OPINION
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The Role of Artificial Intelligence Algorithms in Marine Scientific Research

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INTRODUCTION

The study of marine science is vital to the survival and development of humanity. On the one hand, the oceans act as a global climate regulator, supplying 70% of oxygen and 87.5% of water vapor to the atmosphere while storing large amounts of heat (Petterson et al., 2021). On the other hand, the oceans act as an important part of the global physical system, in which changes in mass-energy, biological, and geological processes can have a significant impact on marine and terrestrial life (Du et al., 2021). However, lacking knowledge of important areas such as the deep sea and polar regions, humans cannot yet decipher certain specific phenomena and patterns in the oceans.

Artificial Intelligence (AI) algorithms are trained on mathematical models with a specific structure using a large amount of statistical data to obtain a fitter that contains the statistical features inherent in the training data. It can be applied to solve optimization problems. As a result, AI algorithms have been very successful in a number of scientific fields, such as autonomous driving (Khan et al., 2021), medical imaging (Hickman et al., 2022), geophysics (Yu and Ma, 2021), and nanoscience (Jiang et al., 2022).

As marine scientific research enters a new era of intelligence and constantly improving marine data, AI can effectively tap into the potential information contained in vast amounts of data. As a result, it is also gaining more and more attention from marine researchers (Logares et al., 2021). The integration of AI technology with traditional models to improve marine safety has also been proven (Khayyam et al., 2020). In addition, data processing problems in marine pollution (Agarwala, 2021), wind and wave energy (Gu and Li, 2022) research can be solved using AI algorithms.

Therefore, this paper reports on the prospects of applying AI algorithmic methods in marine scientific research, mainly monitoring marine biodiversity, deep-sea resource modelling, and predicting SST, tide level, sea ice, and climate. In addition, the paper discusses the current problems of AI algorithms in processing marine data and building predictive models.

RESEARCH AND APPLICATION OF AI IN MARINE SCIENTIFIC RESEARCH

Monitoring Marine Biodiversity

Due to the complexity and specificity of marine ecology, the use of only traditional manual solutions poses great challenges for monitoring the ecological dynamics of species. Therefore, researchers have been working to build monitoring solutions for automatic identification, classification, and prediction using AI algorithms. Allen et al. (Allen et al., 2021) trained a deep convolutional neural network to identify humpback whale songs in over 187,000 hours of acoustic data collected over a 14-year period at 13 different monitoring sites in the North Pacific (**Figure 1A**). The model successfully detected 75s audio segments containing humpback whale songs with an average accuracy of 0.97 and an average area under the receiver operating characteristic curve of 0.992. These results validate the feasibility of applying deep learning models to identify highly variable signals over a wide range of spatial and temporal scales. In order to solve the problem of classifying species in the images detected in the camera system, Allken et al. (Allken et al., 2019) introduced a deep learning network and developed a new training method. In experiments to classify blue whiting, Atlantic herring, and Atlantic mackerel, the results showed a classification accuracy of 94%. As shown in **Figure 1B**, Vanesa et al. combined machine learning and deep learning networks to integrate video/image annotation tools for a pipeline of visual data analysis (Lopez-Vazquez et al., 2022). Their experimental results showed that the scheme was able to obtain comprehensive information on the spatial distribution and temporal dynamics of the ocean in time, with an accuracy of 76.18% of their results.

AI algorithms can provide a large amount of multi-parameter information in monitoring complex marine ecosystems. It provides an effective solution for building a robust and widely distributed marine ecological monitoring network.

Modeling of Deep-Sea Resources

The modeling of seabed resources has always been an important topic in marine scientific research. The combination of artificial intelligence algorithms to build a novel 3D modeling approach has an important role in the re-transportation of deep-water sediments and the reconstruction of the bottom shape of the seabed. Neettiyath et al. (Neettiyath et al., 2019) described a method to estimate the volume distribution of cobalt-rich manganese crusts (Mn-crusts) by combining multi-modal sensor data collected using an autonomous underwater vehicle

