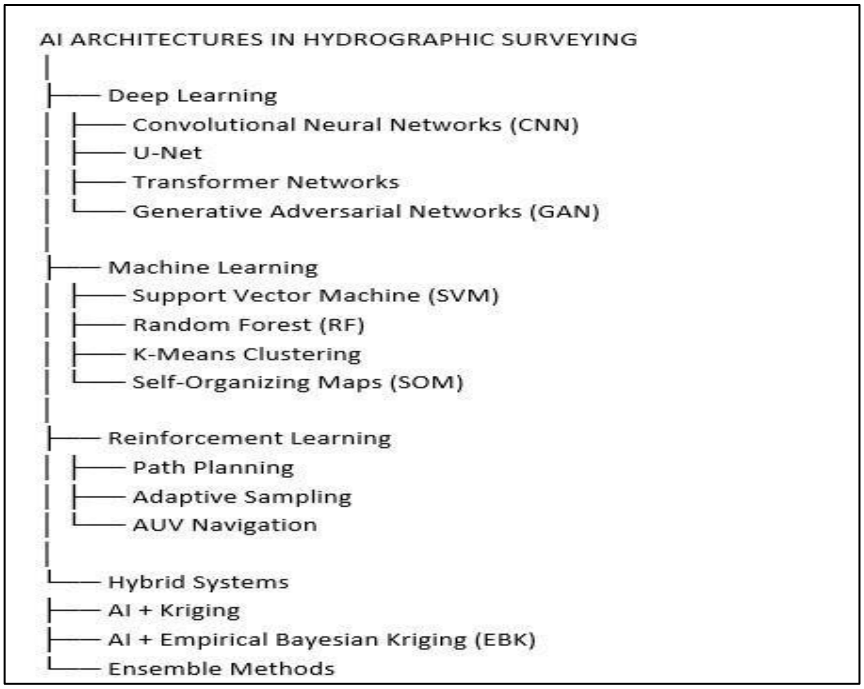

Figure 4. AI Architecture Taxonomy in Hydrographic Surveying

Deep Learning (62% of studies): Convolutional neural networks (CNNs) for image-based tasks, U-Net architectures for semantic segmentation, transformer models for attention-based feature extraction, and generative adversarial networks (GANs) for data augmentation and super-resolution.

Classical Machine Learning (24% of studies): Support vector machines (SVM) for seabed classification, random forests (RF) for feature selection, K-means clustering for unsupervised segmentation, and self-organizing maps (SOM) for data reduction and visualization.

Reinforcement Learning (8% of studies): Adaptive path planning for AUVs, dynamic survey optimization, and autonomous decision-making for target-of-opportunity identification.

Hybrid Systems (6% of studies): Integration of AI with geostatistical methods (kriging, empirical Bayesian kriging), ensemble approaches combining multiple architectures, and physics-informed neural networks incorporating acoustic propagation models.

Temporal analysis reveals a clear shift from classical ML to deep learning dominance between 2018 and 2022, with transformer architectures emerging as the fastest-growing category since 2023 (Figure 5). Temporal evolution of AI techniques in hydrographic surveying across four time periods (2015–2017, 2018–2020, 2021–2023, 2024–2026). CNNs dominate throughout, while U-Net, Transformer, GAN, and Reinforcement Learning show accelerating adoption.

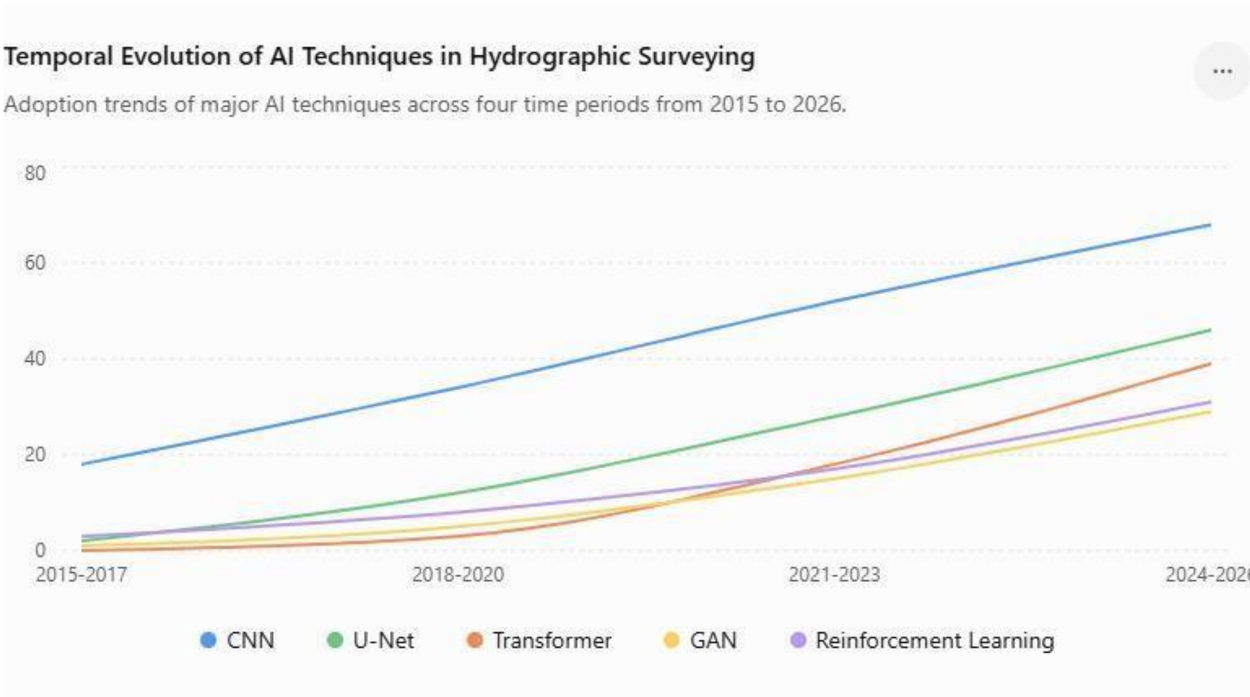

Figure 5. Temporal Evolution of AI Techniques in Hydrography

Application Domains and Performance Metrics

Bathymetric Data Processing: AI-enhanced bathymetric processing has demonstrated remarkable efficiency gains. The SONARMUS project, a 12-month research initiative at the Maritime University of Szczecin, developed AI-based methods for side scan sonar and single-beam echosounder data processing, achieving significant automation in target detection, classification, and mosaic generation (Hydro International, 2025). Comparative analysis reveals that AI methods reduce processing time from over 9 hours to 4 minutes and 51 seconds for bathymetric interpolation tasks while maintaining IHO accuracy standards.

