# AI-based Knowledge Building for Ocean Observation and Ocean Emergency Warning

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**Abstract.** The ocean is home to a large number of species and plays a vital role in the existence of human life. Monitoring ocean health is a primary objective of many nations, as ocean health directly impacts human well-being and existence. In recent decades, technology-enabled ocean monitoring, ocean parameter sensing, and emergency warning systems have gained popularity around the world. The concept of a blue economy also emphasizes the sustainable use of ocean resources to achieve economic benefits while preserving ocean health. This research article discusses the role of ocean observatory systems and artificial intelligence in ocean monitoring. It highlights how these technologies help in the decision making for various warnings, changing parameter forecasting, and developing transformation rules and regulations to support the health of ocean ecosystems, the safety, and livelihood of coastal communities. The work presents the role of AI ocean analytics, its requirements, stakeholders, sensing units, and the network to collect data from the ocean. It can expand ocean-related monitoring possibilities for various applications supporting the United Nations Sustainable Development Goal #14.

**Keywords:** IoT · Artificial Intelligence · Maritime Communication · Ocean Observation System · Emergency Warning · Ocean Health.

## 1 Introduction

The ocean plays a vital role in the lives of coastal communities, which often rely on it for their livelihood. As a result, they are more exposed to natural hazards than inland populations. Strengthening their resilience has become a global priority to ensure both safety and empowerment. This requires providing timely and accurate information about potential threats and early warnings of impending disasters. Such measures enable communities to act promptly, whether by relocating to safer areas or adopting strategies that enhance their resilience.

Many coastal communities rely on daily wave height forecasts for safety (Kuehn, Abadie, Liquet, & Roeber, 2023), as well as warnings about tsunamis, cyclones, coastal floods, sea conditions, and severe weather. In addition to local residents, numerous tourists depend on alerts regarding the safety of beaches and coastal cities across India. Moreover, according to (Nash et al., 2022), over 40% of the global population and many large urban settlements are located in coastal areas. To strengthen the resilience of these communities and monitor ocean health, it is essential to implement Internet of Things (IoT) monitoring systems that collect oceanographic data.

The life and livelihood of coastal communities are deeply affected by the ocean's health and climatic conditions. As ocean health declines, associated ecosystems are disrupted, reducing livelihood opportunities and threatening the safety of coastal fishing communities. Therefore, stronger regulations focusing on ocean health and sustainability are needed. This article contributes to the expansion of ocean monitoring capabilities for various applications, supporting the United Nations Sustainable Development Goal #14.

In this work, we examine the need for an ocean monitoring system and the corresponding analytics at various levels of a multi-tier IoT network for monitoring the ocean environment. IoT devices generate large volumes of data globally (Deng et al., 2020), and transferring these data to centralized cloud servers is not feasible for all applications, particularly in remote oceanic regions. Reliable real-time data transmission is only possible where network connectivity exists. In areas lacking such connectivity, mobile IoT data collection and sensing systems–mounted on vessels or other mobile platforms–are necessary (S, Sabarinath, Anand, & Rao, 2024).

To overcome these challenges, particularly those related to latency and processing delays in transferring data to the cloud, researchers have proposed edge computing, fog computing, and cloudlets to process data closer to the source. Fog computing, in particular, mitigates the latency problem by enabling localized data processing and inference generation. Performing inference at the network's edge requires greater capability to handle AI algorithms. These approaches also face challenges in mobile IoT environments, including limited processing power, increased demands on edge devices, and the need for rapid inference generation. In the context of Marine IoT, these challenges are further exacerbated. Therefore, marine IoT data generated in ocean environments must be collected, stored, and processed in a timely and secure manner to produce actionable insights and critical warnings. However, these environments often lack sufficient storage, computational power, and communication infrastructure. To address these limitations, it is essential to enable data storage and processing at the edge of the network. Much of existing research emphasizes the importance of edge computing, including storage, processing, and analytics. A key strategy within this paradigm is the adoption of a layered storage architecture and the deployment of processing entities closer to IoT devices, which is essential for efficient and reliable data handling (Anand & Ramesh, 2021).

The paper also discusses various marine applications, a hybrid communication architecture, and the importance of stakeholder integration to achieve the envisioned resilience of coastal communities. This work aims to address three key research questions:

1. What are the existing state-of-the-art ocean monitoring systems?
2. What are the possibilities of edge intelligence to promote safety?
3. How can data be opportunistically transferred from the IoT edge to a centralized analytics center?

The research focuses on ensuring a sustainable future for coastal and ocean ecosystems and is aligned with the United Nations Sustainable Development Goal (SDG) #14: "Life Below Water" (Gulseven, 2020). This paper aims to explore the integration of Artificial Intelligence (AI) with Marine Internet of Things (MIoT) for effective ocean monitoring. It presents the Marine IoT architecture and reviews key AI technologies that enhance intelligent decision making in marine applications. The paper focuses on applying AI-integrated MIoT systems for ocean monitoring in the Indian coastal context, with limitations in real-time data availability and current implementation restricted to a conceptual stage.

