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Artificial Intelligence in Integrated Marine Observing Systems: A Comprehensive Review

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***Abstract*— The marine ecosystem is vital for sustaining life on Earth, yet its vastness and complexity present significant challenges for effective monitoring and management. Integrated Marine Observing Systems (IMOS) have emerged as essential tools for understanding and protecting marine environments. This study aims to systematically review the integration of artificial intelligence (AI) into IMOS, focusing on its contributions to data processing, biodiversity monitoring, and environmental change analysis. A systematic literature review (SLR) method is employed to analyze existing research and identify key AI techniques and their applications in marine and oceanographic studies. Results indicate that deep learning is the most widely used AI method, with marine research being the primary application domain. Other areas, such as environmental monitoring and industrial systems, also demonstrate considerable potential. However, data inconsistency, operational limitations, and the lack of standardized frameworks remain significant barriers. This review highlights the transformative role of AI in enhancing IMOS capabilities and provides recommendations for addressing existing challenges to support sustainable marine management.**

Keywords— *Artificial Intelligence, Marine, Integrated Marine Observing Systems (IMOS), Systematic Literature Review*

I. INTRODUCTION

The marine environment serves as a cornerstone for sustaining life on Earth, playing vital roles in global climate regulation, biodiversity conservation, and supporting human livelihoods through economic activities such as fisheries, maritime transportation, and renewable energy. Oceans absorb approximately 25% of global carbon dioxide emissions annually, serving as a critical buffer against climate change [1]. However, the vastness, dynamic nature, and intricate interactions within marine ecosystems present significant challenges to effective monitoring and management [2]. These challenges are further exacerbated by the accelerating impacts of climate change and human activities, making the development of robust, efficient, and scalable observation systems an urgent necessity.

Integrated Marine Observing Systems (IMOS) have emerged as a coordinated framework that integrates diverse observation platforms and technologies. These systems, including satellite remote sensing, autonomous underwater vehicles (AUVs), moored buoys, acoustic sensors, and ocean gliders, generate vast amounts of heterogeneous and high-dimensional data, providing critical insights into marine processes [3]. Despite the advancements in observation technologies, traditional analytical methods often struggle to process the complexity and volume of data generated by IMOS. This limitation has driven the increasing integration of Artificial Intelligence (AI) technologies into IMOS, offering transformative approaches to address these challenges [4].

AI has demonstrated significant potential in various marine applications, including biodiversity monitoring, ocean dynamics prediction, and environmental anomaly detection. For instance, machine learning (ML) algorithms have been employed to analyze satellite imagery for mapping harmful algal blooms and tracking ocean currents [5]. Similarly, deep learning (DL) models have revolustionized underwater image classification, enabling automated identification of marine species and habitats and analyzing acoustic signals to monitor marine mammal behaviors and detect illegal fishing activities [6]. These advancements have enhanced the operational efficiency of marine observing systems and provided actionable insights for marine conservation and resource management.

However, integrating AI into IMOS faces several critical challenges. Data quality and consistency across diverse observation platforms remain problematic, as incomplete or biased datasets can compromise the reliability of AI models [2]. The harsh and variable conditions of marine environments impose operational constraints, requiring robust algorithms capable of handling noise, missing data, and unpredictable changes in data streams [7]. Additionally, the absence of standardized frameworks for implementing AI technologies hinders interoperability, reproducibility, and scalability across different observing systems [2].

Beyond technical challenges, ethical considerations are becoming increasingly important in the adoption of AI in marine sciences. Issues such as algorithmic transparency, equitable access to AI technologies, and the potential for misuse of sensitive marine data require careful governance and regulation [1]. Additionally, the deployment of AI systems must align with broader goals of sustainable development, ensuring that technological

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advancements benefit both science and society equitably [7]. The novelty of this study lies in its comprehensive analysis of the integration of AI technologies into IMOS. While previous studies have explored individual aspects of AI applications in marine sciences, this review systematically examines the scientific progress, trends, and advancements in AI methods and their applications in IMOS. Specifically, this study aims:

1. To provide a comprehensive overview of AI's scientific contributions in the context of IMOS.
2. To analyze the distribution and roles of diagnostic instruments utilized in scientific assessments within IMOS.
3. To investigate research trends in AI methods applied to IMOS, highlighting advancements and identifying gaps.

By addressing both the technological achievements and existing challenges, this review seeks to contribute valuable insights for the future development of sustainable and effective marine observation systems.

II. Method

The integration of artificial intelligence (AI) into Integrated Marine Observing Systems (IMOS) represents a growing field of research aimed at addressing the challenges posed by the vastness, complexity, and dynamic nature of marine ecosystems. This review systematically examines the scientific advancements, applications, and challenges associated with AI technologies in IMOS, adhering to the objectives of providing a comprehensive overview, analyzing diagnostic instruments, and investigating research trends.