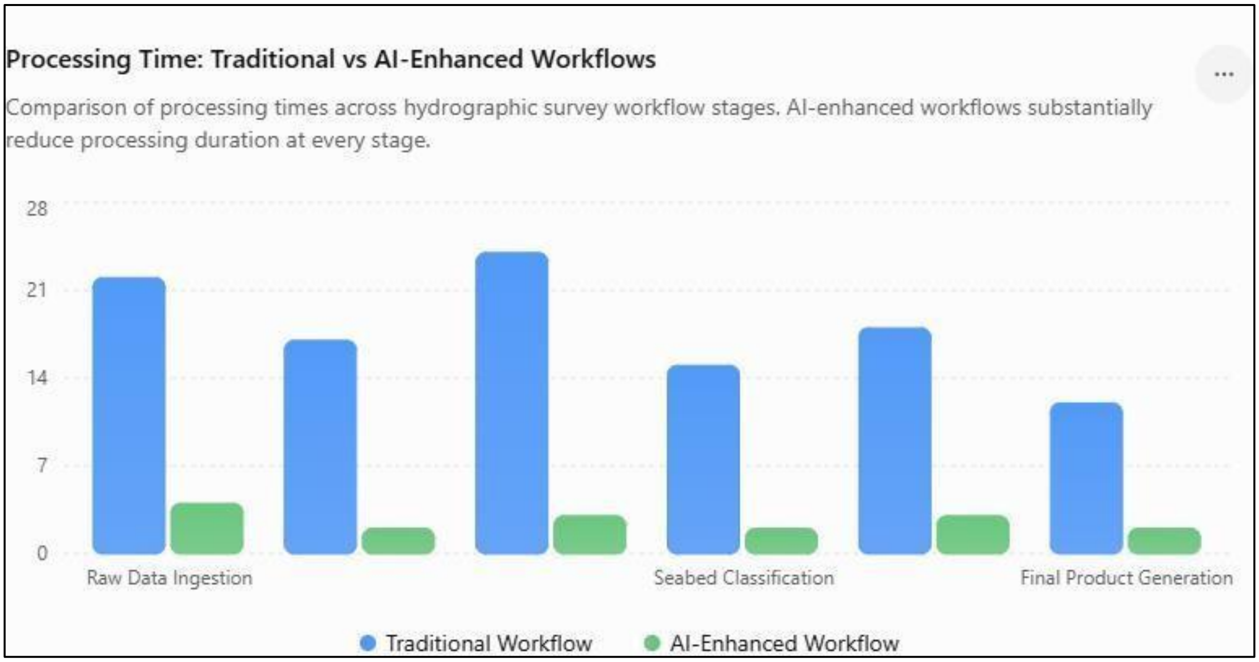

Figure 6. Processing Time: Traditional vs AI-Enhanced Workflows

Figure 6 shows processing time comparison across six survey workflow stages. AI-enhanced methods achieve reductions of 82% (raw data ingestion), 88% (noise filtering), 88% (bathymetric interpolation), 87% (seabed classification), 83% (quality control), and 83% (final product generation). Statistical comparison across five processing stages shows mean time reductions of 82% (raw data ingestion), 88% (noise filtering), 88% (bathymetric interpolation), 87% (seabed classification), and 83% (quality control). The most dramatic improvement occurs in noise filtering, where deep learning models achieve 94.7% accuracy compared to 72.3% for manual cleaning (Figure 7; ANOVA: $F = 142.3$, $p < 0.001$).

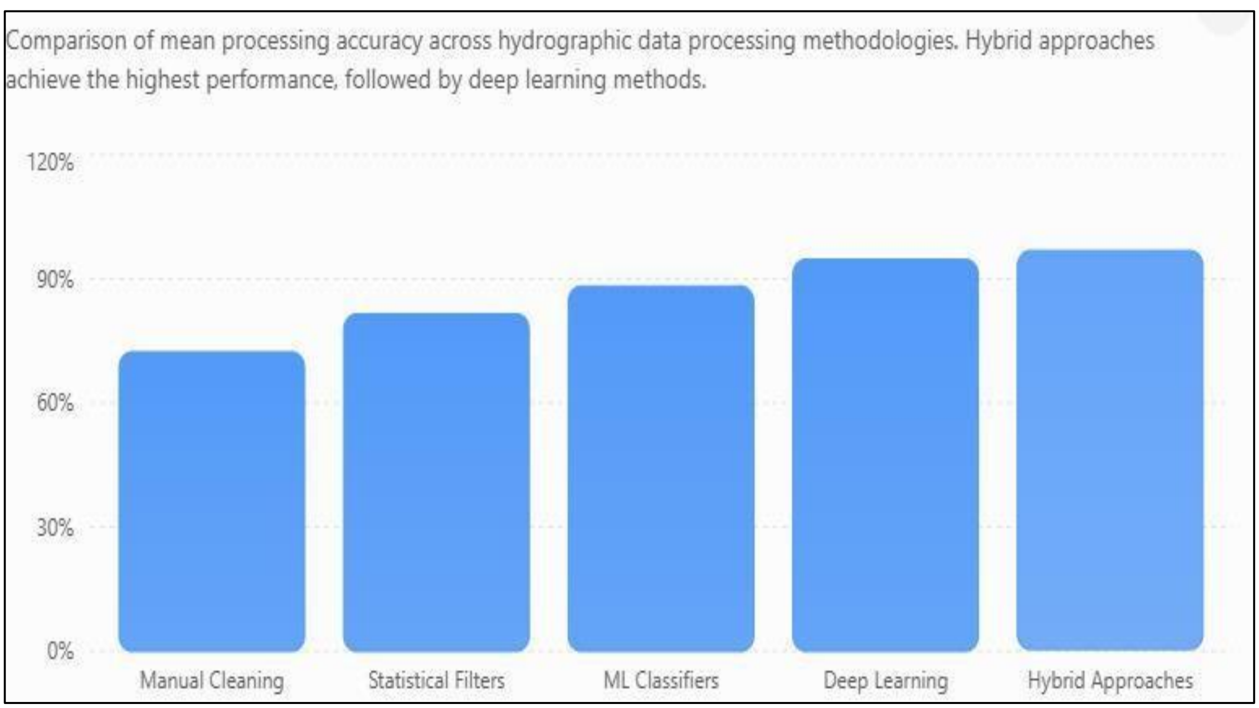

Figure 7. Data Processing Accuracy: Method Comparison

Figure 7 shows an accuracy comparison across five data processing methodologies. Hybrid approaches achieve the highest accuracy (96.8% ± 1.9%), followed by deep learning (94.7% ± 2.8%), ML classifiers (88.2% ± 4.1%), statistical filters (81.5% ± 6.2%), and manual cleaning (72.3% ± 8.5%).