The rest of the paper is organized as follows. Section 2 presents the relevant literature. Section 3 presented the details of the need for AI for Maritime IoT and the proposed architecture. Section 4 discusses the various deep learning methods and their use. Section 5 concludes the work.

## 2 Literature Review

The literature review focuses on the various ocean observatory models, the coastal communities, and the AI used in coastal and ocean monitoring to enhance the risk reduction process. Much of the existing research focused on reducing coastal and ocean pollution for better marine and human health. The ocean provides essential nutrients and food to low-income countries, and the impacts of climate change can result in redistribution of these seafood resources and can also decrease productivity (Nash et al., 2022). A large population living in coastal regions is migrating towards urban coastal areas and this can affect ocean health and society itself due to coastal development and pollution that leads to ecosystem degradation (Nash et al., 2022). Hence, it is highly necessary to promote protection and restoration of ocean ecosystems as oceanic plankton, ocean animals, and plants play a big role in human life. Hence, the research suggests that a close cultural connection with the ocean can help protect it.

Apart from marine pollution, other factors such as overfishing, coastal zone destruction, ocean acidification, sea level rise, coastal flooding, rise in ocean temperature, and intensity of extreme storms also affect the health of both humans and the ocean (Fleming, Maycock, White, & Depledge, 2019). Ocean acidification and pH changes in chemical pollutants result in seafood shortages in some regions. The chemical changes also affect humans and other animal populations and may contribute to the development of various kinds of diseases in humans and animals(Fleming et al., 2019).

The advancement of deep learning, which has achieved human-level accuracy in several domains, has contributed significantly to the recent rise of AI (Zhou et al., 2019). Similarly, IoT systems enable context awareness (Pradeep & Krishnamoorthy, 2019; Pradeep, Krishnamoorthy, Pathinarupothi, & Vasilakos, 2021), as they consist of interconnected intelligent devices and location-aware analytics platforms (Krishnan, Najeem, & Achuthan, 2017). Ocean monitoring and emergency warning systems can also be enhanced using deep learning models integrated with IoT systems. Many researchers are exploring the potential of deep learning and AI in ocean monitoring and forecasting. For example, a neural network-based coastal wave forecasting method is proposed in (Kuehn et al., 2023), which predicts spectral wave parameters using lower-resolution numerical computations. Another study combines deep learning and statistical methods to predict sea surface temperature and significant wave height. Their experiments show that deep learning slightly outperforms machine learning, and both approaches outperform traditional statistical models (Ali et al., 2021).

Many researchers have proposed multi-layer architectures and IoT systems for ocean monitoring, focusing on parameters such as seawater salinity (Yang et al., 2019), ocean acidification (Gopika, Kumar, & Ramesh, 2022), and cognitive ocean networks (CONet)(Lu et al., 2019). Seawater salinity varies spatiotemporally due to factors such as rainfall, evaporation, and depth. Therefore, predicting ocean environmental factors requires multiple input parameters(Yang et al., 2019). To address this, a framework called *Ocean of Things (OoT)* was proposed in (Yang et al., 2019), consisting of three layers for salinity prediction. Similarly, (Lu et al., 2019) presents the *Cognitive Ocean Network (CONet)*, which adopts an edge–fog–cloud layered computing approach.

A five-layer IoT architecture for ocean acidification monitoring was proposed in (Gopika et al., 2022), that includes: (i) a sensing layer (comprising sensing components), (ii) a network layer (connecting sensors using LoRa and OceanNet (Rao, Ramesh, & Rangan, 2016)), (iii) a middleware layer (for real-time data processing, caching, and control), (iv) an application layer (web servers and database query managers), and (v) a business layer (visualization and system management). Another ocean environment monitoring system (Mishra, Singh, & Chaudhary, 2023) involves sensor nodes to collect ocean parameters and use protocols like ZigBee to transmit data to relay sink nodes and, GPRS wireless network for base station connection. The focus was on improving the efficiency and effectiveness of the monitoring system by optimizing energy consumption and balancing utilization by developing algorithms, protocols and routing mechanisms.

Another ocean monitoring system (Mishra et al., 2023) involves sensor nodes for collecting ocean parameters, with data transmitted via ZigBee to relay sink nodes, and then forwarded to a base station using a GPRS wireless network. This system focuses on improving efficiency and effectiveness by optimizing energy consumption and balancing resource utilization through the development of algorithms, communication protocols, and routing mechanisms.