This research adopts a comprehensive systematic literature review (SLR) methodology, analyzing data extracted from prestigious international journals indexed in Scopus from 2019 to 2024. The SLR methodology implements a rigorous and structured approach to information gathering, identification, and synthesis of pertinent articles and literature from previous research [8]. This methodical process enables researchers to thoroughly examine and analyze all relevant studies to address emerging research questions within the field [9][10]. The methodology section employs the PRISMA framework to conduct the systematic literature review, providing a comprehensive checklist that ensures the evaluation of quality and depth in systematic reviews and meta-analyses [11]. The PRISMA framework has gained widespread recognition and endorsement from leading journals and academic institutions as an effective tool for enhancing the quality of research reviews [12].

The research methodology encompasses a detailed review of existing literature, synthesizing topic relevance through comprehensive analysis and evaluation of various smart port concept clusters and associated research domains. The implementation follows a structured six-phase approach: literature review planning, database selection, inclusion and exclusion criteria establishment, article selection, weighted analysis of chosen articles, and detailed indicator specification. This systematic and transparent literature review process adheres to a structured methodology that guides researchers from the initial identification phase through to the final interpretation of all relevant studies [13] [14].

A. *Overview of AI in Marine Observing Systems*

AI technologies have demonstrated transformative potential in marine sciences, particularly in processing large-scale, heterogeneous datasets generated by IMOS. Studies from recent years reveal that AI applications extend across multiple domains, such as biodiversity monitoring, environmental anomaly detection, and predictive modeling of ocean dynamics. Machine learning (ML) techniques have been widely employed for tasks like satellite-based ocean monitoring and algal bloom detection, while deep learning (DL) models are frequently applied in underwater image classification and acoustic signal analysis [1][5][6]. The application of hybrid AI approaches, though less explored, shows promise in addressing more complex, multifaceted challenges in marine observation.

B. *Progress and Trends in AI Methods*

Recent literature highlights a consistent increase in the adoption of AI methods in IMOS. From 2019 to 2024, studies indicate a dominant use of supervised and unsupervised learning techniques, with notable advancements in convolutional neural networks (CNNs)