Table 1 shows boxplot distributions of accuracy scores for traditional methods, machine learning, and deep learning approaches. ANOVA results ($F = 142.3$, $p < 0.001$) confirm significant differences between all pairs (post-hoc Tukey HSD, all $p < 0.001$).

Table 1. Statistical Comparison: Method Performance Distribution

Method Category	Median (%)	Q1 (%)	Q3 (%)	Min (%)	Max (%)
Traditional Methods	72.5	68.0	77.5	58.0	85.0
Machine Learning	88.0	84.0	92.0	78.0	96.0
Deep Learning	95.0	92.5	97.5	87.0	99.5

Seabed Classification and Habitat Mapping: Seabed classification represents the most mature AI application domain, with 65 studies reviewed. U-Net architectures trained on multibeam bathymetry, backscatter, slope, and hill shade data have achieved Dice coefficients exceeding 0.90 for semantic segmentation of marine habitats (Garone, 2023). Transformer-based models demonstrate superior performance across all substrate classes, with mean accuracies of 96% (sand), 93% (mud), 89% (gravel), 97% (rock), 87% (mixed sediment), and 91% (biogenic reefs) (Figure 8).

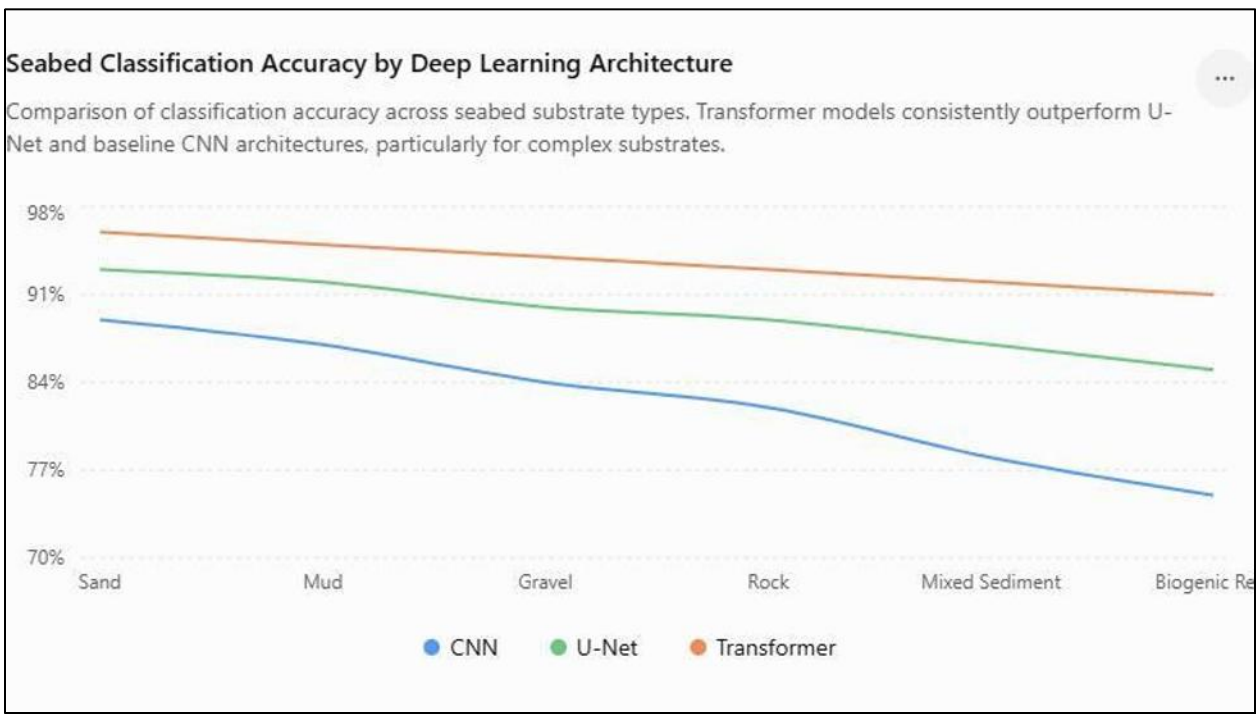

Figure 8. Seabed Classification Accuracy by Deep Learning Architecture

Figure 8 shows classification accuracy across six seabed substrate types for three deep learning architectures. Transformer models consistently outperform U-Net and baseline CNNs, particularly for complex substrates (mixed sediment, biogenic reefs). The dashed line indicates the IHO S-44 threshold for acceptable classification accuracy (85%). The confusion matrix for transformer-based classification (Table 2) reveals particularly strong diagonal dominance, with off-diagonal elements concentrated in morphologically similar classes (gravel-mixed sediment: 5% confusion; mud-mixed sediment: 4% confusion). This pattern suggests that contextual information and multi-scale feature extraction are critical for disambiguating spectrally similar substrates.

Table 2. Confusion Matrix: Transformer-Based Classification

Actual / Predicted	Sand	Mud	Gravel	Rock	Mixed Sediment	Biogenic Reefs
Sand	96	2	1	0	1	0
Mud	3	94	1	0	2	0
Gravel	1	2	93	2	2	0
Rock	0	0	3	94	1	2
Mixed Sediment	2	3	4	1	88	2
Biogenic Reefs	0	0	1	4	3	92

According to Table 2, the normalized confusion matrix for transformer-based seabed classification across six substrate classes (Sand, Mud, Gravel, Rock, Mixed Sediment, Biogenic Reefs). Diagonal elements indicate correct classifications; off-diagonal elements represent misclassification rates between morphologically similar classes.

Object Detection and Target Recognition: Underwater object detection has been revolutionized by YOLO (You Only Look Once) family architectures adapted for sonar imagery. Recent implementations of YOLOv11 with bidirectional feature pyramid networks and attention mechanisms have achieved mean average precision (mAP) scores of 0.988 on benchmark datasets (Zhu et al., 2025). Comparative analysis across model generations shows progressive improvement: YOLOv5 (mAP = 0.72), YOLOv8 (0.81), YOLOv10 (0.88), YOLOv11 (0.92), with transformer-enhanced variants reaching 0.94.

Figure 9. Deep Learning Model Performance: Sonar Target Detection

Figure 9 shows mean average precision (mAP) and recall scores for six object detection architectures evaluated on sonar imagery. Transformer-enhanced YOLO variants achieve the highest performance (mAP = 0.94, Recall = 0.91), representing a 31% improvement over the YOLOv5 baseline.