## 3 AI for Marine IoT Systems

This section outlines the need for and role of AI in ocean monitoring, and explains why it is essential to monitor the ocean using Marine Internet of Things (MIoT) systems. The ocean supports more than 90% of global fisheries, plays a crucial role in the biological and carbon cycles (Ford et al., 2022), and provides livelihoods to a large number of people through fishing, tourism, and research (Virto, 2018). It also helps regulate the global climate and produces nearly 50% of the oxygen required by humans (Virto, 2018).

However, ocean health is increasingly threatened by pollution, ice melting, oil spills (Anand & Vinodini Ramesh, 2021), and ocean warming. These factors negatively impact marine life and human communities, contributing to broader climate change. Maintaining the health of ocean ecosystems is now a pressing global concern and essential for human survival. Therefore, it is critical to deploy technology-enabled systems to monitor the ocean, collect key environmental parameters, analyze both positive and negative changes, develop responsive solutions and alert mechanisms, and inform policy-making for sustainable ocean practices.

Similarly, performing inference at the network's edge requires increased capability to support AI algorithms. Deng and colleagues (Deng et al., 2020) categorize edge intelligence into two types: (i) *intelligence-enabled edge computing* (AI for the edge), which focuses on developing optimal solutions to the key challenges of edge computing; and (ii) *AI on the edge*, which involves building, training, and deploying models directly on edge devices. Recent research has also introduced hybrid approaches to collaborative edge intelligence, involving coordination between edge and cloud resources (Zhou et al., 2019). Zhou et al.(Zhou et al., 2019) further define multiple levels of edge intelligence, ranging from cloud–edge collaboration to fully on-device processing. They also introduce the concept of *intelligence-enabled edge computing (IEC)*, which emphasizes optimization strategies for efficient AI deployment at the edge(Zhou et al., 2019; Deng et al., 2020).

### 3.1 AI for Ocean Emergency and Non-Emergency Services

Monitoring ocean parameters and analyzing the data can create significant opportunities in areas such as the safety and livelihood of coastal communities and fishermen. Providing timely information to relevant stakeholders and coastal populations can influence their actions, leading to meaningful improvements in the overall ocean health ecosystem. For example, activities such as preventing ocean pollution, regulating fishing practices, promoting alternative inland fish cultivation, and reducing fish wastage caused by inadequate storage facilities can all contribute to preserving ocean health.

Recent technological advancements have accelerated our understanding of how humans use–and misuse–ocean ecosystems. Obtaining scientific data is crucial to understanding the local and global impacts of human activities on the ocean (Lubchenco & Haugan, 2023). Another major concern is the threat of ocean-related hazards, which lead to coastal disasters such as floods, erosion, high tides, storm surges, and tsunamis. Both small and large-scale changes occur within the ocean and its ecosystems over space and time (Lubchenco & Haugan, 2023). Therefore, more data are needed to better understand ocean resources and promote responsible stewardship. Effective implementation and utilization of marine Internet of Things systems can provide valuable feedback from the ocean to human stakeholders.

The growing availability of ocean data presents significant opportunities and paves the way for a digital ocean ecosystem. To realize this vision of a connected ocean, new communication pathways must be developed.

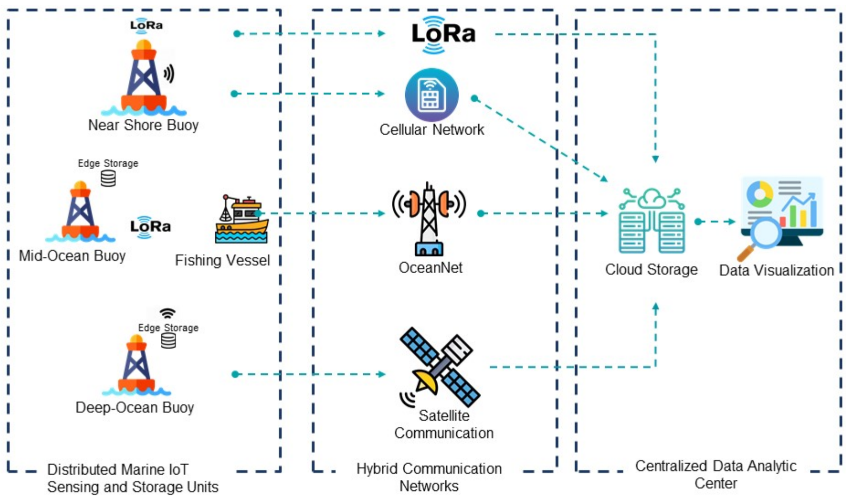


**Fig. 1.** Marine IoT(MIoT) Communication Architecture (S et al., 2024) for Ocean Monitoring and to Enhance Safety of Fishermen

