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SYNTHESIS OF ENVIRONMENTAL
EFFECTS RESEARCH

THE USE OF ARTIFICIAL INTELLIGENCE IN OFFSHORE ENERGY AND ENVIRONMENTAL RESEARCH

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INTRODUCTION

Overview of Artificial Intelligence

Artificial intelligence (AI) is the branch of computer science that involves the creation of computer systems capable of performing complex tasks that usually require human intelligence. AI now permeates daily life with tools like chatbots or advanced search engines. However, AI is much more than these applications and has been a core part of scientific research and technological development for longer than most realize. The concept of AI began in the mid-twentieth century as a vision to replicate the way humans think and behave (Wilson 2024). It has evolved over decades with advances in machine learning and deep learning, which allowed for the processing of larger datasets and more complex computations as computers became more powerful.

An AI system consists of various types of algorithms, which are step-by-step procedures designed to solve specific problems, including performance optimization, pattern recognition for identifying trends or features, classification of data into predefined categories, and regression for predicting outcomes based on input data. These systems can be divided based on different criteria, such as types of tasks, methods, or problem domain. The major fields include machine learning, deep learning, natural language processing, computer vision, reinforcement learning, and generative AI (Figure 1). AI is used across a variety of research fields, including studies assessing the environmental effects of offshore energy development.

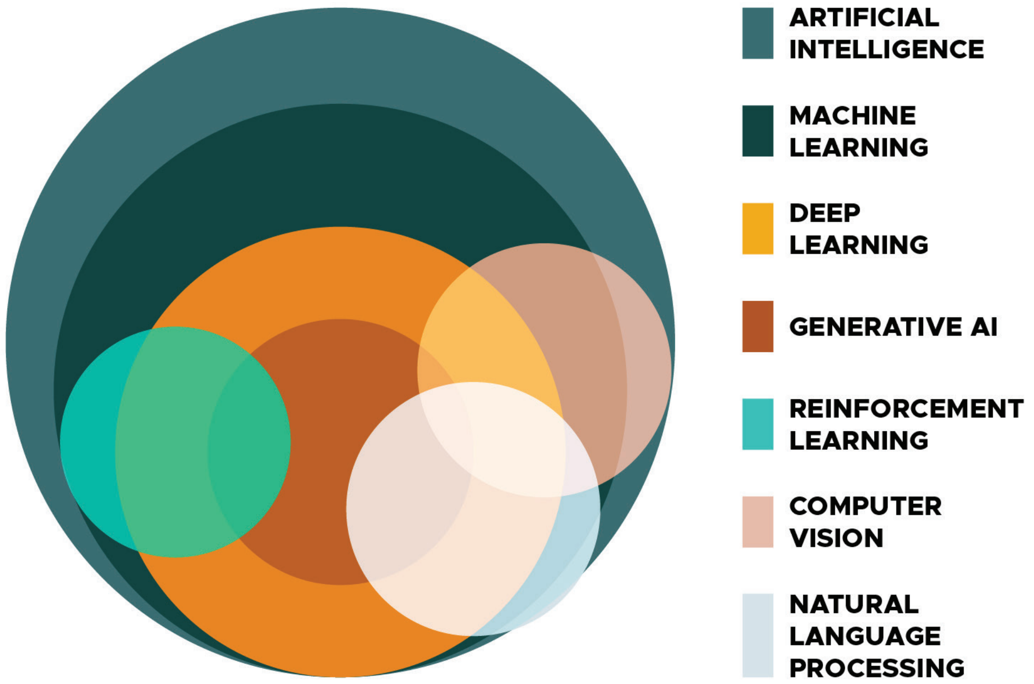

Figure 1. Euler diagram illustrating artificial intelligence taxonomy. Note that fields are not strictly separated but often overlap each other, depending on the nature of the data and research or engineering objectives. *Image from Pacific Northwest National Laboratory.*

Key Terminology

- **Artificial intelligence (AI):** AI involves techniques that equip computers to perform tasks requiring human-like intelligence, such as decision-making, learning, reasoning, and problem-solving.
- **Machine learning:** As a subset of AI, machine learning enables computers to learn from data and improve their performance without explicit programming.
- **Deep learning:** As a subset of machine learning, deep learning uses brain-inspired multi-layered neural networks to learn complex, nonlinear patterns from large datasets.
- **Generative AI:** A type of deep learning designed to generate new realistic content (such as texts, audio, images, and videos) by learning patterns from existing data.
- **Reinforcement learning:** As a type of machine learning, reinforcement learning teaches agents to make decisions by rewarding desired behaviors and penalizing undesired ones as they interact with their environment.
- **Computer vision:** An application domain that uses machine learning, deep learning, or generative AI to enable machines to interpret and understand visual information from the world such as images and videos.
- **Natural language processing:** An application domain that uses machine learning, deep learning, or generative AI to allow computers to understand, interpret, and generate human language, making communications between humans and machines possible.

AI has evolved through several phases, beginning with early rule-based systems and progressing into statistical machine learning in which algorithms detect patterns from data without being explicitly programmed.

Examples of machine learning algorithms:

- **K-nearest neighbors**: An algorithm that classifies a data point based on the majority class among its closest labeled neighbors.
- **Support vector machines**: A method of finding the optimal boundary that maximizes the margin between different classes.
- **Decision trees**: A model that recursively splits data based on feature values to create a tree-like structure for classification or regression.
- **Random forests**: An ensemble method that combines many decision trees to improve predictive accuracy.

These traditional machine learning models were powerful for structured, low-dimensional problems, but they struggled when data became large, high-dimensional, or unstructured. The rise of artificial neural networks, and later deep learning, was motivated by their ability to automatically learn hierarchical representations of data, reducing the need for handcrafted features and allowing models to scale with growing datasets and computational power.

