Cover Page

This paper is going to be about how computer scientists can utilize FathomNet, a database of ocean images curated by sources such as the Monterey Bay Research Institue and National Geographic, subject-matter experts, and citizen scientists, to create ocean imaging machine learning algorithms that can help us better understand our changing oceans. This paper will also cover specific use cases of machine learning algorithms that utilize FathomNet's database.

The intended audience of this paper would be those in the computer science field that are interested in machine learning and applying it to ocean research, but not necessarily those that know a great deal about marine science. My style guide choice for this essay is MLA.

Technical Discussion Outline

A. Introduction
B. Who created FathomNet and Why?
C. How is FathomNet Different From Other Databases?
D. How to Join the Community, Contribute to the Database, and Navigate the Platform
E. FathomNet and Machine Learning Algorithms– Use Case #1
F. FathomNet and Machine Learning Algorithms– Use Case #2
G. FathomNet and Machine Learning Algorithms– Use Case #3

Abstract— *The FathomNet ocean image database is a valuable resource for researchers, scientists, and ocean enthusiasts seeking to better understand the our changing oceans. This paper provides a comprehensive overview of what FathomNet is, why it is important, how its data are curated, who it is intended for, and how it can be used to create machine learning algorithms that will help the world better understand our oceans.*

Introduction

FathomNet: An Open, Underwater Image Repository for Automated Detection and Classification of Midwater and Benthic Objects gave a great summary of what FathomNet is, why it is important, who it is intended for, and how it can be used to better understand our oceans: To understand our changing oceans, research institutions and private sectors create ocean-going platforms with cameras to observe parts of the ocean humans cannot traverse and also collect images overtime. These platforms create a plethora of data, which can be very useful, but the problem is that humans cannot process and analyze these data fast enough to make this data useful. Ocean researchers actually manually annotate and label their images and videos and this simply isn't scalable.

Data scientists and researchers have used these data to create machine learning algorithms that can help categorize unknown species in the ocean and also produce predictions of ocean health, but due to the lack of standardization in ocean data, few annotation tools, and the lack of imagery curated by subject-matter experts, these algorithms are not as powerful as they could be. This is why FathomNet was created. FathomNet is a public platform (website) where existing ocean data are curated and annotated by reliable sources such as the Monterey Bay Research Institute (MBARI) and National Geographic, and also allows the public (experts or not) to contribute to the database with their own annotated images. Subject-matter experts can go on FathomNet and also verify whether or not images have been properly annotated. As more data are created, the database will grow. This database is open to a wide audience– From the general public to experts in marine sciences. Not only does FathomNet provide a rich dataset of labelled ocean images, but also provides interactive maps, search functions, and image processing software.

Who Created FathomNet and Why?

The FathomNet "About Us" page gave an summary on who created the platform and why it was created: In 2018, MIT Media Lab held an event, hosted by Kathy Croff Bell, "... former Director of the Open Ocean Initiatives and founder of Ocean Discovery League…", that challenged attendees to create pitches about gaps in ocean exploration to get funding from National Geographic and/or the MIT Media Lab. Kakani Katija, "... Principle Engineer at the MBARI…", pitched the initial idea for FathomNet. Many researchers in this field know how much image data (animals, geological structures, etc.) is created and how difficult it is for the very few subject-matter experts to classify all these images.

The MBARI, at the point of this pitch, had 30+ years of manually annotated and reliably curated underwater ocean videos and images gathered by underwater robotics. These data was ready to mined, and if repackaged for machine learning algorithms, could address the ever-present problem of too much data and little resources to categorize it. Other researchers/scientists/subject-matter experts were very intrigued– Ben Woodward (CEO of CVisionAI), Grace Young (formerly Oxford University), Gilbert Montague (formerly

OpenROV), Genevieve Flaspholer (MIT), Joshua Gyllinksy (URI)– and so, the idea of a large, reliable database of ocean images and videos for machine learning was pitched at the MIT Media Lab event and gained funding from National Geographic, NOAA (National Oceanic and Atmospheric Association), and the MBARI. This is how and why FathomNet was born. Anyone can use the platform– Whether or not you are a subject-matter expert, you can use FathomNet to test your own algorithms or simply take in all the data it has available.