**Table 1.** Hybrid Communication Sectors and Communication Network Details

| Region | Distance | Communication | Technology | Cost |
|---|---|---|---|---|
| Nearshore sector | 15 km | Cellular network | 4G/5G | Low |
| Mid-Ocean sector | 70 km | OceanNet | Long-Range Wi-Fi | Medium |
| Deep Ocean sector | 120 km | Satellite | Satellite | High |

### 3.2 MIoT System Hybrid Communication Architecture

The proposed hybrid communication architecture is an extension of the Marine IoT (MIoT) network (S et al., 2024) with local storage, learning, and processing capabilities, as shown in Figure 1. The communication network architecture is the same as that of the MIoT network, which consists of a hybrid set of networks such as the cellular network, OceanNet (Rao et al., 2016), and satellite communication. The network is designed to collect ocean parameters for analytics and to enhance both the livelihoods and safety of fishermen, as well as the health of the ocean ecosystem. Depending on the distance from the coast, the availability of fixed infrastructure, and the accessibility of potential networks, the ocean region is divided into three distinct sections. The three regions on which we are focused are (i) the nearshore regions/nearshore sector: which can utilize cellular network and the offshore mobile communication network OceanNet (Rao et al., 2016) (which is developed to support the coastal fisher communities); (ii) for the mid region/ Mid-Ocean sector - OceanNet (Rao et al., 2016) can be utilized to collect information from the MIoT systems to the analytical center. The network formed this way might experience intermittent connectivity and density and often result in opportunistic communication using store-carry-forward mechanism (Anand, Ramesh, et al., 2018); (iii) For the deep ocean regions satellites (such as Low Earth Orbit(LEO)) can be used to exchange information between the IoT systems in that region, as other network alternatives are not practical there. Table 1 shows the details such as distance from shore, connectivity, cost etc (S et al., 2024). The multi-communication strategy facilitates efficient data collection in maritime areas, enabling the design of an ocean observatory system for various purposes, thereby achieving SDGs 14.1 and 14.3.

### 3.3 Distributed Marine IoT Sensing Units

To effectively collect data for ocean monitoring, it is essential to have affordable and modular autonomous ocean observation units with standardized communication protocols to ensure improved interoperability (Whitt et al., 2020). The Marine IoT autonomous data acquisition unit includes:

- **IoT Ocean Sensing Unit on Fishing Vessels:** Sensing units installed on fishing vessels help monitor and gather data from the ocean throughout the regions covered during a fishing trip. The collected ocean parameters, along with geo-locations, can be stored in a controller installed on the vessel. This controller acts as a storage unit and enables data processing at the edge, without the need to transfer it immediately to the analytical center on shore.
- **IoT Ocean Sensing Unit on Buoys:** IoT ocean monitoring sensing units can be mounted on *buoys* (Gopika et al., 2022), which are floating platforms typically anchored to the seabed. An additional fixed storage unit is required as part of the ocean monitoring system attached to the buoys.

### 3.4 Intelligent Layer for Edge Processing Storage and Data Dissemination

A multi-faceted approach is required to develop an emergency warning system for coastal fishing communities and for coastal regions that attract tourists who visit beaches daily for recreation and family activities. This research focuses on developing a people-centered, multi-hazard early warning and information dissemination system, along with strategies to enhance resilience, reduce vulnerability, and increase safety. Due to intermittent connectivity, the system will rely on asynchronous cloud support. The processing and storage components are categorized into three layers, namely: the one closest to the IoT, i.e., the Edge Storage and Processing Unit (ESPU); the Analytic Center Processing Unit; and Cloud Processing. The details of the various components of the processing and storage sub-system are listed below:

- **Edge and Fog Layers for Local Storage and Processing**: In an ocean environment, it is always not possible to have a real-time communication option and hence local storage and processing units are necessary close to the IoT units. This helps to store the sensed data locally near the IoT units. It helps prevent data loss. Edge storage is necessary in every data acquisition IoT unit to prevent data loss and for efficient monitoring. Figure 2 shows the Knowledge-Building Layer, where the edge layer maintains only local knowledge, while the fog layer aggregates broader-area knowledge collected from multiple IoT units.
- **Data Analytics Center:**The data at the edge layer needs to be periodically transmitted to the analytic centre. It can even be quantized data, as the captured parameters usually change over time; this is especially applicable in the case of buoy-based data collection units, where the location is largely fixed. The collected data will be added to the dataset to improve deep learning models for spatio-temporal data analysis and the prediction of impending disasters.
- **Centralized Cloud Enabled Repository Layer**:Historical and multi-sensor data can be stored in the cloud layer, which is primarily used for preserving historical records and supporting data analysis as required. These data can be used to develop robust forecasting models in the future.