Artificial neural networks—hereafter referred to as neural networks—are computational models inspired by the human brain that mimic how biological neurons communicate and make decisions. Similar to a human brain, where neurons are connected to each other, neural networks also have interlinked "neurons" that represent mathematical functions that take inputs, process the information, and return outputs (Figure 2).

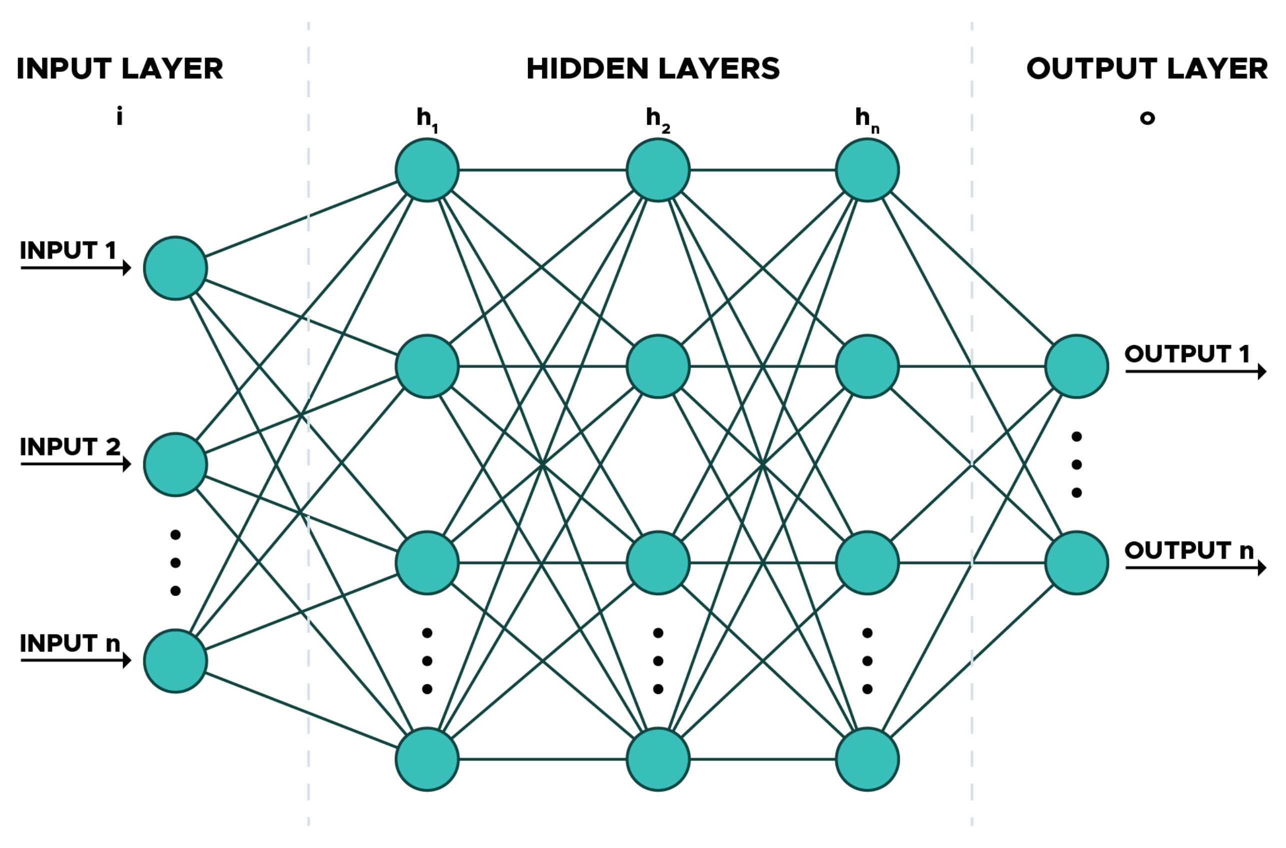

Figure 2. Example of a neural network architecture. *Illustration adapted from Bre et al. (2017)*

Deep learning encompasses a range of network architectures. Table 1 describes eight examples of basic architecture types that are or could be used for offshore energy development. The architectures can also be mixed to form hybrid, multi-architecture models.

Table 1. Examples of different neural network architectures.

Type	Applications	Definition
Feedforward neural network	• *Classification* • *Regression* • *Pattern recognition*	The most basic neural network: information flows in one direction from input to output without any cycles or loops.
Convolutional neural network (CNN)	• *Image classification* • *Semantic segmentation* • *Object detection*	Neural network with a specific architecture, called a convolutional layer, that extracts spatial features and efficiently processes grid-like data such as images.
Recurrent neural network	• *Text summarization* • *Language modeling* • *Time series analysis*	Neural network that processes sequential data, in which the order of elements matters, such as text, audio, video, and time series data.
Autoencoder	• *Dimensionality reduction* • *Feature learning* • *Data compression* • *Anomaly detection*	Neural network with encoder-decoder architecture, in which the encoder compresses input data into a lower-dimensional representation and the decoder reconstructs the original input from the compressed data.
Transformer	• *Text summarization* • *Question answering* • *Text generation* • *Code generation*	Neural network based on self-attention mechanisms to process input sequences, which allows each word to focus on other relevant words in the sequence. Transformers can process all elements in parallel, resulting in faster training time and better long-range dependencies.
Generative adversarial network	• *Image generation* • *Text generation* • *Data augmentation*	Neural network with generator-discriminator architecture. The generator creates new data similar to the training data. The discriminator distinguishes between real data from the existing training data and new data created by the generator.
Diffusion model	• *Image generation* • *Data augmentation* • *Image synthesis* • *Data quality enhancement* • *Data restoration*	Neural network that generates new data by progressively adding random noise to data, then reversing the process to reconstruct it.
Graph neural network	• *Network analysis* • *Recommendation systems* • *Object relationship understanding*	Neural network that represents data, problem domains or environments in a graph structure, organized as nodes and edges. This structure is suitable for learning relationships and dependencies within complex interconnected systems.