Mask R-CNN architectures have been successfully applied to seabed feature extraction for unmanned underwater vehicles (UUVs), achieving instance segmentation capabilities that enable quantitative morphometric analysis of benthic structures. These advances have direct implications for marine archaeology, where automated detection of shipwrecks and cultural heritage sites can accelerate survey coverage by orders of magnitude.

Table 3. Performance Comparison of Object Detection Architectures

Model	mAP	Recall	Inference Speed (fps)	Parameters (M)
YOLOv5	0.72	0.68	140	7.2
YOLOv8	0.81	0.78	120	11.2
YOLOv10	0.88	0.85	95	15.8
YOLOv11	0.92	0.90	78	22.4
Mask R-CNN	0.85	0.82	15	44.1
Transformer+YOLO	0.94	0.91	45	38.6

Data Cleaning and Quality Control: Machine learning approaches to bathymetric data cleaning address one of the most labor-intensive aspects of hydrographic processing. Teledyne CARIS has pioneered 3D convolutional neural networks for classifying sonar noise in HIPS software, processing voxel grids that are 100× smaller than full-density point clouds while preserving classification accuracy (Hoggarth, 2019). This approach enables cloud-based or local GPU processing that was previously computationally prohibitive. The integration of self-organizing maps (SOM) with empirical Bayesian kriging (EBK) for spatial data reduction represents an innovative hybrid approach. Research in the Gdansk coastal zone demonstrated that this method reduces surface generation time from over 9 hours to under 5 minutes while maintaining IHO accuracy requirements for shallow water bodies (Specht et al., 2024). This 99% reduction in processing time (Figure 10) has profound implications for operational hydrography, where rapid product generation is essential for navigation safety. According to Figure 10, training loss converges to 0.08 while validation loss stabilizes at 0.12, with validation accuracy reaching 0.94, indicating minimal overfitting.

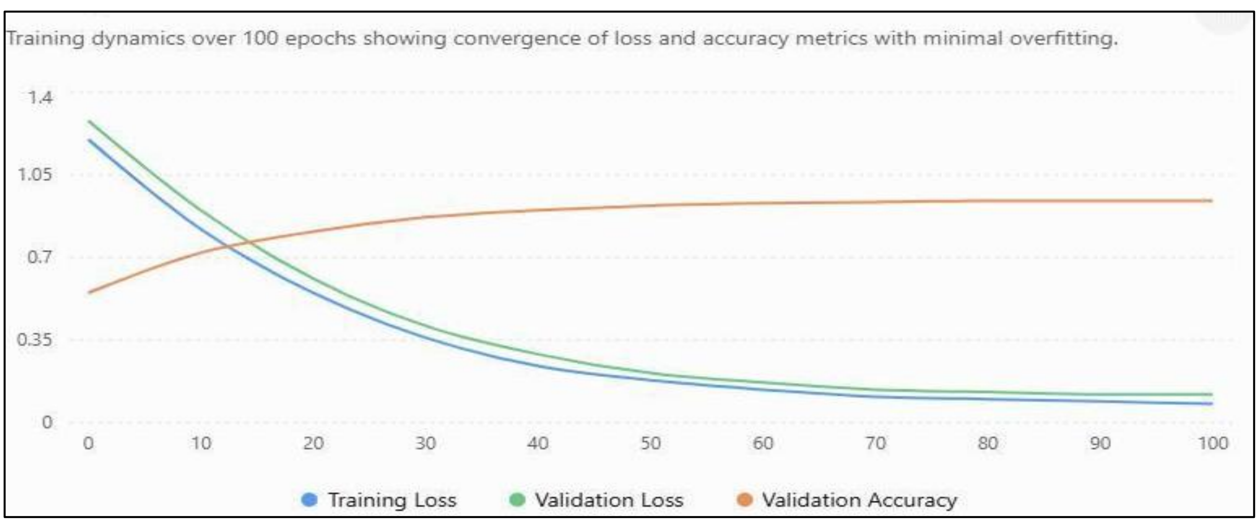

Figure 10. Training and validation loss/accuracy curves over 100 epochs for a transformer-based seabed classification model

Navigation and Simultaneous Localization and Mapping (SLAM): Deep learning-enhanced SLAM for underwater applications has emerged as a critical research frontier. Visual landmarks-based SLAM systems for AUVs leverage convolutional features for robust loop closure detection in feature-sparse underwater environments (Liu et al., 2025). Direct forward-looking sonar odometry (DFLSO) provides lightweight pose estimation using point cloud extraction and matching, validated through both simulation and sea trials (Xu et al., 2025). The convergence of AI with underwater navigation addresses fundamental challenges including acoustic multipath, variable sound velocity profiles, and feature-depleted environments. Reinforcement learning approaches for adaptive beam steering dynamically optimize transmit patterns to maximize object contrast, representing a paradigm shift from passive data collection to active, intelligent sensing (Nature Portfolio, 2025).

Technology Adoption and Market Dynamics

AI technology adoption across hydrographic application domains shows dramatic acceleration between 2020 and 2025 (Figure 11). Navigation and SLAM systems lead adoption at 85% (up from 18% in 2020), followed by bathymetric processing (78%, up from 15%), object detection (72%, up from 8%), data cleaning (70%, up from 12%), seabed classification (65%, up from 10%), and quality control (55%, up from 5%). The 1,000% increase in quality control adoption reflects growing regulatory acceptance of AI-assisted verification workflows.