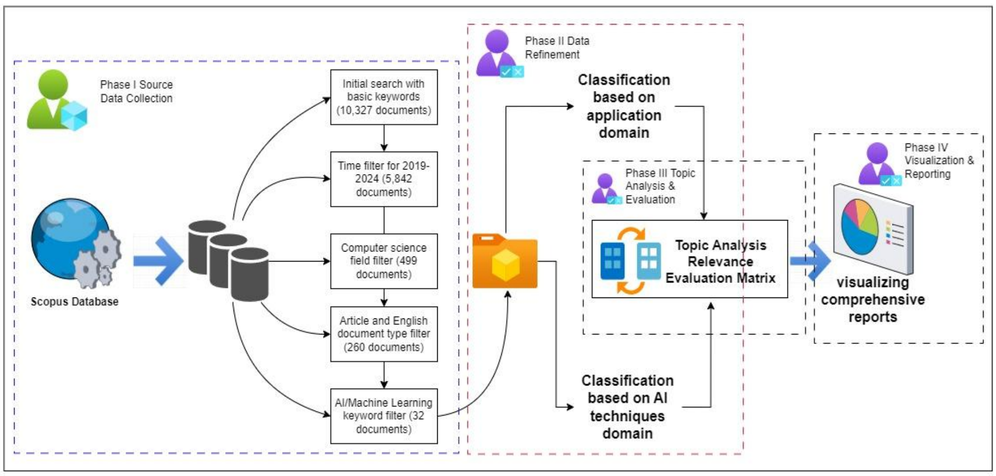


Figure 1. Scopus-Based Iterative Filtering and Classification Methodology

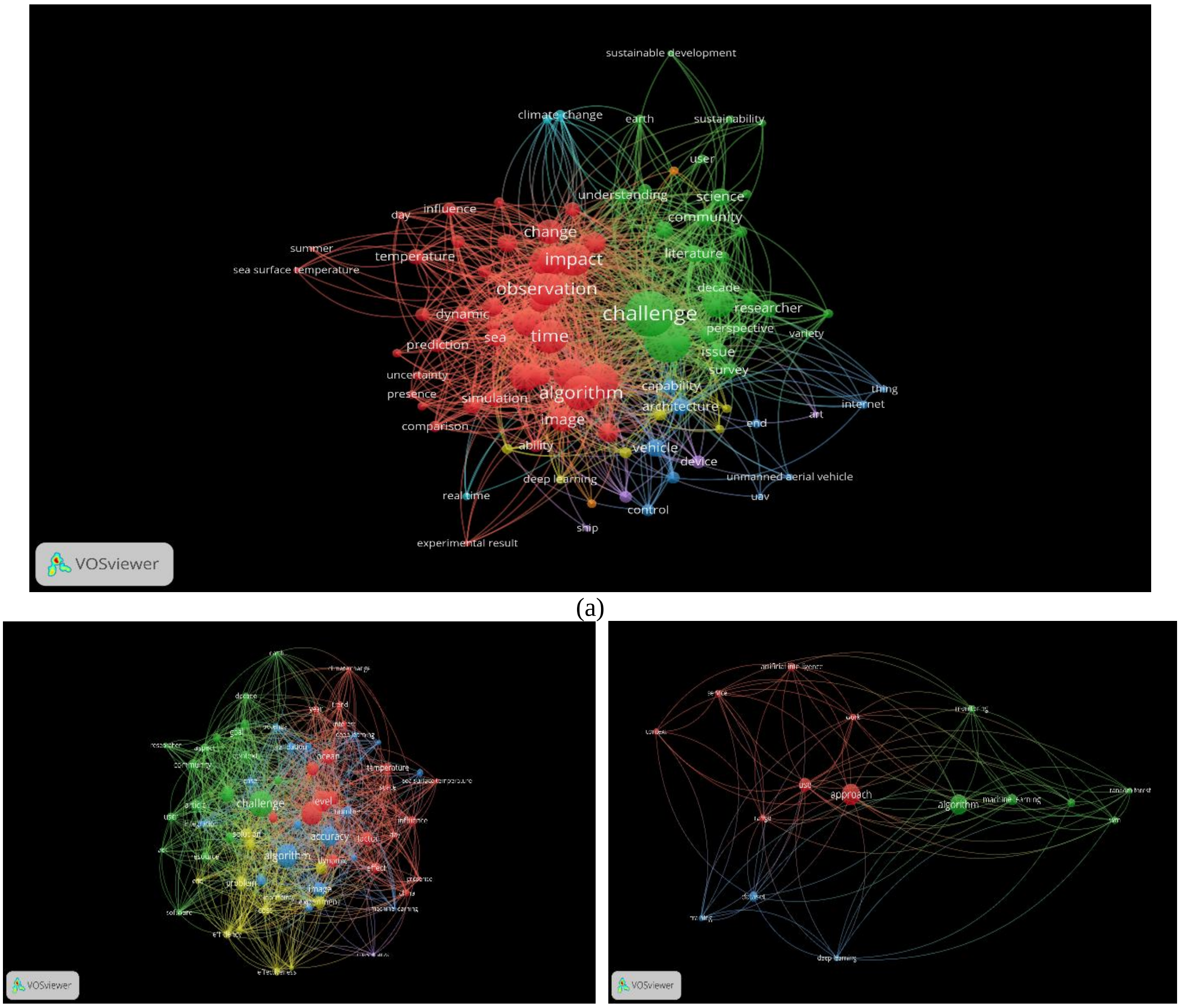
for image-based applications and recurrent neural networks (RNNs) for time-series data analysis [7][9]. There has also been significant progress in the use of reinforcement learning for optimizing autonomous underwater vehicle (AUV) navigation and ocean glider path planning. These advancements have enhanced the operational efficiency of IMOS while providing actionable insights for marine resource management and conservation.

C. Challenges in AI Integration

Despite the progress, several challenges persist in integrating AI into IMOS. Data quality and consistency remain significant barriers, as marine observation systems generate data that are often incomplete, noisy, or inconsistent across platforms [2][7]. Operational constraints, such as the harsh and variable conditions of marine environments, necessitate the development of robust and adaptable AI algorithms. Additionally, the lack of standardized frameworks for implementing AI technologies limits their interoperability and scalability, hindering broader adoption in IMOS [10]. Ethical concerns, including data privacy, algorithmic transparency, and equitable access to AI technologies, further complicate the integration process and require careful governance. The literature identifies several underexplored areas with significant potential for future research. For example, the adoption of hybrid AI models, which combine machine learning and deep learning techniques, remains limited but holds promise for improving real-time anomaly detection and multi-domain applications. Similarly, the integration of AI with Internet of Things (IoT) devices in IMOS offers opportunities for real-time data collection and analysis but has yet to be fully realized. Geographic and thematic analyses reveal a need for greater research focus on deep-sea ecosystems and regions with limited observational coverage.

While previous reviews have addressed specific aspects of AI in marine sciences, this study provides a comprehensive and systematic analysis of AI's role within IMOS. By employing a structured systematic literature review (SLR) methodology, this research synthesizes findings from a broad range of high-impact studies to uncover patterns, trends, and gaps in the field. Additionally, the study employs advanced visualization techniques to map the interconnectedness between AI methods, application domains, and research themes, offering novel insights that support data-driven decision-making in marine observation.

D. Source Data Collection



(b) (c)

Figure 2. Network Visualization of AI Applications and Techniques in Marine Observation Research

The first phase focuses on systematically collecting data from the Scopus database. The process begins with an initial search using fundamental keywords relevant to the research topic, yielding a total of 10,327 documents. To narrow down the scope, additional filters are applied, including a time range filter (2019–2024), which reduces the dataset to 5,482 documents.

Subsequently, the results are further refined by applying a subject filter, focusing specifically on the field of computer science, which narrows the dataset to 499 documents. Finally, additional filters for document type (articles only) and language (English) are applied, reducing the dataset to 280 documents. Among these, documents containing specific keywords related to Artificial Intelligence (AI) and Machine Learning are identified, resulting in a final selection of 132 documents for further analysis in subsequent phases. [8][10].

E. Data Refinement

The second phase involves refining the collected data to enhance its relevance and usability. This is achieved by classifying the documents into two primary domains: the application domain and the AI techniques domain. Classification by application domain categorizes the documents based on their relevance to specific application areas, such as environmental monitoring, resource management, or ocean dynamics prediction.