Using AI in Offshore Energy and Environmental Research

Potential environmental effects associated with offshore energy development include underwater noise, vessel strike risk, wind turbine collision risk, habitat disturbance, changes to oceanographic dynamics, and changes in water quality (SEER 2022). Environmental stressors from offshore energy development can be categorized according to the different phases of the project life cycle (Table 2). The strategic use of AI during each project phase may help streamline monitoring, research, and impact reduction measures by providing predictive modeling, real-time analysis, and enhanced mitigation. This report focuses on the use of AI for offshore energy and environmental research, which does not encompass the full range of available methods or potential uses in other energy sectors.

Descriptions of Representative AI Applications

- **Image classification**: A fundamental task in computer vision that aims to understand and categorize an image into a specific label.
- **Semantic segmentation**: A fundamental task in computer vision that aims to classify each pixel in an image into a category (like pixel-wise classification), providing a detailed map of objects and regions within the image.
- **Object detection**: A computer vision task that aims to identify and locate objects within an image or video frame by drawing bounding boxes around them.
- **Object tracking**: A computer vision task that aims to follow the movement of detected objects across multiple video frames to understand their trajectories over time.
- **Pose estimation**: A computer vision task that aims to predict the orientation and position of an object or body, often by identifying key points such as joints or angles.
- **Attention mechanisms**: A type of feature learning techniques that are typically integrated inside neural networks (like transformers or CNNs) to help the networks decide what input data to focus on.
- **Ensemble learning**: A machine learning technique that aims to improve prediction accuracy and reliability by combining multiple individual models.
- **Principal component analysis**: A statistical dimensionality reduction method to simplify a large dataset without losing data accuracy.
- **Clustering**: An unsupervised (meaning predefined categories and correct answers are not required) machine learning technique that aims to group unlabeled data into clusters based on their characteristics and similarity.
- **Deep reinforcement learning**: Using deep neural networks to solve reinforcement learning problems, such as estimating the action to take (policy-based) or the value of a state (value-based).
- **Physics-informed neural networks**: A type of neural network that incorporates physical laws and domain knowledge into training so that more accurate and well-generalized predictions can be made compared to traditional neural networks.
- **Large language models**: Models that are pretrained on massive amounts of text data, designed for natural language processing tasks such as understanding, summarizing, and generating human language.
- **Retrieval-augmented generation**: A hybrid approach that combines retrieval (finding relevant information) and generation (creating text), enhancing large language models by adding the ability to search external sources.
- **Explainable AI**: A field of AI that focuses on making models more transparent, trustworthy, and interpretable so that users can assess the model's reasoning and ensure fairness and reliability.
- **Probabilistic graphical models**: Models that represent complex probabilistic relationships among variables with a graph to encode conditional dependencies, enabling better reasoning and inference under the uncertainty.

Table 2. AI techniques with applicable tasks (e.g., monitoring, modeling, mapping, planning, surveying) identified by project phase.

Primary Capability	AI Technique	Project Phase			
		Siting/Pre-construction	Construction	Operation & Maintenance	Decommissioning
Seeing & Detecting	Image classification	Seabed surveys			
	Semantic segmentation	Seabed surveys			
	Object detection			Wildlife monitoring	
	Object tracking			Wildlife monitoring	
	Pose estimation			Wildlife monitoring	
	Attention mechanisms			Wildlife monitoring	
Learning From Data	Ensemble learning	Seabed surveys Species distribution modeling		EMF mapping	
	Neural networks (general)	Seabed surveys	Underwater noise modeling	Entanglement monitoring EMF mapping	Underwater noise modeling
	Principal component analysis			EMF mapping	
	Clustering	Seabed surveys	Underwater noise modeling		Underwater noise modeling
Decision & Planning Tools	Deep reinforcement learning		Vessel route planning		Vessel route planning
Physics Guided Simulation	Physics-informed neural networks		Underwater noise modeling		Underwater noise modeling
Information & Knowledge Support	Large language models	Environmental impact assessment			
	Retrieval-augmented generation	Environmental impact assessment			
Transparency & Understanding	Explainable AI	Species distribution modeling		EMF mapping	
	Probabilistic graphical models	Environmental impact assessment			

Note that these are representative (but not exhaustive) examples based on the papers cited in this document. The listed AI techniques could also be applied to other tasks (not highlighted), or new AI techniques could be added.

PROJECT SITING AND PRECONSTRUCTION

The siting and preconstruction phase of offshore energy development generates large amounts of data and involves complex environmental, regulatory, and logistical challenges (SEER 2022, 2025). AI can be used in the context of seabed surveys, species distribution modeling, and environmental impact assessments to improve the accuracy and efficiency of data processing and decision-making.

Seabed Surveys

Before offshore energy construction, geophysical and hydrographical surveys are conducted to characterize the seafloor, map the seabed, and assess site conditions, typically using optical, acoustic, and hyperspectral sensors. Sensors may be towed at the surface or near the seafloor and may be attached to the hull of the survey vessel and/or to autonomous underwater vehicles. Seabed surveys produce large amounts of data that must be processed and analyzed. While traditional analysis methods are labor-intensive, the integration of AI offers the potential to identify patterns, anomalies, and potential hazards in less time compared to manual interpretation.