### 3.5 Data Dissemination

Data dissemination is organized into four communication verticals covering both architecture and stakeholder considerations, as detailed below:

- Warning Dissemination System: Disseminating risk knowledge to all stakeholders requires designing a common alert mechanism, and it is highly necessary to have local communities' help and suggestions in designing interventions that align with local needs, knowledge, and perspectives. Because warning has to be aligned with the knowledge, experience and perspectives

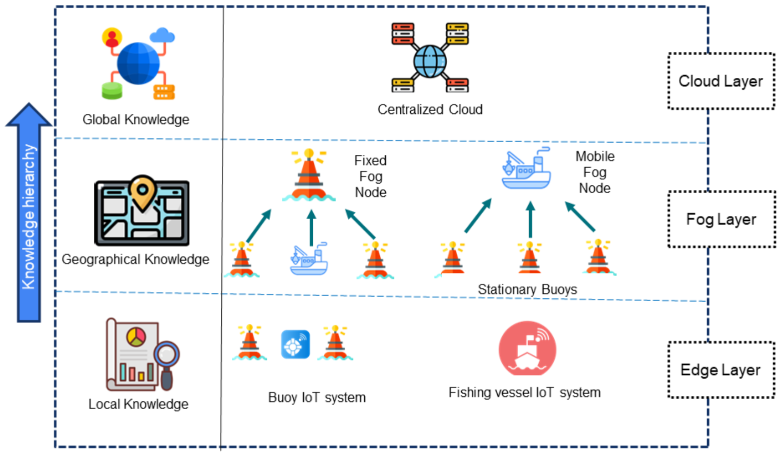


**Fig. 2.** Data Analytics Hierarchy of proposed multi-layer AI for MIoT System

of the coastal communities. If they are aware of how to interpret and perceive a warning level, their actions will be well aligned to take action. Hence, it requires a co-design approach and focused group discussions.

– Data Dissemination Network: Real-time (zero-latency), low-latency, far-real-time, and high-latency message transmission strategies are required.
– Vertical and Horizontal information dissemination: Horizontal information dissemination is always needed; however, it is one of the problems as well during an emergency because it can spread assumptions and fake messages, which can hinder effective response and rescue strategies, as fake news and fake information prevent optimal use of time and resources during an emergency. So it is highly necessary to receive direct reception of emergency warnings from the disaster managers of the state. Chatbots or common protocols allow and ensure communities understand the risk and respond to different alerts or warnings properly because fake warnings several times can demotivate people to take proper action on any warnings.
– Stakeholder engagement and responsibility sharing: Stakeholder engagement and identifying community members to share roles and responsibilities are necessary for any sustainable solutions and initiatives. Social cohesion and vulnerability index mapping are also required for proper stakeholder engagement, capacity building, and role identification to increase the resilience of the coastal fisher communities (Anand, Raj, Sai, N Rao, & Vinodini Ramesh, 2023). Similarly, the coastal communities are prone to natural disasters; hence, adaptation planning strategies should involve the younger generation in coastal communities. Social contagion is considered a powerful tool, as people tend to copy the thoughts, feelings, and actions of their socially connected peers (Airoldi & Christakis, 2024). Hence, it is necessary to identify the right individuals from the community who can form useful community-level social networks and initiate desirable cascades of actions at the community level.

### 3.6 MIoT Applications

Ocean observatory system paves the way for new ocean and coastal community-related projects :

- **Oil Spill:** Oil spills are one of the most common forms of marine pollution (Anand & Vinodini Ramesh, 2021), and they can significantly affect fisheries, maritime tourism, transportation (Li et al., 2020), marine ecosystems, local economies, and coastal communities (Zhang et al., 2019). While oil spill waste management and holistic computational frameworks for oil spill response already exist (Mohammadiun et al., 2021), more advanced intelligent techniques and IoT systems are needed for accurate detection and tracking of oil spills. In particular, machine learning and deep learning can be used to assess risks and predict the spread and impact of spills.
- **Sea Ice Detection:** Sea ice poses a significant threat to marine navigation and transportation safety (Li et al., 2020). AI and other ocean observation systems can play a crucial role in detecting changes in sea ice distribution and generating timely alerts, as well as providing guidance on the necessary measures to ensure safe navigation and transportation.
- **Ocean Acidification Monitoring System**: Sensing units installed on buoys and fishing vessels can be utilized to monitor ocean acidification levels effectively.
- **Ocean Wave-Height Forecasting**: Ocean warming has several impacts on the Earth system and is closely linked to the water and carbon cycles (Cheng et al., 2022). It can alter surface salinity and contribute to global ocean heat uptake (Cheng et al., 2022). Ocean warming is responsible for more than one-third of global sea level rise, leading to saltwater intrusion, coastal erosion, flooding in low-lying areas, and the intensification of tropical cyclones. AI-enabled marine IoT systems can assist in forecasting ocean wave height.
- **Ocean Emergency Warning Systems:** Ocean warming, oil spills, pollution, and both natural and human-induced ocean-related hazards have a significant impact on coastal fishing communities. An Ocean Emergency Warning System is crucial for the safety of fishermen and the protection of global fisheries. Such systems can be used to disseminate timely emergency alerts and warnings to fishermen and coastal populations, helping to save lives and reduce risk.
- **Sustainable Fish Catch Information:** If sufficient information on fish availability and distribution in the ocean is available, enhanced fishing strategies can be developed—such as when to plan fishing trips and where to go. This data can also inform policies that promote sustainable fishing practices.
- **Ocean Pollution Monitoring System:** Marine plastic pollution is one of the most significant challenges affecting ocean health. Monitoring and controlling ocean pollution remains an open research area. Effective management and mitigation of marine plastic pollution require a comprehensive assessment of its status and trends, with appropriate spatial and temporal resolution. Evaluating the regional and global extent of plastic pollution,