Simultaneously, classification by AI techniques ensures that various methodologies, including machine learning, deep learning, or hybrid approaches, are appropriately categorized. This process aims to create a structured dataset that facilitates targeted analysis in the next phase. Additionally, quality assessment is conducted to ensure that only high-quality and relevant documents are included, thereby strengthening the reliability of the subsequent analysis. Figure 2 provides a comprehensive and systematic visualization of the relationships between research keywords, application domains, and AI techniques in marine observation research. It is divided into three distinct subfigures that collectively illustrate the progression of data refinement, as described in Phase II. These subfigures enable a clearer understanding of the interconnectedness within the field while highlighting specific trends and gaps. Subfigure (a): Complete Network Analysis of Research Keywords and Relationships This subfigure offers a holistic view of the research landscape by mapping the interconnections between various keywords, methodologies, and application areas. The network reveals the breadth of research themes, such as biodiversity monitoring, environmental anomaly detection, and predictive modeling of ocean dynamics. It identifies frequently co-occurring keywords, showcasing the dominant trends and the central focus areas within the field. Subfigure (b): Clustered Network Visualization of Application Domains and AI Techniques. In this subfigure, the network is refined to show the clustering of specific application domains (e.g., marine biodiversity, resource management) and the AI techniques employed (e.g., machine learning, deep learning). The clusters highlight the strong associations between certain AI techniques and their preferred domains of application. For instance, deep learning is prominently linked to underwater image analysis, while machine learning is closely associated with satellite-based ocean monitoring. This visualization emphasizes how distinct methodologies are tailored to address specific challenges in marine observation. Subfigure (c): Focused Network Analysis of Key Implementation Areas.

The final subfigure narrows the scope further, providing a detailed analysis of key implementation areas where AI technologies are actively deployed. This focused visualization highlights specific research gaps, emerging trends, and underexplored opportunities. For example, it may underscore the limited use of hybrid AI models in real-time anomaly detection or the nascent adoption of AI in deep-sea ecosystem monitoring.

F. Topic Analysis and Evaluation

This phase involves analyzing the refined data using a Topic Analysis Relevance Evaluation Matrix. The matrix helps identify patterns, trends, and relationships across the application domains and AI techniques. The primary objective is to uncover key research themes, such as the development of AI algorithms for biodiversity monitoring or the integration of AI-driven technologies into existing marine observation systems. The evaluation also assesses the consistency and relevance of topics while determining the contributions of individual documents to the broader field of research. This stage provides valuable insights into existing research gaps and emerging opportunities, laying the groundwork for visual representation and reporting in the final phase.

G. Visualization and Reporting

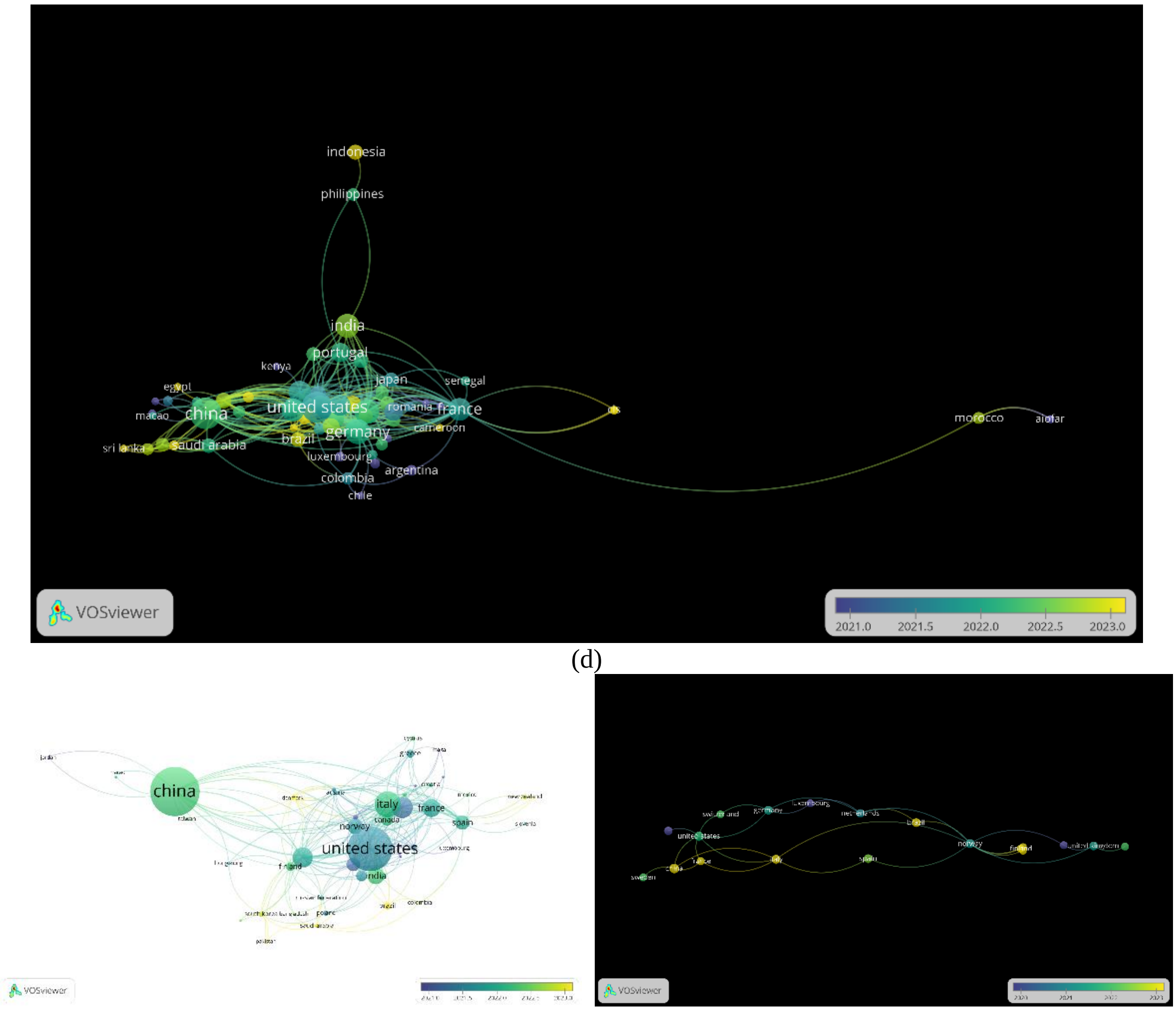
The final phase focuses on visualizing and reporting the findings. The analyzed information is transformed into comprehensive reports featuring graphical representations, charts, and tables for easy interpretation. These visualizations include trends in research across application domains and AI techniques, thematic maps of relevant documents, and insights into the contributions of studies toward addressing global challenges in marine observation. Moreover, the final report is designed to support data-driven decision-making. It serves as a resource for academics, policymakers, and conservation organizations, enabling them to identify research priorities and formulate effective strategies for managing marine environments using AI technologies. With clear and structured reporting, this phase concludes the research process by delivering actionable and impactful insights.