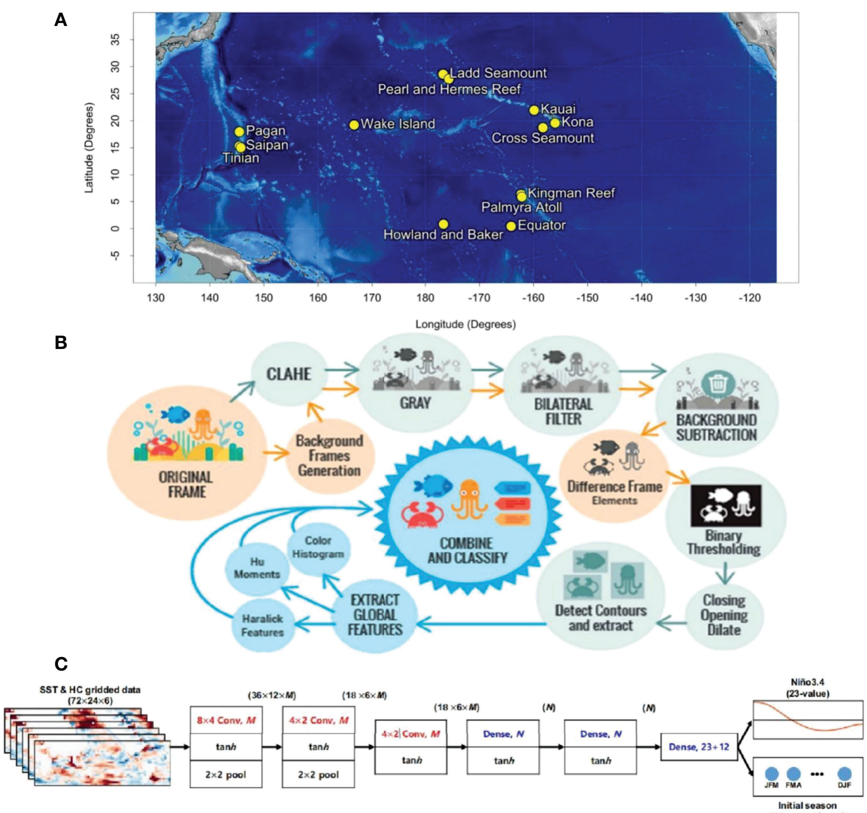

FIGURE 1 | **(A)** Map of the 13 acoustic recording locations. (Allen et al., 2021). **(B)** Image processing pipeline (Lopez-Vazquez et al., 2022). **(C)** Architecture of the All-season CNN (A_CNN) model for ENSO forecasts (Ham et al., 2021).

(AUV). The AUV uses a sub-bottom sonar to calculate the thickness of Mn-crusts and a light-profile mapping system to generate 3D color reconstructions of the seafloor. A machine learning classifier was used to classify the 3D map into one of 3 types of seafloor-crust, sediment, and nodules. Percentage coverage of Mn-crusts and estimates of the mass of Mn-crusts per unit area were determined along AUV transects based on inferred thicknesses. This approach provides a novel method to estimate the distribution of Mn-crusts over large areas. De et al. (De La Houssaye et al., 2019) combined modern programming techniques in computer vision, machine learning, and deep learning applications with traditional geoscientific linear regression architectures. Then the data were trained end-to-end to predict the O^{18}/O^{16} isotope ratio as an independent global proxy for the geological age of marine sediments over time. Ratto et al. proposed an alternative approach to ocean ray tracing through a combination of machine learning and generative adversarial networks (GAN) (Wang et al., 2017). Their experimental results demonstrate that GANs trained on thousands of small scenes generated by ray-tracing models can be used to generate megapixel scenes faster with a consistent spectrum and minimal processing artifacts (Ratto et al., 2019).

The use of AI algorithms to overlay and display different ocean state data on top of a 3D platform enables the management, integration, and analysis of ocean basic, target, and derived data. It provides a common and standardized tool for activities such as studying the structure and function of ocean systems and revealing the various patterns of ocean phenomena.