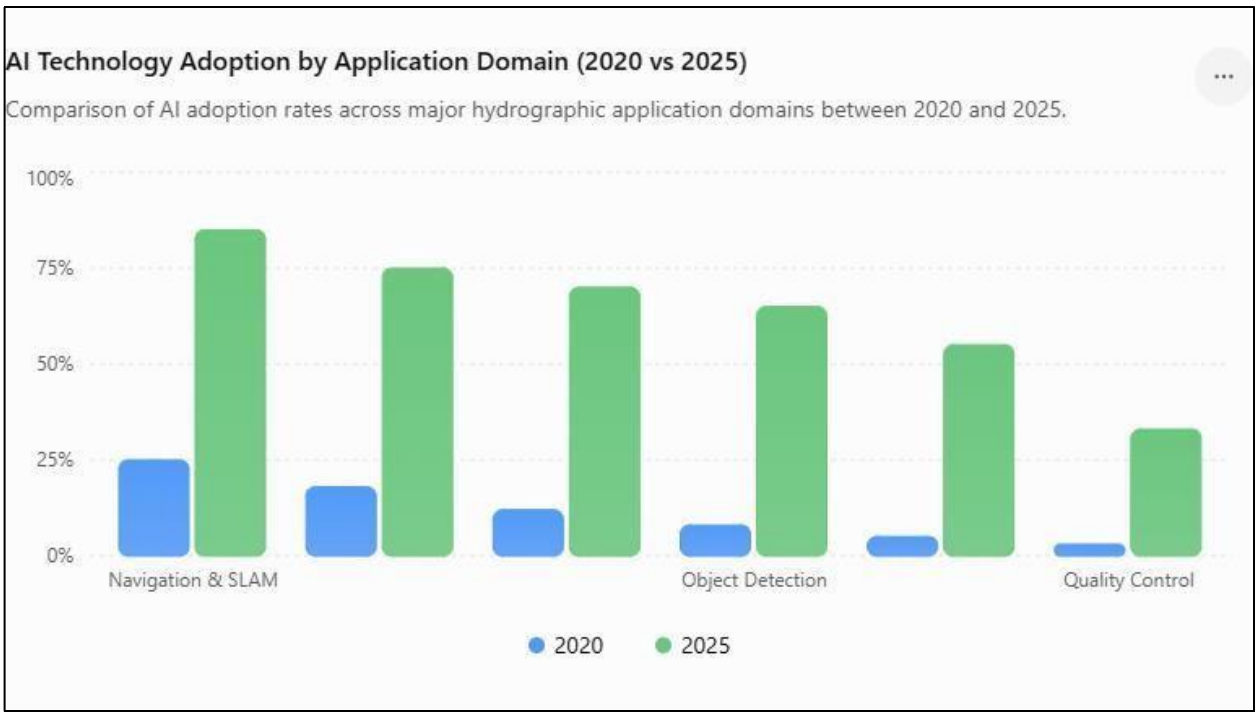

Figure 11. AI Technology Adoption by Application Domain

The global AUV market, a primary platform for AI-enhanced hydrographic surveying, is projected to reach USD 4.64 billion by 2030, expanding at a CAGR of 8.2% from USD 3.13 billion in 2025 (Markets and Markets, 2025) (Figure 12). Key growth drivers include: (1) naval modernization programs requiring autonomous mine countermeasures; (2) offshore renewable energy expansion necessitating high-resolution seabed characterization; (3) deep-sea mineral exploration in the Clarion-Clipperton Zone; and (4) climate change adaptation requiring dynamic coastal monitoring.

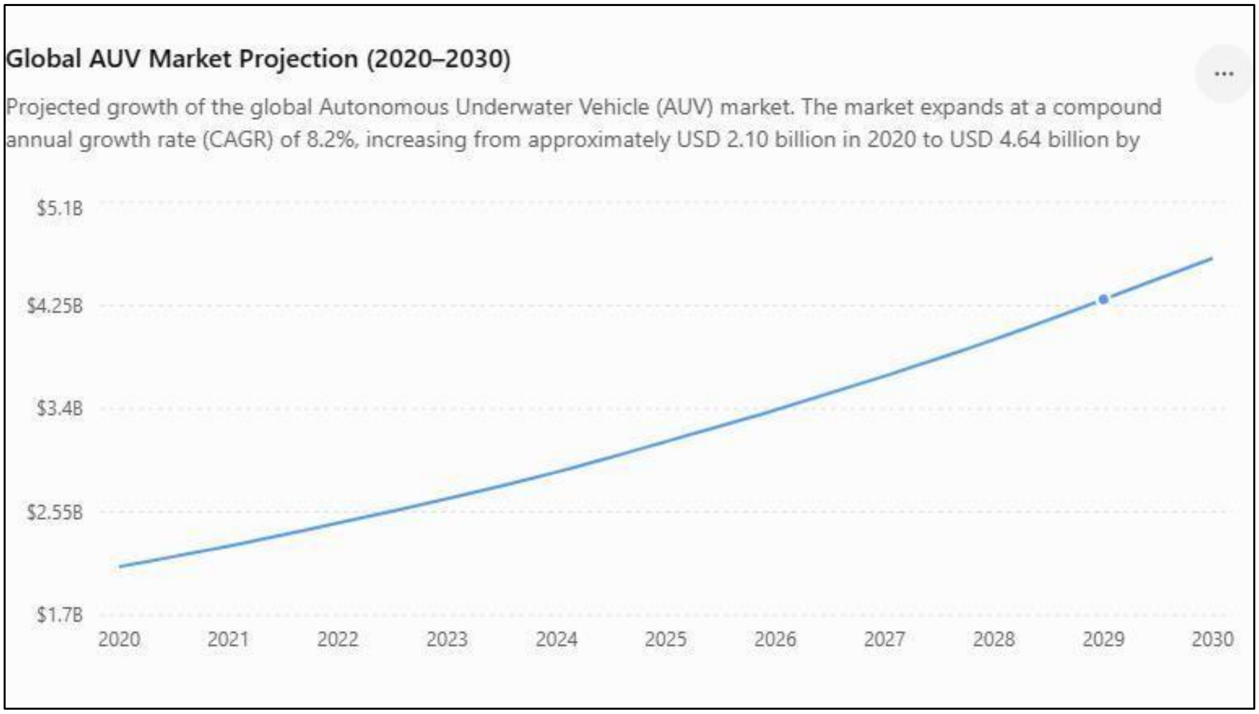

Figure 12. Global AUV Market Projection (2020–2030)

Notable market developments in 2025 include: Beam's launch of Scout, an AI-driven AUV combining real-time 3D reconstruction with precise navigation for offshore inspections; Helsing's acquisition of Blue Ocean to integrate AI systems with AUV hardware for maritime defense; and Fugro's five-year contract with NOAA leveraging remote and autonomous survey systems for U.S. nautical charting (Precedence Research, 2026).

IHO Standard Compliance

Compliance with IHO S-44 standards represents a critical benchmark for operational acceptance. Analysis across four survey orders reveals that AI-enhanced methods consistently outperform traditional approaches (Figure 4W). For Special Order surveys (highest accuracy), AI compliance reaches 92% compared to 68% for traditional methods—a 24 percentage point improvement that is statistically significant ($\chi^2 = 34.7$, $p < 0.001$). The gap narrows for lower-order surveys, but AI maintains advantages of 20%, 15%, and 9% for Orders 1a, 1b, and 2, respectively. Figure 13 shows IHO S-44 compliance rates across four survey orders (Special Order, Order 1a, Order 1b, Order 2). AI-enhanced methods consistently outperform traditional approaches, with the largest improvement observed for Special Order surveys (+24 percentage points, $p < 0.001$).