Examples:

- **Pillay et al.** (2020) used a clustering algorithm for multibeam backscatter data to create seafloor substrate classifications.
- **Hansen et al.** (2021) applied a random forest algorithm, a type of ensemble learning, to classify boulders from topo-bathymetric lidar data.
- **Mohamed et al.** (2020) trained machine learning classifiers (K-nearest neighbor, support vector machines, and bagging algorithms) independently and combined them to develop three-dimensional (3D) maps of benthic habitats from video camera images.
- **Grabbert et al.** (2024) used a CNN to estimate spectrally derived bathymetry from satellite imagery accounting for factors such as clouds, turbidity, ice, seabed habitat, and sun elevation.

Species Distribution Modeling

Understanding the species presence, habitat use, and ecological drivers that influence spatial distribution and behavioral interactions can inform siting decisions. Species distributions often depend on complex, nonlinear interactions among environmental variables such as temperature, precipitation, and elevation. Random forest applications can model these complex relationships without requiring prior assumptions about the data structure. Predictive modeling, such as species distribution modeling, can be used to assess suitable habitats for species by analyzing species occurrence data and environmental factors to predict where a species is likely to occur or thrive.

In recent years, the focus has shifted from traditional statistical methods (e.g., regression models) to machine learning applications because they provide more flexibility and adaptability. Yet it can be difficult to understand why and how machine learning models make their predictions because only inputs and outputs are visible. To improve the behavior and decisions of models and make them more interpretable by humans, researchers can use explainable AI to reveal the reasoning behind machine learning predictions.

Examples:

- **Ji et al.** (2024), **Valavi et al.** (2021), and **Friedland et al.** (2021) used tree and ensemble learning models, such as random forest and AdaBoost, to manage complex and variable ecological data and provide interpretable results that operate well across variable data conditions.

- **Ryo et al.** (2021) used local interpretable model-agnostic explanation, a type of explainable AI, to interpret local-scale behavior of a species distribution model by removing unnecessary complexity from a global model and better understanding how it arrives at local predictions.

Environmental Impact Assessment

As multiuse spatial planning expands globally, there is a growing need to consider the population-level consequences and cumulative impacts on marine species (Bailey et al. 2014). Environmental impact assessments are a process to identify, predict, evaluate, and mitigate the biophysical, social, and other relevant effects of development proposals prior to major decisions being made (International Association for Impact Assessment; **www.iaia.org**). AI can speed up the management and processing of large datasets in real time, enable faster and more precise analyses of potential environmental impacts, and improve data interpretation, which can reduce uncertainties and enhance confidence in decision-making processes.

Examples:

- **Gerassis et al.** (2021) used Bayesian networks, a probabilistic graphical model that represents a set of variables and their conditional dependencies, to statistically capture relationships among environmental variables, identify relevant patterns, and minimize human bias during evaluation.
- **Arslan et al.** (2024) integrated an energy-specific large language model with multi-source retrieval-augmented generation to enhance decision-making by providing comprehensive energy sector insights through a question answering system.

Research Recommendations for Project Siting and Preconstruction

1. **Fuse multimodal data with multimodal model tasking.**
   Most seabed surveys focus on seabed sediment classification, which depends solely on images, whereas environmental impact assessments are text documents. However, there are benefits to leveraging both inputs. For example, vision language models (a combination of large language models with vision encoder) are a multimodal architecture that process both visual and textual data. They can integrate knowledge from both modalities, such as visual question answering (answer with open-ended questions given an image and a text-based question) and image captioning (automatically generate a text description for a given image).
2. **Develop AI chatbots specialized in offshore energy and environmental research.**
   AI chatbots are used frequently for business and personal applications. However, general chatbots are not one-size-fits-all solutions, where the answers are often too generic and lack expertise. Customized chatbots can handle more nuanced language and workflows, offering more accurate, detailed, and personalized responses with domain-specific knowledge. Chatbots tailored to offshore energy could help with decision-making during the siting and preconstruction phase.

CONSTRUCTION

During the construction phase, stressors to marine life can include construction noise and increased vessel traffic (SEER 2022, 2025). Pile driving monopile or jacket foundations into the seafloor is necessary for long-term stability of these structures, but the high-intensity underwater noise generated during this process can disturb or harm marine mammals, sea turtles, and fish. In addition, transporting materials and personnel to ocean construction sites can increase vessel traffic and the potential for collisions with marine mammals and sea turtles.

Underwater Noise Modeling

Underwater noise pollution is a persistent concern that affects a variety of marine life. However, it is challenging to develop physics-based models to mathematically describe how sound waves move and interact with sea life underwater. These simulations typically take days of computing time and require large amounts of processing power. The use of neural networks can address this computational challenge. Neural networks can also be used for classifying underwater acoustic events and decoding complex marine mammal communication and behavior.

Examples:

- **Mallik et al.** (2024) built a data-driven underwater ocean acoustic propagation and scattering modeling system based on a convolutional recurrent autoencoder network to improve long-term time horizon prediction stability of sound wave dynamics.
- **Coffey et al.** (2019) used region-based convolutional neural networks to detect and analyze ultrasonic vocalizations within a short period of time.
- **Frasier** (2021) used a suite of machine learning algorithms to classify cetacean echolocation clicks from large underwater acoustic data.
- **Gubnitsky et al.** (2025) applied a graph-based clustering algorithm to automatically detect sperm whale communication signals, or codas, by separating groups of clicks based on similarity.

Smart Vessel Routing and Traffic Management

Route planning determines the best possible pathway from a starting point to a destination while avoiding obstacles and meeting certain goals like efficiency, safety, or minimal environmental impact. Traditional route planning algorithms can be used (e.g., Dijkstra, A*, and ant colony algorithms), but there are limitations when applying these algorithms to large areas. Such limitations can be mitigated by reinforcement learning, which is a machine learning application where an AI agent learns to make decisions by trial and error. Through the process of receiving rewards for good actions and penalties for bad actions, the AI agent learns an optimal policy that maps situations to actions with maximized cumulative rewards.