Prediction of Ocean Parameters

Sea surface temperature (SST), tide level, and sea ice are crucial parameters of the global ocean that can profoundly affect climate and marine ecosystems. To achieve accurate and comprehensive predictions for the short and medium-term domains of SST, Xiao (Xiao et al., 2019) proposed a spatiotemporal deep learning model that captures the correlation of SST across time and space. The model uses convolutional long and short-term memory as the building block and is trained in an end-to-end manner. Experiments using 36 years of satellite SST data in the East China Sea sub-region show that the proposed model outperforms persistence models when judged using multiple methods. It means that the proposed model is highly promising for accurate, convenient short, and medium-term daily SST field predictions. Riazi (Riazi, 2020) proposed a simple and effective deep neural network that can estimate future tidal levels based on the forces and factors affecting the tidal range. The main advantages of the proposed method are that the input layer can be kept as small as possible and the input data can be accessed. In addition, one network can be used for different beaches as the input data is based on the primary cause of tides. Gregory (Gregory et al., 2020) predicted the September mean sea ice extent in the Arctic region. They used a complex network statistics method that was developed by constructing spatiotemporal homogeneity regions and subsequently deriving remote connections between them. Ultimately, high prediction results are obtained in the Gardiner Islands, Eastern Siberia, and the Kara Sea by exploiting relationships in climatic event series data. Ham et al. developed an all-season convolutional neural network (A_CNN) model. The model predicts the El Niño/Southern Oscillation (ENSO) phenomenon by extracting various complex network metrics (Ham et al., 2021). The results reveal a combination of various climate precursors of ENSO events that act differently over time, thus demonstrating the potential of the A_CNN model as a diagnostic tool (**Figure 1C**).

The above case provides an idea to collect environmental information such as marine meteorology, sea temperature, and sea ice and combine them with predictive analysis by AI algorithms (e.g., support vector machines, long and short-term memory, and convolutional neural networks). And then, the correlation and basic laws of climate and environmental parameters are obtained to predict future trends. This provides support for information services for various marine activities such as marine resource utilization, fisheries, and shipping.

DISCUSSION

In recent years, AI algorithms have been widely used in marine science. A lot of research has been done on AI algorithms in processing marine biodiversity and deep-sea resource data information. Moreover, the research on predicting climate change based on ocean information parameters is also deepening. However, there are still many challenges in using AI algorithms for marine science due to the multi-source nature of current marine data and the complexity of algorithmic models.

Many marine data have been accumulated with the robust operation of various sensors such as satellite remote sensing, buoys, and shipborne instruments. That provides a large amount of sample space for AI algorithms. However, it is difficult to form uniform selection criteria in terms of the quality of sample data and sample richness, which affects the quality of model construction.

Therefore, multiple methods can be used to build data with different dimensions and characteristics during the training data construction process. In addition, as the processing methods mainly depend on the needs of different applications and the cognitive background of the users, the pre-processing data methods have an important influence on the construction of the models. The future development of AI algorithms should be geared toward multiple data formats with a view to reducing the significant amount of time spent on data preparation and thus improving the overall model building efficiency.

There are numerous artificial intelligence algorithmic models, and there is no consensus on which model is more suitable for solving a specific marine data mining problem. Detailed comparisons and conclusions have not yet been drawn, making practical applications difficult. Multiple training strategies are often used, including adjustments to parameters and training methods, and detailed comparisons are made during model construction through a large number of experimental comparisons to build a more accurate model.

AI algorithms in marine science not only improve the efficiency of marine data processing and break the traditional technical bottleneck. Moreover, it is of great significance for discovering marine laws, cognitive marine environment, revealing its interaction mechanism, protecting and using marine resources, marine disaster prevention, and mitigation.

However, as marine data enters the era of information-rich big data, it has the characteristics of diversity and complexity. The current big data analysis methods mainly rely on conventional standard data types and lack the integrated analysis system of scientific data. Therefore, "smart sensors" with high-efficiency data transmission should be continuously developed for automatic sampling. Secondly, an existing marine data management infrastructure should be used to enhance data processing and management to make data machine-readable. Finally, with the in-depth integration of marine science and big data technology, the application and intelligent management of marine information will gradually improve.

AUTHOR CONTRIBUTIONS

MJ: original draft preparation and editing. ZZ: writing— review and project administration. All authors contributed to the article and approved the submitted version.

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