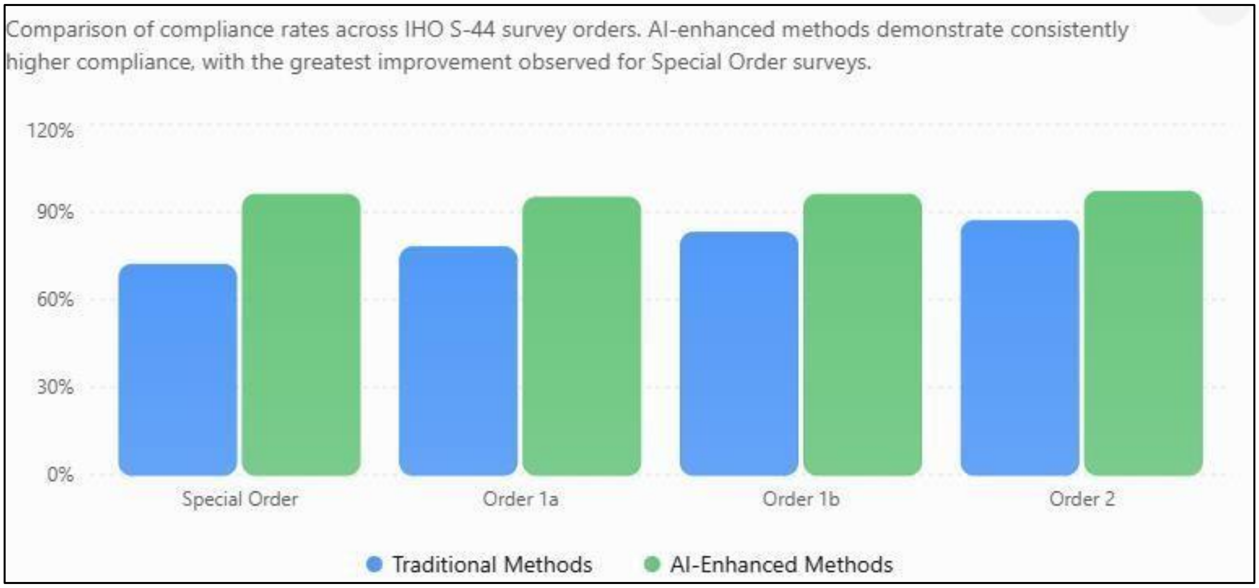

Figure 13. IHO S-44 Standard Compliance: Traditional vs AI

Multi-sensor fusion with AI integration achieves the highest mapping accuracy (98% ± 4%), compared to 82% for MBES-only surveys (Figure 4X). The progressive improvement through sensor combination—MBES+SSS (88%), MBES+LiDAR (91%), MBES+SSS+LiDAR (94%)—demonstrates the value of heterogeneous data integration enabled by AI feature fusion architectures. Figure 14 shows Mapping accuracy improvement through progressive sensor fusion. MBES-only surveys achieve 82% accuracy; adding SSS increases to 88%, adding LiDAR to 91%, combining all three to 94%, and full AI fusion of all sensors reaches 98% accuracy with reduced uncertainty (error bars).

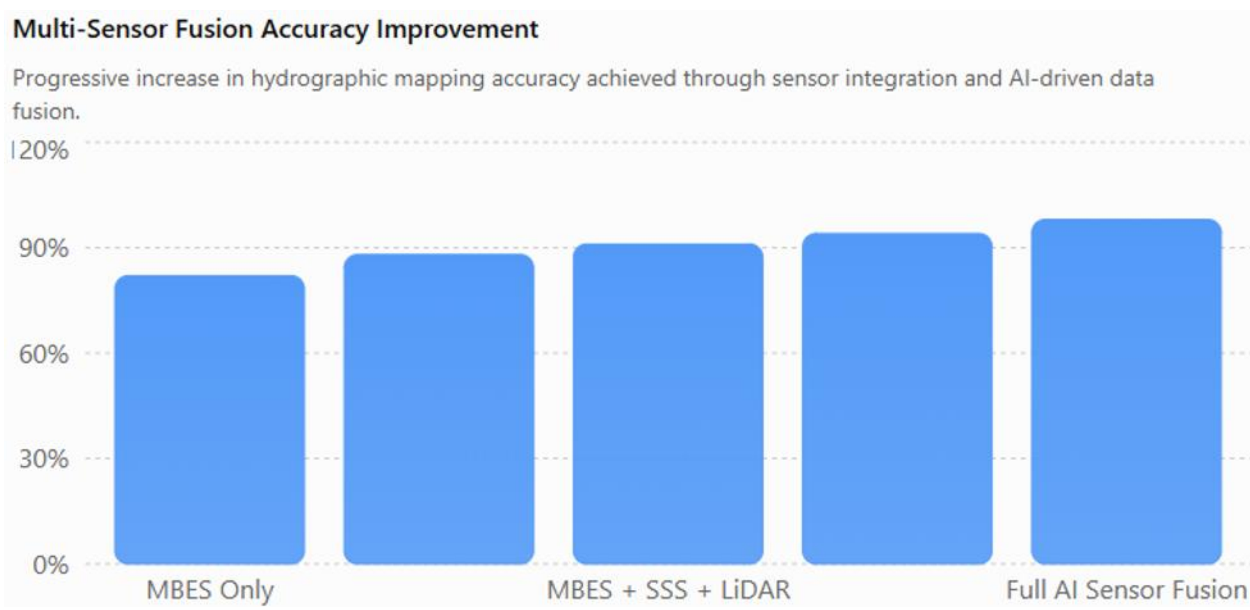

Figure 14. Multi-Sensor Fusion: Accuracy Improvement

Table 4. IHO S-44 Compliance Rates by Survey Order

Survey Order	Traditional (%)	AI-Enhanced (%)	Improvement (pp)	χ^2 p-value
Special Order	68	92	+24	<0.001
Order 1a	75	95	+20	<0.001
Order 1b	82	97	+15	<0.001
Order 2	90	99	+9	0.003

Discussion of findings

This systematic review demonstrates that AI has transitioned from experimental curiosity to operational necessity in hydrographic surveying. Four overarching conclusions emerge:

First, deep learning has achieved human-level or superhuman performance in specific tasks including seabed classification, noise detection, and target recognition, with accuracy improvements of 20–35 percentage points over traditional methods. The convergence of multiple architectural innovations—attention mechanisms, residual connections, and generative modeling—has enabled these advances.