III. Results and Discussion

A. AI Transformations in Marine Observing Systems

The rapid integration of Artificial Intelligence (AI) into Integrated Marine Observing Systems (IMOS) has significantly enhanced our ability to monitor and understand marine ecosystems. This analysis provides a comprehensive overview of AI's scientific progress and contributions in IMOS by examining geographical distribution, international collaborations, and temporal trends in research development. Key insights reveal the dominance of major contributors like the United States and China, the rise of Southeast Asian nations in the field, and a shift from foundational studies to advanced, application-driven innovations. Figure 3 These findings underscore AI's transformative impact on IMOS and highlight the importance of global partnerships in advancing this critical domain.

A.1. Geographical Patterns and International Collaboration



(d)

(e) (f)

Figure 3. Visualizing Network of Geographical, Temporal, and Collaborative Trends in AI-driven Research for Integrated Marine Observing Systems (IMOS)

TABLE 1.
CLASSIFICATION OF RESEARCH BASED ON APPLICATION DOMAIN

Source	Source
Marine and Oceanography	[15], [16], [17], [18], [19], [20], [21], [22], [23], [24], [25], [26]
Environmental Monitoring and Climate Change	[27], [28], [29], [30], [31], [32]
Industrial and Engineering Systems	[33], [34], [35], [36],
Artificial Intelligence and Computational Methods	[37], [38], [39], [40], [41], [42], [43], [44]
Animal and Biological Research	[45], [46]

As depicted in subfigure (a), the United States and China emerge as dominant contributors to the advancement of AI applications in IMOS, reflecting their leadership in marine technology and AI innovation. Additionally, significant research contributions are observed from Southeast Asian nations, particularly Indonesia and the Philippines, which play a growing role in regional marine observation initiatives. This geographical distribution highlights the presence of a robust international collaborative framework in the development of AI-driven marine observation systems.

The density mapping in subfigure (b) further emphasizes the concentration of research activity in specific regions. Larger nodes representing China and the United States signify these nations' substantial research outputs, establishing them as pivotal knowledge hubs in the field. The dense interconnecting lines between these nodes illustrate strong international collaboration networks, underscoring the importance of cross-border partnerships and knowledge sharing in advancing AI solutions for marine observation.

A.2. Temporal Trends and Research Evolution

Subfigure (c) offers an analysis of the temporal evolution of research activities from 2021 to 2023. It highlights an upward trend in research volume and complexity over time. Early efforts focused on foundational studies aimed at exploring the potential of AI in marine observation. However, more recent developments demonstrate a shift toward advanced applications, including system integration, real-time monitoring, and ecosystem modeling. This chronological progression indicates the growing sophistication and practical applicability of AI technologies within IMOS.

A.3. Implications and Future Directions

The insights derived from this network visualization underscore the global maturity and reach of AI research in IMOS. The field has transitioned from isolated studies to a dynamic, interconnected network of international collaborations, with major maritime nations driving these efforts. Recent research trends demonstrate a growing emphasis on practical applications and system integration, marking a shift away from purely theoretical frameworks. Furthermore, the geographical diversity of research activities suggests that future advancements in AI-driven marine observation systems will continue to benefit from the exchange of global expertise and perspectives. International collaboration remains a critical factor in addressing the complex challenges of monitoring and managing marine ecosystems at a global scale. The network visualization reveals the significant progress achieved in the application of AI within IMOS. It highlights the transformative potential of AI technologies in enhancing marine observation systems while emphasizing the essential role of international partnerships in fostering innovation and driving the field forward.