Examples:

> - **Zha et al.** (2019) improved a traditional route planning algorithm—the A* algorithm, which is used to find the shortest path between two points—with reinforcement learning.
> - **Li et al.** (2024) used a deep Q-network algorithm, which is a type of deep reinforcement learning algorithm to learn an optimal policy based on its current state, to allow autonomous service vessels to learn optimal actions within development areas.

Considering that planned areas for development can be dense and obstacle-rich environments, these types of reinforcement learning-assisted route planning algorithms can offer valuable insights for vessel routing in similarly complex maritime settings to optimize safe and efficient traffic flow. Applications might include dynamic routing for autonomous surface vehicles and unmanned surface vehicles used for inspection or environmental monitoring, and optimizing vessel routes to minimize disturbance to marine life.

Research Recommendations for Construction

1. **Integrate physics-based and data-driven models.**
   Physics-based approaches that numerically model a system's behavior (e.g., sound propagation through water) using fundamental principles of physics can achieve high fidelity but are computationally expensive and sensitive to environmental parameters. However, data-driven models such as neural networks are efficient in predicting outcomes, adapt better to varying environments as they learn complex patterns from data, and do not explicitly rely on physical equations. Therefore, the integration of these two types of approaches (e.g., physics-informed neural networks) is expected to provide better overall performance, including accuracy, speed, and adaptability.

2. **Use real-time multi-path planning in dynamic environments.**
   Offshore construction (and decommission) scenarios require real-time, multi-route planning in dynamic environments due to the complex, unpredictable, and high-risk nature of marine operations. Ocean conditions, such as waves, currents, wind, and weather, change rapidly, so vessels and autonomous systems must constantly adapt their movements in near real time. Multiple vessels usually operate simultaneously within a confined space, often with overlapping routes, so multi-path planning is also necessary. Finally, dynamic environments reflect not only physical changes in the ocean but also the presence of sensitive species and protected areas or unexpected obstacles like debris or traffic.

OPERATIONS AND MAINTENANCE

Operations and maintenance phase stressors may include bird and bat collisions and avoidance, electromagnetic fields, habitat disturbance, and entanglement (SEER 2022, 2025). Recent research trends on environmental monitoring and mitigation at offshore development sites are increasingly centered around the use of AI to enhance precision, efficiency, and real-time responsiveness. AI-powered systems now integrate multi-sensor inputs, such as radar, thermal cameras, and acoustic detectors, to automatically detect, classify, and track wildlife activities. As each sensor has unique pros and cons, the incorporation of different types of sensors can complement each other for more useful information collection.

Birds and Bats

Acoustic monitoring is often used to assess the presence and activity patterns of birds and bats. Microphones are deployed to capture sounds in the environment and convert the sounds into visual spectrographic representations (such as waveforms and spectrograms), which are analyzed to detect and identify species. In the early 2010s, acoustic monitoring began incorporating basic machine learning classification methods to perform quantitative feature-based classification of sounds. Key characteristics were manually extracted from audio signals and then used as inputs for traditional machine learning algorithms (e.g., support vector machines, random forests). More recently, researchers have leveraged the success of CNNs to detect and classify events in audio data, such as human speech recognition (Hinton et al. 2012).

Examples:

- **Mac Aodha et al.** (2018) developed an open-source system for automatic bat search-phase echolocation detection using a CNN to directly learn features of European bat echolocation calls from audio data.
- **Kahl et al.** (2021) developed a CNN to identify 984 bird species from North American and European spectrogram data.

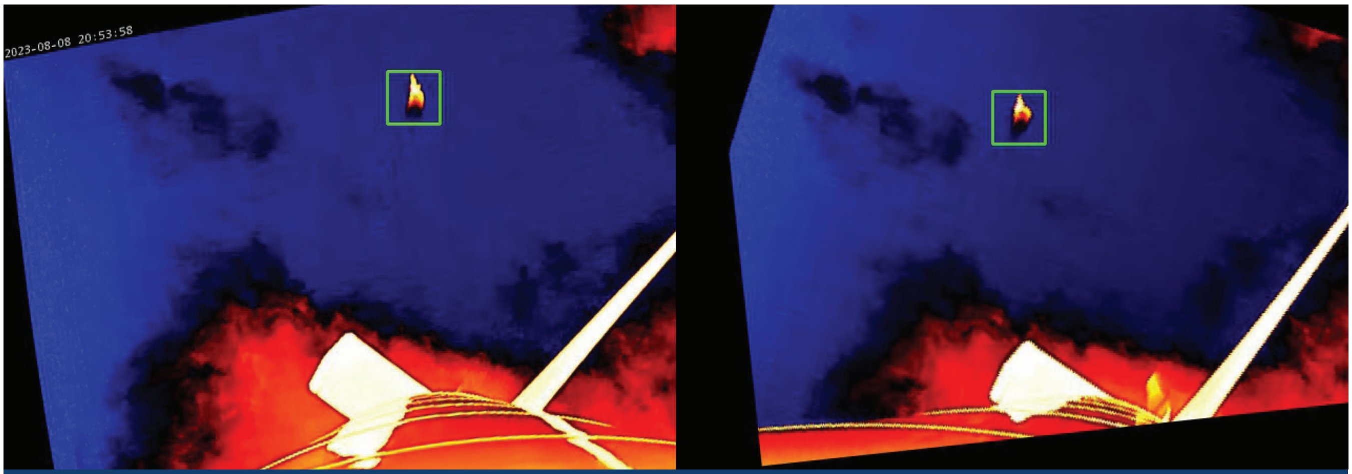

Figure 3. Example of annotated bat species using National Laboratory of the Rockies' (NLR's) WEBAT software with bounding boxes applied to stereo-video frames from NLR's Flatirons Campus. *Image by Sora Ryu, National Laboratory of the Rockies*

Video cameras, both visual and thermal, and lidar are important tools for tracking flight trajectories, body posture, and behavior in 3D space, which may help in understanding species interactions with offshore infrastructure (Figure 3). Object detection algorithms (e.g., YOLO, Faster R-CNN, Single Shot MultiBox Detector) localize, identify, and segment objects of interest within an image. Hence, the use of object detection models with video monitoring can classify bats and birds, predict their bounding boxes, and assign labels to each. Object tracking algorithms (e.g., SORT, Deep SORT, ByteTrack) follow the movement of the same object across frames, which can be used to get trajectory data of flying objects. Pose estimation algorithms (e.g., OpenPose, PoseNet, HRNet) locate key body parts and determine how the body is positioned or shaped. This helps track bat and bird wing angles and flight posture, which can improve estimates of collision risk.