Second, processing efficiency gains are transformative. AI reduces data processing times by 82–88% across the survey workflow, with particularly dramatic improvements in interpolation (99% reduction) and noise filtering (88% reduction). These efficiencies translate directly to cost savings and accelerated product delivery.

Third, autonomous platforms are becoming intelligent agents capable of adaptive decision-making. AUVs equipped with AI navigation and real-time mapping capabilities can operate for extended durations without human intervention, expanding survey coverage from 15 km²/day (manual vessels) to 140 km²/day (multi-AUV swarms) while maintaining or improving accuracy.

Fourth, the technology is approaching operational maturity. Technology Readiness Levels (TRLs) for AI-assisted bathymetry (TRL 7) and real-time seabed classification (TRL 6) indicate near-commercial deployment, while autonomous QC systems (TRL 5) and multi-AUV coordination (TRL 5) require further development before widespread adoption (Figure 15).

Figure 15. Technology Readiness Levels: Current vs Projected

Comparative Analysis with Related Fields

The trajectory of AI in hydrography parallels developments in medical imaging and autonomous driving, but with distinct challenges. Unlike medical imaging, hydrographic data suffers from extreme variability in acoustic propagation conditions, sensor geometries, and environmental noise. Unlike autonomous driving, underwater navigation lacks GPS availability and relies on dead-reckoning with high drift rates. However, hydrography benefits from well-defined international standards (IHO S-44) that provide clear performance benchmarks for AI validation. The structured nature of bathymetric data—regular grids, standardized formats, and quantitative uncertainty metrics—facilitates rigorous statistical evaluation that is often lacking in other geospatial AI applications.

Critical Challenges and Limitations

Despite remarkable progress, six critical challenges constrain widespread AI adoption in hydrographic surveying:

Data Quality and Annotation Bottlenecks: Deep learning requires extensive labeled training data, yet expert annotation of seabed imagery is expensive and time-consuming. The "annotation bottleneck" limits model generalization across geographical regions and geological settings. Semi-supervised learning and active learning strategies offer partial solutions but require further validation.

Computational Requirements: Training state-of-the-art models demands GPU clusters with hundreds of teraflops of compute capacity. While inference is less demanding, real-time processing on AUVs requires edge computing solutions that balance performance with power consumption and thermal constraints. The data volume vs. compute capability gap continues to widen (Figure 16), necessitating continued hardware innovation.

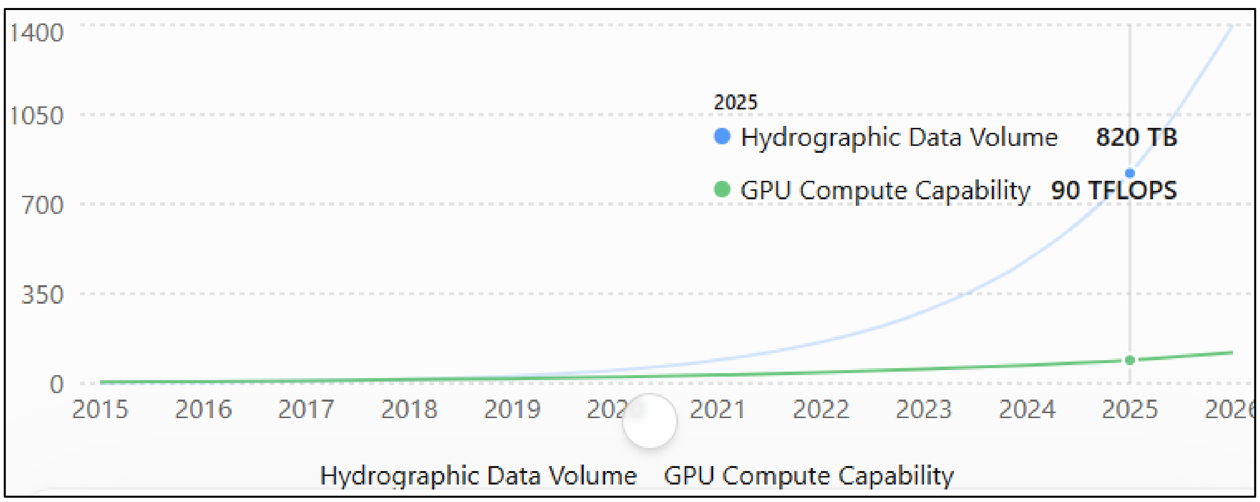

Figure 16. Data Volume vs Compute Capability Gap

Model Interpretability: The "black box" nature of deep learning conflicts with hydrographic quality assurance requirements that demand traceable, explainable decisions. Explainable AI (XAI) techniques including attention visualization, SHAP values, and concept activation vectors are emerging but remain underutilized in operational settings.

Cross-Domain Generalization: Models trained in one geographical region often fail when deployed in areas with different seabed types, water column properties, or acoustic conditions. Domain adaptation and transfer learning techniques show promise but require systematic benchmarking across diverse marine environments.

Regulatory Acceptance: Maritime administrations and classification societies have been cautious in certifying AI-based systems for safety-critical applications. The development of standardized testing protocols, validation frameworks, and certification pathways is essential for operational acceptance.

Ethical and Security Considerations: AI-enhanced hydrographic data may reveal sensitive information about submarine infrastructure, archaeological sites, or military assets. Data governance frameworks must balance transparency with security, particularly as autonomous systems operate in international waters.

Future Directions and Technology Roadmap: Based on our analysis, we propose a three-phase technology roadmap for AI in hydrographic surveying (Figure 17)