along with its ecological risks, is crucial for ensuring long-term ocean sustainability (Shim et al., 2022).

## 4 Role of AI Technologies for MIoT Applications

AI can play a pivotal role in numerous ocean-related applications, such as emergency warning systems, ocean parameter monitoring, species distribution analysis, sustainable fishing practices, pollution detection, marine organism monitoring, and forecasting of various parameters that impact ocean ecosystems.

### 4.1 AI Techniques and Approaches

The following AI techniques and approaches can support MIoT systems in ocean-related applications.

**Deep Learning and Machine Learning** :Deep learning and machine learning are essential for extracting accurate patterns from collected data. These insights can be utilized by ocean emergency warning units to send alerts to relevant stakeholders, including fishermen at sea. They can also inform the development of new guidelines to address ocean pollution and overfishing. By enabling direct learning from data, deep learning can significantly improve the accuracy of classification and prediction as the volume of available data increases over time. It can also be used to identify high-risk species and educate fishermen about their role in the ecosystem.

**Cognitive Computing** :To develop intelligence and decision-making abilities, computers need the capability to emulate human thinking (Chen, Herrera, & Hwang, 2018). Cognitive computing is derived from the human learning process and is therefore considered superior to traditional machine learning in reasoning tasks. A smart IoT system embedded with cognitive computing can support decision-making and provide critical suggestions to humans (Chen et al., 2018). Existing case studies on smart city applications are promising, as many recent implementations have leveraged cognitive computing to enable context-aware predictions and intelligent decision-making (Al-Quayed et al., 2025).

**Reinforcement learning** :Similar to cognitive computing, reinforcement learning is also inspired by the human learning process (Chen et al., 2018). It supports long-term improvements in machine intelligence by learning through rewards and penalties for incorrect outputs. The ambient environment is also a critical factor in the human learning process (Chen et al., 2018).

**Federated Learning** :In applications where privacy is a concern—such as sustainable fishing practices—and where large-scale data processing is required in deep ocean environments, it is highly recommended to use privacy-preserving techniques such as federated learning. In particular, for deep ocean monitoring, federated computing is preferable, as federated learning enables edge nodes to collaboratively train models without sharing raw data, thereby enhancing both privacy and efficiency.

**Tiny ML** :Tiny Machine Learning (TinyML), similar to Federated Learning, enables learning capabilities directly on IoT devices. The goals of the TinyML framework are to run machine learning algorithms on-device, reduce costs, and provide low-latency services. It also enhances privacy and improves data security. TinyML is particularly well-suited for environments with limited resources, offering the ability to analyze IoT data locally. This allows each IoT device to operate more intelligently by incorporating ML algorithms within the device itself (Dutta & Bharali, 2021).

**Large Language Models** :Recent advances in large language models (LLMs) can be leveraged to develop intelligent solutions for data collection and transmission to shore-based systems for further processing. LLMs have enabled the creation of highly intelligent data collection agents that can operate at edge nodes. Small-scale LLMs are particularly suitable for deployment at the edge, especially in scenarios where power, storage, and computing capabilities are limited.

### 4.2 Challenges and Open Research Problems

There are many challenges in realizing the envisioned ocean emergency warning system. The first and foremost challenge is data availability. Currently, very little data is available for the Indian context to support such systems. Data is essential for developing learning algorithms and models to predict ocean conditions, which can be utilized for ocean emergency warning dissemination. Developing and deploying Marine IoT systems may require years of effort to collect the necessary input for these developments. The convergence of AI, IoT, and data analytics can improve real-time decision-making (Elgazzar et al., 2022). Since AI can learn from data generated through IoT devices, data analytics is an indispensable and significant aspect of any IoT deployment across various domains that support intelligent decision-making (Elgazzar et al., 2022). In this context, data analytics can play a crucial role in forecasting various parameters and producing early inferences, helping stakeholders make timely decisions.