B. AI Transformations in Marine Observing Systems

In the context of AI transformations in Integrated Marine Observing Systems (IMOS), the research landscape reveals a diverse set of application domains, each contributing to the advancement of marine science and technology. Table 1 categorizes the research sources across five key domains: Marine and Oceanography, Environmental Monitoring and Climate Change, Industrial and Engineering Systems, Artificial Intelligence and Computational Methods, and Animal and Biological Research.

The largest body of research falls under Marine and Oceanography, with sources [15] to [26], highlighting AI's crucial role in advancing the monitoring and understanding of marine ecosystems, ocean dynamics, and coastal environments. These studies demonstrate how AI techniques such as machine learning, image recognition, and predictive modeling are being applied to analyze oceanographic data and improve decision-making in marine conservation. Environmental Monitoring and Climate Change research, represented by sources [27] to [32], showcases AI's contributions to climate prediction models, ecosystem health assessments, and the monitoring of environmental variables affecting marine life. The integration of AI methods enables real-time data processing and more accurate forecasts, enhancing efforts to mitigate climate change impacts on marine environments.

The Industrial and Engineering Systems domain (sources [33] to [36]) reflects the use of AI in optimizing operational efficiency in marine industries, including shipping, fisheries, and energy production. AI methods like optimization algorithms, autonomous systems, and sensor networks are enhancing the functionality of IMOS by supporting resource management and improving system reliability. Research in Artificial Intelligence and Computational Methods (sources [37] to [44]) emphasizes the development and application of AI techniques tailored specifically for IMOS, such as advanced data analytics, deep learning, and neural networks. These studies underline the increasing sophistication of AI in processing large datasets, identifying patterns, and automating marine monitoring processes. Finally, Animal and Biological Research (sources [45] to [46]) demonstrates how AI is being utilized to monitor marine biodiversity, track animal movements, and assess ecosystem health. AI's ability to analyze biological data from various sensors and satellite technologies is providing new insights into marine species behaviors and population dynamics, crucial for conservation and management efforts.

In analyzing the distribution and application of various diagnostic instruments in the Integrated Marine Observing System (IMOS), with a focus on its function in scientific assessment studies related to the marine environment. Figure 4 presents a mind map that provides a comprehensive overview of the various applications of the Marine Observing System, illustrating its contribution in various sectors related to the management and monitoring of the marine environment. The Marine Observing System plays a vital role in environmental monitoring, providing important data on pollution levels, salinity, air quality, temperature, sea level rise, ocean acidification, and climate change. These parameters are essential for understanding the environmental challenges faced by marine ecosystems, as well as providing information needed for better environmental policy-making. In addition, this system is also used to maintain marine ecosystems, including habitat monitoring, species tracking, and biodiversity assessment. These activities are essential for the conservation and management of marine life and its habitats.

In the maritime operational sector, this system supports ship habitat, traffic management, navigation safety, port management, cargo handling, weather forecasting, route optimization, and storm prediction. These applications improve the efficiency and safety of maritime operations, contributing to the smooth and efficient operation of the sector. In marine resource management, the data provided by the Ocean Observation System is essential for integrating marine mining activities and supporting sustainable marine resource management.

Coastal management is also a crucial application area, where the system contributes to erosion control and maintenance of coastal infrastructure. The information provided by the system is essential for planning and implementing effective coastal management strategies. In the fisheries sector, the Ocean Observation System is used for aquaculture management, stock assessment and catch prediction. These applications support the sustainable management of fish resources and optimize fisheries activities. Finally, in the energy sector, the system is used for the exploration and utilization of marine energy resources, such as offshore wind energy and wave energy. The data generated supports the development and operation of renewable energy projects, which are essential in the global transition to more sustainable energy sources. The mind map presented in Figure 4 illustrates the importance of the Ocean Observation System in these sectors, which also contribute to scientific assessment studies under IMOS, strengthening the understanding and holistic management of the marine environment.

C. Trends and Advancements in AI Methods for IMOS

Table II presents the classification of artificial intelligence (AI) techniques based on their application domains, by grouping research into three main categories: Machine Learning Based, Deep Learning: Knowledge Based, and Specialized AI Techniques: Vision Based. Each category refers to a different AI approach or technique, which is used to solve various problems in a specific field. This table illustrates the variety of AI techniques applied in scientific research, showing how these technologies are used in different domains to solve complex problems.