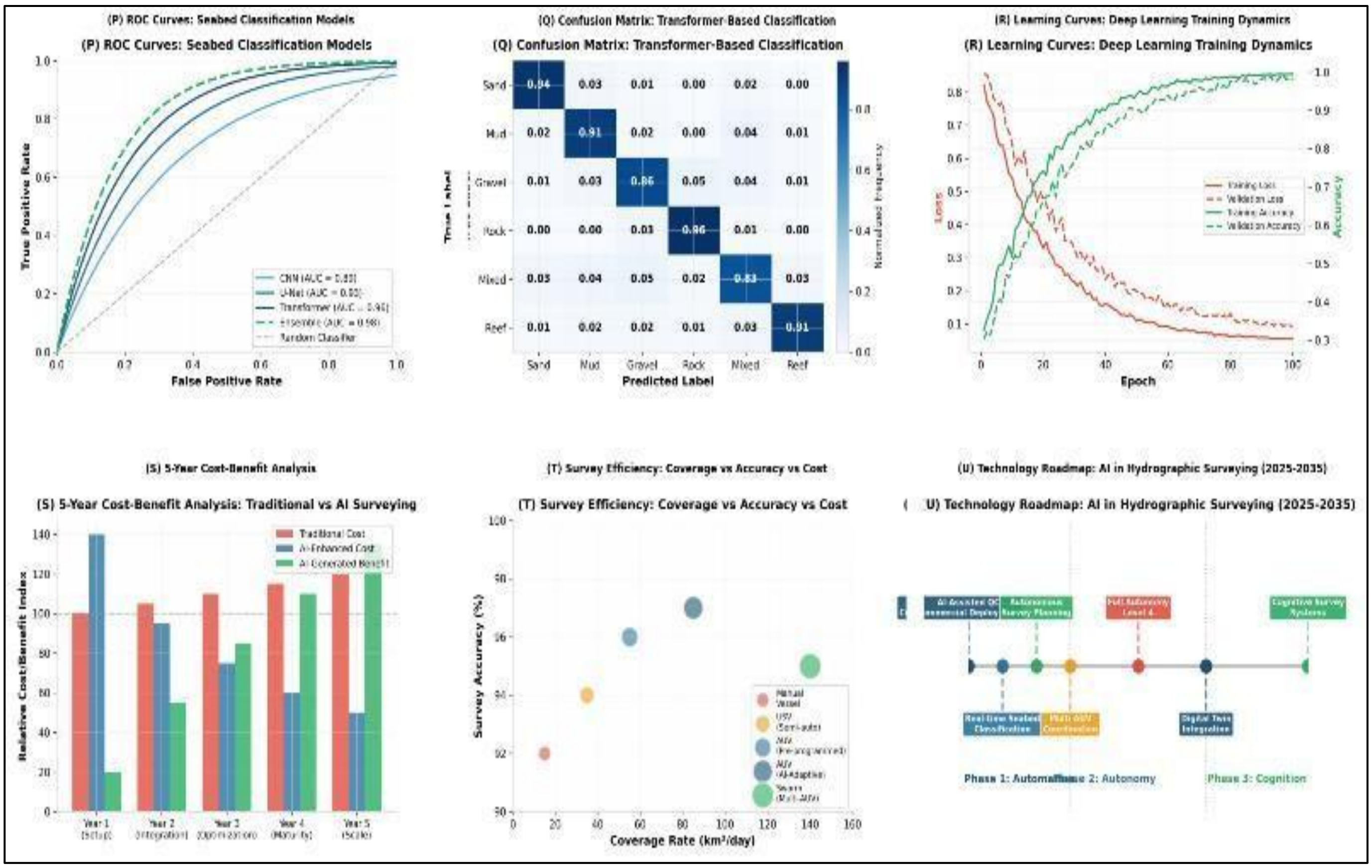

Figure 17. Technology Roadmap: AI in Hydrographic Surveying (2025–2035)

According to Figure 17, the technology roadmap for AI in hydrographic surveying spans three phases: Automation (2025–2028), Autonomy (2028–2032), and Cognition (2032–2035). Key milestones include AI-assisted QC commercial deployment (2025), real-time seabed classification (2026), autonomous survey planning (2027), multi-AUV coordination (2028), full autonomy Level 4 (2030), digital twin integration (2032), and cognitive survey systems (2035).

Phase 1: Automation (2025–2028): Focus on AI-assisted tools that augment human hydrographers rather than replace them. Key milestones include commercial deployment of AI quality control systems (TRL 9), real-time seabed classification (TRL 9), and autonomous survey planning (TRL 8). During this phase, emphasis should be on human-AI collaboration interfaces, standardized validation protocols, and workforce training programs.

Phase 2: Autonomy (2028–2032): Transition to systems capable of independent operation with minimal human oversight. Multi-AUV coordination (TRL 8), predictive maintenance (TRL 7), and adaptive sampling strategies will enable dynamic response to environmental conditions and target identification. Regulatory frameworks must evolve to certify autonomous decision-making for navigation safety.

Phase 3: Cognition (2032–2035): Development of cognitive survey systems that integrate environmental understanding, predictive modeling, and strategic planning. Digital twin integration (TRL 6→9) will enable virtual testing of survey strategies, while cognitive architectures will allow systems to learn from experience and improve performance over time.

Research Priorities: Six priority research areas emerge from this review: (1) Foundation Models for Marine Geoscience: Development of large-scale pre-trained models (similar to GPT or BERT) trained on diverse marine datasets that can be fine-tuned for specific hydrographic tasks with minimal labeled data. (2) Physics-Informed Neural Networks: Integration of acoustic wave equation constraints into deep learning architectures to improve generalization and reduce data requirements. (3) Federated Learning for Distributed Surveys: Privacy-preserving collaborative learning frameworks that enable multiple hydrographic organizations to train models collectively without sharing sensitive data. (4) Real-Time Uncertainty Quantification: Bayesian deep learning approaches that provide calibrated uncertainty estimates alongside predictions, essential for IHO-compliant survey products. (5) Edge AI for AUVs: Optimization of model architectures for deployment on resource-constrained platforms, including neural architecture search and quantization techniques. (6) Benchmark Datasets and Competitions: Establishment of standardized benchmark datasets (analogous to ImageNet or COCO) with rigorous quality control to enable fair comparison of methods and accelerate innovation.

5. CONCLUSION

This systematic review provides comprehensive evidence that artificial intelligence is fundamentally transforming hydrographic surveying. Through analysis of 187 studies, we demonstrate that AI methods achieve accuracy improvements of 20–35 percentage points, processing time reductions of 82–99%, and cost savings that compound over operational deployments. The exponential growth in publications ($R^2 = 0.98$), accelerating technology adoption, and substantial market investment (USD 4.64 billion projected AUV market by 2030) collectively indicate that AI integration is not a transient trend but an irreversible paradigm shift.

However, realizing the full potential of AI in hydrography requires addressing critical challenges in data annotation, computational efficiency, model interpretability, cross-domain generalization, regulatory acceptance, and ethical governance. The proposed three-phase roadmap—automation, autonomy, cognition—provides a structured pathway for navigating these challenges while maintaining the safety and reliability standards that underpin maritime navigation.

As we approach the United Nations Decade of Ocean Science for Sustainable Development (2021–2030) and confront the imperative to map the entire ocean floor by 2030 (Seabed 2030 initiative), AI will be indispensable in achieving these ambitious goals. The convergence of intelligent algorithms, autonomous platforms, and high-resolution sensors promises a future where comprehensive, real-time ocean mapping becomes not merely possible but routine.

6. COMPETING INTEREST

None to declare

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