Examples:

- **Alqaysi et al.** (2021) developed a YOLOv4-based ensemble model for bird detection in grayscale video collected around wind turbines.
- **Vasilopoulos et al.** (2022) deployed unmanned aerial vehicles equipped with cameras and processing data with YOLOv5 and DeepSORT to detect objects and track their changing positions through time, respectively.
- **Breslav et al.** (2014) applied a model-based framework using multiple cameras to estimate the 3D pose of bats and understand how bats behave and maneuver in the wild.

Marine Mammals and Sea Turtles

AI-powered passive acoustic monitoring systems are central to monitoring whales and dolphins. They use machine learning to analyze underwater sound recordings in real-time and distinguish species-specific vocalizations (similar to underwater noise modeling discussed in the Construction Phase section). AI is also being tested in thermal and video imaging systems to detect surfacing whales or sea turtles from platforms or drones, even under low-visibility conditions. Object detection models, often used for avian species, are being applied to detect and classify marine mammals and sea turtles and to identify underwater sounds by visualizing spectrograms as images. Moreover, predictive models, trained on environmental data and historical sightings, can help in forecasting animal presence and guiding near real-time mitigation measures like the delay and suspension of operations.

Examples:

- **Gray et al.** (2019) and **Gonzalez Nunez et al.** (2024) combined drone technology equipped with high-resolution cameras to detect sea turtles using object detection models and CNNs.
- **Hamard et al.** (2024) processed spectrograms generated from hydrophone data using a Faster R-CNN to detect and classify marine mammal vocalizations from other underwater sound.
- **Khan et al.** (2022) and **Adam et al.** (2025) identified individual whales and sea turtles using key facial or fluke features with neural networks.

Pelagic Fish

Compared to marine mammal monitoring, fish monitoring at offshore infrastructure relies more heavily on subsurface technologies and population-level data, as fish remain underwater and often move in large schools. Currently, tracking entire fish schools as a group is more common and practical for large-scale ecological and fisheries research, whereas tracking individual fish within a large school is extremely difficult. Individual tracking is done selectively on key species (like tuna or sharks) to understand detailed behavior. Among other monitoring techniques, pelagic fish species monitoring uses acoustic telemetry, satellite telemetry, underwater video, and environmental DNA sampling (Yang et al. 2024) with AI for analyzing movement patterns, species detection in imagery, and population trends from genetic traces.

Examples:

- **Wang et al.** (2017), **Jenrette et al.** (2022), and **Liu et al.** (2022) used CNNs to distinguish species of sharks or individual fish within a school from photos and video.

Benthic Organisms

Monitoring data from benthic communities can be processed by the combination of object detectors and multi-object trackers. However, this combination does not completely resolve the problems of complex seabed environments where targets are often obstructed or blurred (Er et al. 2023). Hence, it is important to find effective but more advanced feature extraction methods that could avoid degraded computer vision performance in such complex marine conditions.

Examples:

- **Liu et al.** (2024) improved models to detect obstructed marine benthic organisms by integrating the Global Context Block Attention, a type of attention mechanism that captures the overall context, allowing the model to understand the full scene and identify objects even when partially hidden.
- **Lyu et al.** (2023) enhanced the ability for extracting features of small-sized and blurred marine benthic organisms, using the Interactive Global Attention, which is a type of attention mechanism that fuses local information (e.g., fine details of organisms) and global information (e.g., overall scene context) in a parallel interactive way where different parts of the image interact and share information.

Entanglement

Marine wildlife can become entangled in offshore energy infrastructure (e.g., cables and mooring lines) or debris (e.g., derelict fishing gear) that is snagged by energy infrastructure (often referred to as secondary entanglement; see SEER 2022). AI can be used to predict mooring line tensions and degradations, which can detect malfunctions in mooring systems and potential entanglement events; however, further inspection would be necessary to confirm actual entanglements. Such events could be confirmed by integrating the presence data of marine wildlife with prediction models. Considering that the tension sequential data (e.g., wave loads) are unpredictable and nonlinear, recurrent neural networks are one of the most applicable architectures to train for this use.

Examples:

- **Yang et al.** (2023) predicted mooring line tension by leveraging a reservoir computing model that uses a fixed recurrent neural network to process time-dependent input data with only the output layer being trainable, decreasing the cost of training.
- **Chen et al.** (2025) built a hybrid prediction framework for dynamic tension predictions of semisubmersible production platform mooring systems using long short-term memory networks, which is a type of recurrent neural network designed to capture long-range dependencies in sequential data.

Electromagnetic Field Effects on Marine Life

Electromagnetic fields (EMFs) are generated by the flow of electricity through transmission cables and may influence the behavior of certain fish and invertebrate species (SEER 2022). Figure 4 shows an illustration of an undersea power cable. Some species rely on the Earth's natural geomagnetic fields for navigation, orientation, and predation. Artificially generated EMFs may influence these behaviors, potentially disrupting movement patterns, migratory routes, and/or foraging behavior in magnetically sensitive organisms. However, the extent and ecological significance of these effects are unclear and vary with species, distance between the animal and EMF source, and other factors (Hutchison et al. 2020). Neural network-based EMF field exposure level predictions can be performed in various contexts, including urban environments, but this approach could also apply to subsea transmission cables.