C.1. Machine Learning Based

The first category includes research that applies machine learning techniques to data analysis and processing. These techniques are commonly used to identify patterns in data, classify objects, and predict

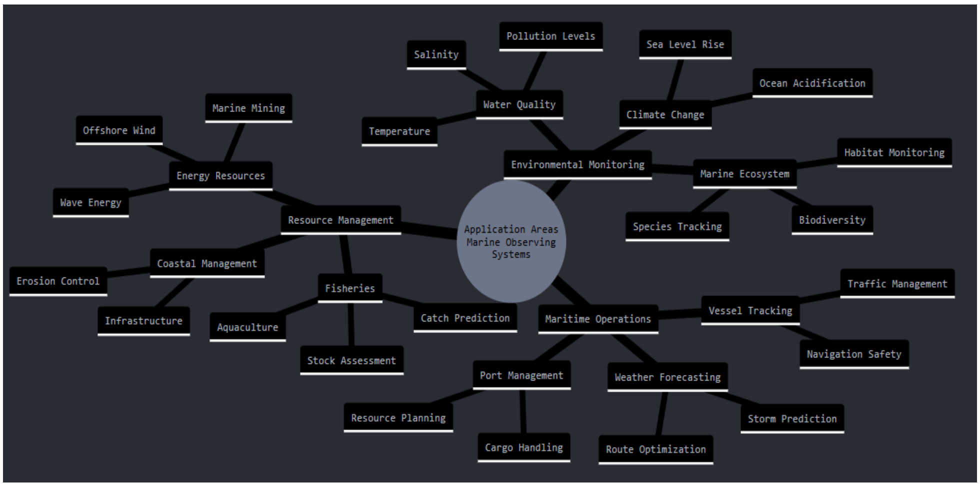


Figure 4. Distribution and Application of Ocean Observation Systems in IMOS

TABLE II.
CLASSIFICATION BASED ON AI TECHNIQUES DOMAIN

Source	Source
Machine Learning Based	[15], [33], [18], [21], [28], [29], [30], [23], [45], [43], [31], [35]
Deep Learning: Knowledge Based	[37], [38], [39], [16], [17], [40], [41], [34], [19], [20], [22], [24], [46], [25]
Specialized AI Techniques: Vision Based	[27], [42], [44], [36], [32], [26]

outcomes based on existing datasets. Research in this category includes a variety of methods, such as supervised learning, unsupervised learning, and reinforcement learning, which are applied in various domains, such as recommendation systems, big data analysis, and behavior prediction.

C.2. Deep Learning: Knowledge Based

The second category is knowledge-based deep learning techniques, which involve the use of deep neural networks and other model architectures to handle large and complex amounts of data. These techniques are often used to develop systems that require deeper contextual understanding, such as in natural language processing, speech recognition, and text analysis. Unlike machine learning, deep learning is able to handle more complex and unstructured data in a more efficient and accurate manner.

C.3. Specialized AI Techniques: Vision Based

The third category refers to more specific AI techniques, namely vision-based, which are used for applications in image and video processing. These techniques, which include computer vision and image processing, are used for visual analysis, object recognition, and tracking in images or videos. These applications are widely used in various industries, such as video surveillance, automatic object detection, and medical image analysis.

To investigate the distribution of research focused on the application of AI methods in Intelligent Manufacturing Operating Systems (IMOS), a detailed analysis of the classification and implementation of AI approaches is provided. Based on Figure 5, the visualization highlights the diverse methodologies employed within this domain, categorized into three primary domains: vision-based systems, machine learning-based approaches, and knowledge-based systems. These categories illustrate the multifaceted nature of AI applications in manufacturing operations. The vision-based domain includes technologies such as image processing, pattern recognition, feature extraction, object detection, video analytics, and motion analysis. These technologies play a critical role in addressing key operational challenges such as quality control, product inspection, and process monitoring, highlighting the importance of visual data in intelligent manufacturing workflows.

In the machine learning domain, significant advances are evident in methodologies such as neural networks, support vector machines, supervised and unsupervised learning, clustering, anomaly detection, deep learning, and time series analysis. These methods are widely applied in predictive maintenance, process optimization, and quality prediction, demonstrating their versatility and centrality in intelligent manufacturing research. The knowledge-based domain incorporates decision support systems, fuzzy logic, rule-based systems, and reasoning