When handling ocean data using various sensors and IoT devices coupled with AI, it is essential to incorporate and leverage robust routing protocols, computing processes, and ensure access to appropriate tools. Future work should also focus on model-context protocols and AI agent frameworks while building the knowledge base necessary to monitor and alert the relevant stakeholders. This will enable timely actions to reduce human activities that accelerate the degradation of the ocean and enhance the safety and livelihoods of coastal communities.

## 5 Conclusions

Ocean monitoring systems coupled with AI can offer significant benefits to people living in coastal regions. Advanced AI-based analysis and multi-layered computing architectures can provide timely information while maintaining network reliability. AI for Marine IoT can enhance traditional Maritime IoT systems by extracting greater value from the collected data. AI-powered marine monitoring solutions can support Sustainable Development Goal #14 by enabling intelligent, continuous monitoring of ocean conditions. Moreover, the hybrid communication architecture of MIoT ensures enhanced real-time insights from the diverse data collected from the ocean. This has the potential to benefit various sectors, including marine safety and warning systems, aquaculture, and fishing operations.

Future developments include designing AI models for ocean monitoring and integrating chatbot systems to effectively deliver warning messages and other critical information inferred from Marine IoT data. As part of our ongoing work, we plan to deploy the system in a coastal village in Kerala, India, leveraging the existing OceanNet infrastructure. Improved spatio-temporal analysis of ocean characteristics can also inform policy-making and encourage behavioral changes in coastal communities, promoting a more harmonious relationship with the ocean.

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## References

Airoldi, E. M., & Christakis, N. A. (2024). Induction of social contagion for diverse outcomes in structured experiments in isolated villages. *Science*, *384*(6695), eadi5147. Retrieved from https://www.science.org/doi/abs/10.1126/science.adi5147 doi: https://doi.org/10.1126/science.adi5147

Ali, A., Fathalla, A., Salah, A., Bekhit, M., Eldesouky, E., et al. (2021). Marine data prediction: an evaluation of machine learning, deep learning, and statistical predictive models. *Computational Intelligence and Neuroscience*, *2021*.

Al-Quayed, F., Humayun, M., Alnusairi, T. S., Ullah, I., Bashir, A. K., & Hussain, T. (2025). Context-aware prediction with secure and lightweight cognitive decision model in smart cities. *Cognitive Computation*, *17*(1), 1–12.

Anand, S., Raj, D., Sai, A. A., N Rao, S., & Vinodini Ramesh, M. (2023). Techno-social synergy for disaster resilience in coastal communities: A sustainable approach. In *Proceedings of the 24th international conference on distributed computing and networking* (pp. 366–371).

Anand, S., & Ramesh, M. V. (2021). Multi-layer architecture and routing for internet of everything (ioe) in smart cities. In *2021 sixth international conference on wireless communications, signal processing and networking (wispnet)* (pp. 411–416).

Anand, S., Ramesh, M. V., et al. (2018). Performance analysis of delay tolerant network routing protocols in a heterogeneous vehicular network. In *2018* *ieee international conference on computational intelligence and computing research (iccic)* (pp. 1–6).

Anand, S., & Vinodini Ramesh, M. (2021). An iot based disaster response solution for ocean environment. In *Adjunct proceedings of the 2021 international conference on distributed computing and networking* (pp. 19–24).

Chen, M., Herrera, F., & Hwang, K. (2018). Cognitive computing: Architecture, technologies and intelligent applications. *IEEE Access*, *6*, 19774-19783. doi: https://doi.org/10.1109/ACCESS.2018.2791469

Cheng, L., von Schuckmann, K., Abraham, J. P., Trenberth, K. E., Mann, M. E., Zanna, L., ... others (2022). Past and future ocean warming. *Nature Reviews Earth & Environment*, *3*(11), 776–794.

Deng, S., Zhao, H., Fang, W., Yin, J., Dustdar, S., & Zomaya, A. Y. (2020). Edge intelligence: The confluence of edge computing and artificial intelligence. *IEEE Internet of Things Journal*, *7*(8), 7457–7469.

Dutta, L., & Bharali, S. (2021). Tinyml meets iot: A comprehensive survey. *Internet of Things*, *16*, 100461.

Elgazzar, K., Khalil, H., Alghamdi, T., Badr, A., Abdelkader, G., Elewah, A., & Buyya, R. (2022). Revisiting the internet of things: New trends, opportunities and grand challenges. *Frontiers in the Internet of Things*, *1*, 1073780.

Fleming, L. E., Maycock, B., White, M. P., & Depledge, M. H. (2019). Fostering human health through ocean sustainability in the 21st century. *People and Nature*, *1*(3), 276–283.