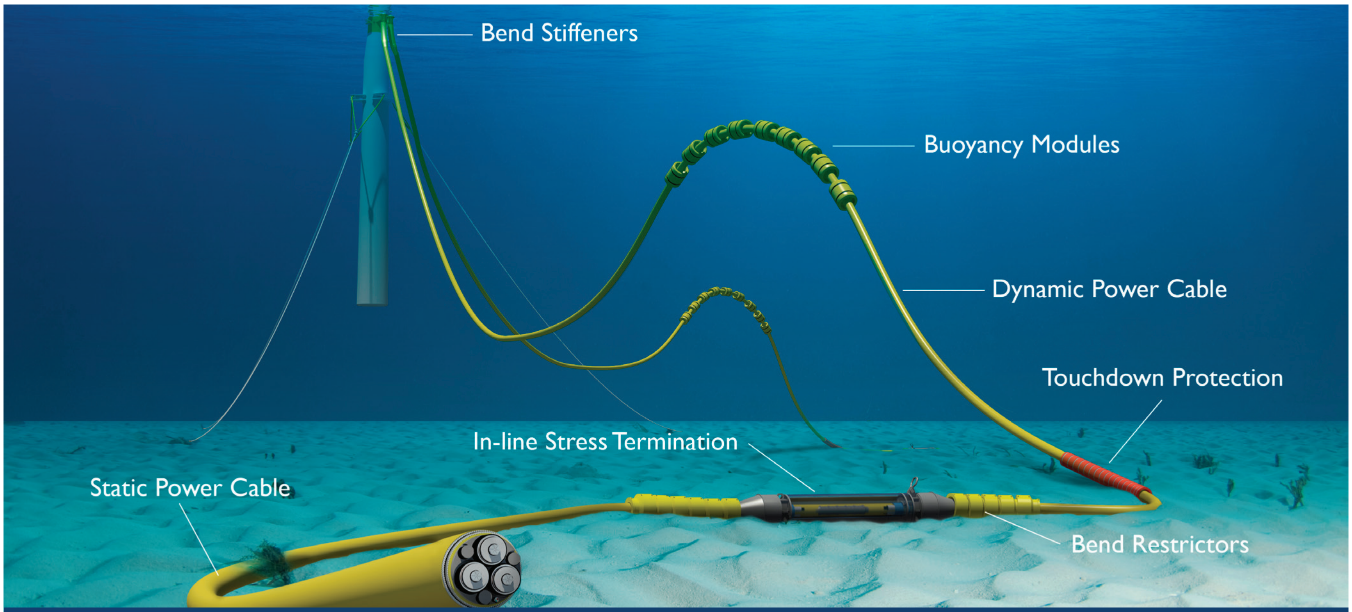

Figure 4. Electromagnetic fields from underwater transmission cables may influence the behavior of marine wildlife.
Illustration by Joshua Bauer, National Laboratory of the Rockies 66313

Examples:

- **Manassas et al.** (2025) explored ExtraTreesRegressor, an ensemble machine learning method based on random forests, and feedforward neural networks as prediction models to estimate electric field strength at ground level in an urban environment.
- **Kiouvrekis et al.** (2024) tested six machine learning approaches, including random forest, neural networks, and linear regression, to construct electric field strength maps across urban areas with Internet of Things sensor data. Ensemble methods outperformed simpler models in predicting electric field strength. The authors also employed SHAP, a type of explainable AI, to understand underlying factors influencing EMF exposure within urban environments, finding that the importance ranking of characteristics differed across the model types.
- **Xu et al.** (2025) performed principal component analysis to understand the physiological and behavioral effects of EMF radiation from offshore energy infrastructure.
- **Alihodzic et al.** (2021) used fully connected feedforward neural networks to estimate electric field intensity and magnetic flux density near high-voltage overhead transmission lines.

Research Recommendations for Operations and Maintenance

1. **Benchmark datasets for wildlife monitoring in both individuals and groups.**
   Although several monitoring systems are commercially available and in use, there are few publicly available benchmark training datasets, making it difficult to compare model performance. Dataset benchmarking is essential in that it provides a standardized way to compare different models on the same task and same data with assured reliability and generalizability. While many AI applications already benefit from established dataset benchmarks, particularly in domains like object detection and tracking in urban environments focused on people or vehicles, these benchmarks are not suitable for wildlife monitoring. It is important to develop a benchmark that is tailored to detect and track birds, bats, marine mammals, pelagic fish, and benthic organisms within offshore energy development sites. Furthermore, this benchmark should account for both individual and group-level dynamics, as many of these species, such as birds, bats, and fish, frequently move in groups and exhibit collective behavior.

2. **Address the challenges of object detection and tracking.**
   Underwater object detection and tracking are difficult due to varying marine environmental conditions and poor-quality data, such as blurry underwater images and noisy audio files. In many cases, the targeted objects are hidden or too small to be detected. As described in the Benthic Organisms section, attention mechanisms can be added to object detection models to address these challenges. Other techniques can be helpful as well, such as multiscale feature fusion, which combines features extracted at different scales, making the model capable of recognizing both big and small objects; anchor-free architectures, which do not rely on predefined boxes to guess object locations and classifications but instead directly predict key points or centers from images, making it easier to detect small objects; and customized anchor sizes, which tune the default detection bounding box sizes to better fit small objects. Generative AI models, such as diffusion models, may enhance underwater image and audio quality by effectively denoising data as well as restoring lost details.