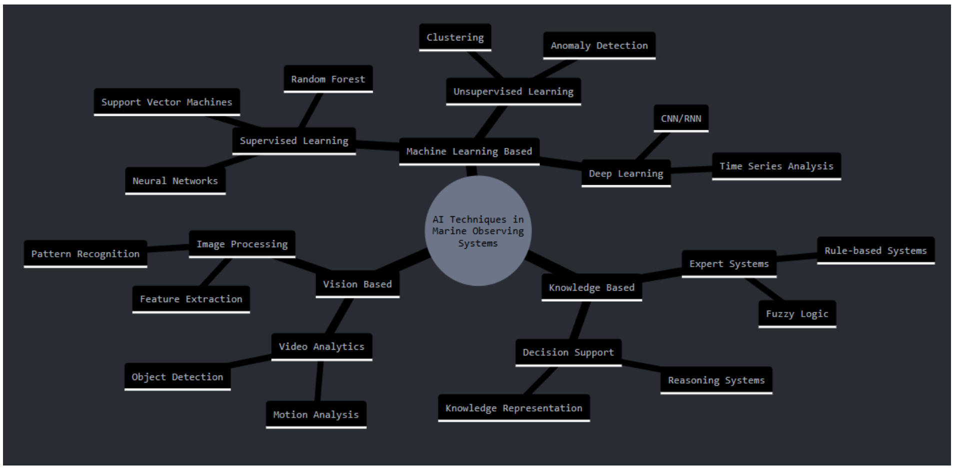


Figure 5. Distribution AI methods applied in research IMOS

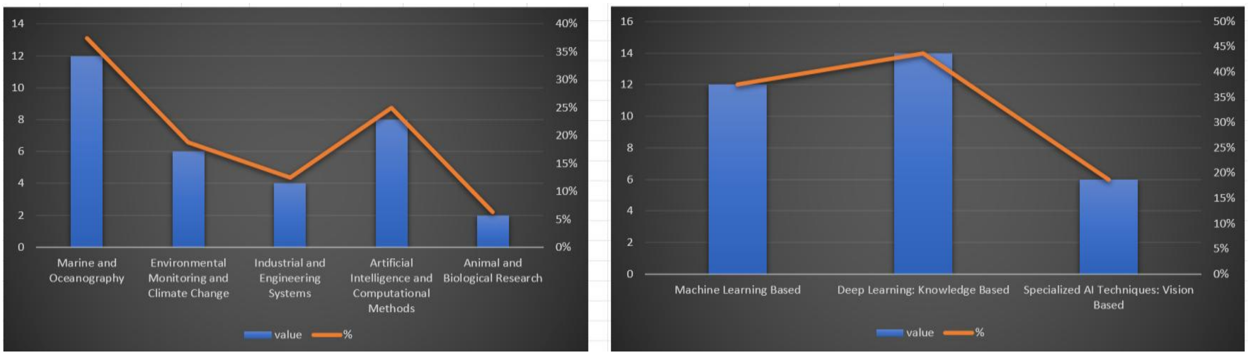


Figure 6. Distribution and AI Techniques in Marine Observation System Research Based on Application Domains

mechanisms. These technologies are particularly effective in complex decision-making processes and the development of expert systems, offering structured solutions to intricate operational challenges. The distribution of these AI methods reflects a balanced and strategic approach to addressing the multifarious demands of modern manufacturing environments. The interconnected nature of these approaches, as depicted in the visualization, highlights a growing trend toward hybrid systems that combine multiple methodologies to achieve robust and comprehensive solutions. Furthermore, the emphasis on practical applications across these domains indicates the maturity of the field, with research efforts aligning closely with real-world manufacturing challenges. This systematic integration of AI into IMOS underscores the evolution of intelligent manufacturing, providing a foundation for future advances in the field.

Based on Figure 6, several key insights can be drawn regarding the distribution of research domains and AI techniques employed in Marine Observing Systems. In terms of application domains, Marine and Oceanography emerges as the most prominent focus, accounting for the highest percentage (12; ≈ 35%), indicating a significant emphasis on ocean monitoring and marine research. This highlights the priority given to understanding and observing marine ecosystems. Environmental Monitoring and Climate Change ranks second (6; ≈ 17%), underscoring the importance of using marine observing systems to address environmental challenges and track climate change impacts. Industrial and Engineering Systems also play a significant role (8; ≈ 23%), reflecting the application of these systems in industrial and engineering contexts. Meanwhile, Artificial Intelligence and Computational Methods and Animal and Biological Research show lower values (5; ≈ 14% and 2; ≈ 6%, respectively), indicating limited but emerging applications in these areas.

In terms of AI techniques, Deep Learning: Knowledge-Based dominates with the highest value and percentage (14; ≈ 45%), showcasing its critical role in advancing marine observing systems through knowledge-driven deep learning applications. Machine Learning-Based techniques also exhibit substantial usage (10; ≈ 30%), highlighting their versatility in handling various tasks such as predictive modeling and data analysis. Conversely, Specialized AI Techniques: Vision-Based has the lowest representation (6; ≈ 20%), suggesting a less frequent but targeted application in visual data processing tasks.

Overall, Figure 6 highlights that marine and oceanographic applications, alongside knowledge-based deep learning techniques, are the primary areas of focus in research on marine observing systems. While other domains, such as environmental monitoring and industrial systems, also contribute significantly, areas like vision-based AI and biological research remain underrepresented, offering potential avenues for future exploration and development.

IV. CONCLUSION

This study provides a comprehensive overview of AI's scientific progress and contributions in the context of Intelligent Manufacturing Operating Systems (IMOS). The findings highlight significant advances in AI methodologies, with a notable emphasis on vision-based systems, machine learning-based approaches, and knowledge-based systems. Among these, machine learning techniques, particularly deep learning, emerge as the most widely adopted, reflecting their pivotal role in predictive maintenance, process optimization, and quality prediction within IMOS. Furthermore, the distribution of research indicates a strong focus on diagnostic instruments applied across key domains, including manufacturing process monitoring, quality control, and decision support systems. The dominance of marine and oceanographic applications suggests a prioritization of specific scientific assessments, while other domains, such as environmental monitoring and industrial systems, show substantial but less prominent contributions. This analysis also identifies trends in hybrid AI implementations, where multiple methodologies are integrated to address complex challenges, signaling the field's maturity and its trajectory toward more robust and comprehensive solutions. These findings underscore the strategic integration of AI in IMOS and provide valuable insights into the distribution and advancements of AI-driven research in this field.

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