Ford, D. A., Grossberg, S., Rinaldi, G., Menon, P. P., Palmer, M. R., Skákala, J., ... Ciavatta, S. (2022). A solution for autonomous, adaptive monitoring of coastal ocean ecosystems: Integrating ocean robots and operational forecasts. *Frontiers in Marine Science*, *9*, 1067174.

Gopika, K., Kumar, N., & Ramesh, M. V. (2022). Iot based ocean acidification monitoring system with ml based edge analytics. In *2022 4th international conference on inventive research in computing applications (icirca)* (pp. 345–353).

Gulseven, O. (2020). Measuring achievements towards sdg 14, life below water, in the united arab emirates. *Marine Policy*, *117*, 103972.

Krishnan, P., Najeem, J. S., & Achuthan, K. (2017). Sdn framework for securing iot networks. In *International conference on ubiquitous communications and network computing* (pp. 116–129).

Kuehn, J., Abadie, S., Liquet, B., & Roeber, V. (2023). A deep learning superresolution model to speed up computations of coastal sea states. *Applied Ocean Research*, *141*, 103776.

Li, X., Liu, B., Zheng, G., Ren, Y., Zhang, S., Liu, Y., ... Wang, F. (2020). Deep-learning-based information mining from ocean remote-sensing imagery. *National Science Review*, *7*(10), 1584–1605.

Lu, H., Wang, D., Li, Y., Li, J., Li, X., Kim, H., ... Humar, I. (2019). Conet: A cognitive ocean network. *IEEE Wireless Communications*, *26*(3), 90–96.

Lubchenco, J., & Haugan, P. M. (2023). *The blue compendium: From knowledge* *to action for a sustainable ocean economy.* Springer.

Mishra, J. P., Singh, K., & Chaudhary, H. (2023). Research advancements in ocean environmental monitoring systems using wireless sensor networks: a review. *TELKOMNIKA (Telecommunication Computing Electronics and Control)*, *21*(3), 513–527.

Mohammadiun, S., Hu, G., Gharahbagh, A. A., Li, J., Hewage, K., & Sadiq, R. (2021). Intelligent computational techniques in marine oil spill management: A critical review. *Journal of Hazardous Materials*, *419*, 126425.

Nash, K. L., Van Putten, I., Alexander, K. A., Bettiol, S., Cvitanovic, C., Farmery, A. K., ... others (2022). Oceans and society: feedbacks between ocean and human health. *Reviews in Fish Biology and Fisheries*, 1–27.

Pradeep, P., & Krishnamoorthy, S. (2019). The mom of context-aware systems: A survey. *Computer Communications*, *137*, 44–69.

Pradeep, P., Krishnamoorthy, S., Pathinarupothi, R. K., & Vasilakos, A. V. (2021). Leveraging context-awareness for internet of things ecosystem: Representation, organization, and management of context. *Computer Communications*, *177*, 33–50.

Rao, S. N., Ramesh, M. V., & Rangan, V. (2016). Mobile infrastructure for coastal region offshore communications and networks. In *2016 ieee global humanitarian technology conference (ghtc)* (pp. 99–104).

S, V., Sabarinath, S., Anand, S., & Rao, M. V., Sethuraman Ramesh. (2024). Miot: An iot system for dynamic ocean monitoring and data collection. In *2024 sixth international conference on wireless communications, signal processing and networking (wispnet).*

Shim, W. J., Kim, S.-K., Lee, J., Eo, S., Kim, J.-S., & Sun, C. (2022). Toward a long-term monitoring program for seawater plastic pollution in the north pacific ocean: Review and global comparison. *Environmental Pollution*, 119911.

Virto, L. R. (2018). A preliminary assessment of the indicators for sustainable development goal (sdg) 14 “conserve and sustainably use the oceans, seas and marine resources for sustainable development”. *Marine Policy*, *98*, 47–57.

Whitt, C., Pearlman, J., Polagye, B., Caimi, F., Muller-Karger, F., Copping, A., ... others (2020). Future vision for autonomous ocean observations. *Frontiers in Marine Science*, *7*, 697.

Yang, J., Wen, J., Wang, Y., Jiang, B., Wang, H., & Song, H. (2019). Fog-based marine environmental information monitoring toward ocean of things. *IEEE Internet of Things Journal*, *7*(5), 4238–4247.

Zhang, B., Matchinski, E. J., Chen, B., Ye, X., Jing, L., & Lee, K. (2019). Marine oil spills—oil pollution, sources and effects. In *World seas: an environmental evaluation* (pp. 391–406). Elsevier.

Zhou, Z., Chen, X., Li, E., Zeng, L., Luo, K., & Zhang, J. (2019). Edge intelligence: Paving the last mile of artificial intelligence with edge computing. *Proceedings of the IEEE*, *107*(8), 1738–1762.