3. **Explore opportunities to integrate AI with wildlife monitoring systems to facilitate more efficient data transfer and minimization measures.**
   Integrating monitoring systems with AI can allow faster data processing and enable near real-time decision-making. In addition, processing data on-site may reduce the amount of data transferred to shore. Moreover, integrating monitoring systems with the facility's system control and data acquisition system may offer automated and precise curtailment controls for species-specific collision risk. This proactive approach can leverage AI's ability to interpret complex data streams and respond adaptively to changing conditions, ultimately supporting smarter and more sustainable minimization measures.

4. **Leverage digital twin technologies to design, simulate, and optimize smart curtailment systems.**
   Digital twins are high-fidelity, model-based dynamic simulations that automatically update with real-world data to mirror real-time behavior and conditions. This technology works as a powerful tool to design, simulate, and optimize decision-making and response strategies in advance, before working in the real world. Digital twins can simulate environmental conditions, predict system responses, evaluate various scenarios, and fine-tune monitoring and mitigation strategies for maximum efficiency and minimal impact. Through continuous feedback and data integration, digital twins can support adaptive decision-making and performance optimization, which can lead to the implementation of intelligent, responsive mitigation systems.

DECOMMISSIONING

Decommissioning involves the process of removing infrastructure at the end of its service. For example, decommissioning a wind energy site includes dismantling wind turbines, removing foundations, and repowering or repurposing the site. As in the construction phase, increased vessel activity and underwater noise levels are anticipated during decommissioning. The same AI-based strategic vessel routing and noise propagation techniques may therefore be applicable in both phases. Monitoring changes to the benthic habitat after decommissioning can also offer valuable insights on assessing both long-term environmental impacts of the initial installation and the ecological recovery process after infrastructure removal, leading to future offshore energy development strategies that prioritize marine ecosystem health. A suite of AI techniques can play a pivotal role by enabling automated analysis, enhanced pattern recognition, and predictive modeling at spatial and temporal scales and resolutions that would not be feasible with traditional methods. Given how long offshore energy infrastructures persist (e.g., the lifespan of an offshore wind farm can exceed 20 years), AI tools will likely improve by the time many sites are decommissioned.

CAUTIONS WHEN USING AI

Although the use of AI can improve the effectiveness and efficiency of environmental research and mitigation, there are several areas that require further clarification and transparency to ensure this relatively new tool is used in robust and scientifically credible ways. Below are aspects of AI that need further attention.

Transparency: Comprehensive information is necessary about the dataset (e.g., origin of data, how data were collected and verified, size of the training dataset) and the model (e.g., reasoning behind the model's output, how the internal workflow functions).

- Concerns about intellectual property for a given AI tool can be balanced with the need for scientific credibility of results (i.e., the level of detail in reports/publications can be adjusted to protect IP and "trade secrets" while maintaining sufficient transparency).
- Explainable AI can be explored to make the AI systems more interpretable.
- Employ the Findability, Accessibility, Interoperability, Reuse, AI Readiness & Reproducibility or (FARR) principles (www.farr-rcn.org) when using AI.

Validation: Evidence on the performance of AI models is required to ensure it works as intended. This could include:

- Information on the accuracy of model(s) used (e.g., 99% accuracy of classifying bats from other biological objects).
- Information on human involvement throughout the process to review outputs, place results in ecological context, and provide ethical oversight.

Generalization and robustness: AI models need to maintain their performance in new environments or with unseen data that differ from what they are trained on (e.g., prediction capability of mooring tension for different sea conditions, EMF prediction on different areas).

AI readiness: Well-maintained infrastructure, high-quality data, robust governance, and data maturity are required to effectively deploy and manage AI systems. This could include:

- Robust data pipelines to effectively collect, process, and store large volumes of data, offering seamless data flow for AI systems.

- High-quality data used for training AI systems.
- Skilled personnel to design, implement, and maintain AI models, ensuring AI systems operate to their full potential.
- AI governance strategy to ensure models align with organizational goals and regulatory standards while mitigating risks such as bias or misuse.
- AI-ready datasets that are clean, structured, relevant, and properly annotated, ensuring that they are in the right format to train and validate AI models.
- Model optimization for deployment on edge devices (e.g., cameras, drones, sensors) with limited computational resources, memory, and power, focusing on reducing the model size while maintaining performance.

In addition, the use of AI has its own environmental impacts related to energy consumption, greenhouse gas emissions, water usage, rare earth metal extraction, and electronic waste. Thus, advancing AI applications and their use in environmental research and mitigation will need to coincide with making AI more efficient and sustainable (Bolón-Canedo et al. 2024; Xiao et al. 2025).

CONCLUSION

Applying AI to environmental research has the potential to **(1)** automate repetitive and manual processes, **(2)** solve complex problems that require optimization and strategy by processing large amounts of data, identifying patterns, and making better and faster decisions, and **(3)** improve model performance (in addition to learning new data and adjusting to changes in data) without explicit reprogramming. However, there are concerns regarding the use of AI from both data and model perspectives, particularly in data transparency and quality, and model transparency, validation, and generalization. In summary, the following key areas should be addressed to fully realize the potential of AI and effectively apply these technologies in real-world, complex, dynamic environments:

- Multimodality to combine diverse data sources
- Explainable AI to improve transparency
- Scalable and efficient AI to deploy on edge devices
- Real-time and context-aware AI to adapt to dynamic environments
- Dataset benchmarking to compare model performance
- Digital twins to simulate systems with controls.

As AI continues to rapidly advance, its impact on ocean energy development and environmental conservation will expand. More than just automating repetitive and manual processes, AI is reshaping our approach to energy infrastructure and enabling more sustainable, reliable, and efficient solutions on a global scale. However, many challenges remain unsolved. More advanced, intelligent, and collaborative research methods are needed to achieve complex missions.

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