FathomNet: A global image database for enabling artificial intelligence in the ocean provided Figure 1, which shows the disparity between the raw ocean images the ocean research community has access to (by the MBARI and other organizations) vs. the images needed for data scientists to create useful machine learning algorithms (a and c vs. b and d). This article continued to explain why this platform is imperative to understand our oceans: Labeled data via annotation is critical for deep learning machine algorithms. With a platform like this, computer scientists can be enlisted to create automated imagery analysis with labeled data without being subject matter experts in ocean research.

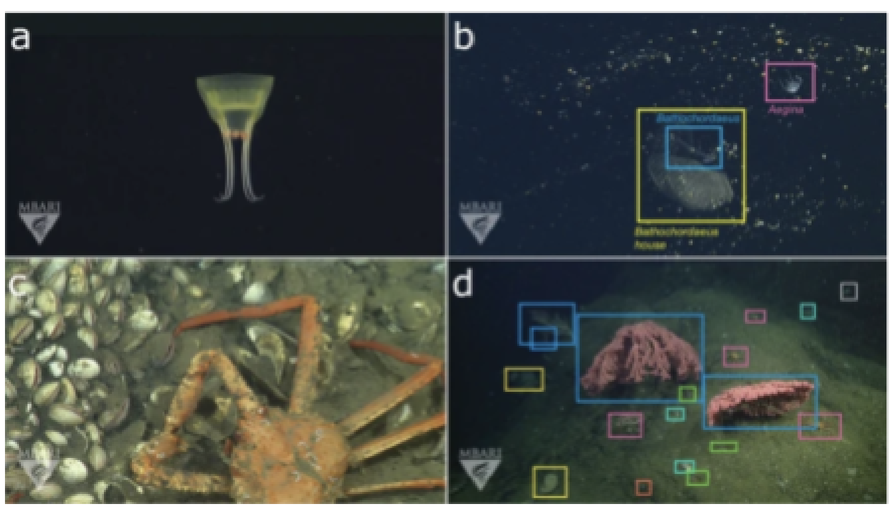

Fig. 1 Image Comparison

How is FathomNet Different From Other Image Databases?

While there are many image databases available, like ImageNet, there are few that are specifically designed for underwater imagery. One of the key strengths of FathomNet is the large number of images that have been manually annotated and curated by subject-matter experts. This means that the database is made up of high quality, reliable images that can be used to train machine learning algorithms to classify underwater objects and organisms with a more accuracy than ever before. In addition, the collaborative nature of the platform means that the database is constantly growing and improving, with new images and annotations being added all the time.

FathomNet also has a unique taxonomy system that allows for more specific categorization of images. This allows for richer and more unique images to train machine learning algorithms with.

Fig. 2 Compares Images From ImageNet (another image database) and FathomNet. FathomNet has more specific species types and more variety in animal movement/angles.

How to Join the Community, Contribute to the Database, and Navigate the Platform

If you're interested in contributing to the ever-growing database of oceanic images and videos, FathomNet makes it very easy to do so. Once again, the “About Us” page on FathomNet explains how one can join the FathomNet community and begin to contribute. To join the community, simply create an account with your preferred email. Once you have created your account you can now do the following:

1. Upload your annotated ocean images/videos to your FathomNet collection
2. Verify images and labels if you are a deemed a subject-matter expert by FathomNet
3. Download images from FathomNet for your own work
4. Share your code, machine learning model weights, etc. on the FathomNet GitHub Repository
5. Create “How-To” videos related to using FathomNet to help out the community

To contribute to your collection, in a section called “My Collection”, click the button “+ Add Collection”.

Fig. 3 My Collections Page

From there, you are prompted to input the required information to upload the CSV of your contribution like the name of the rights holder, owner institution code, dataset ID, license agreement, date of most recent modification, etc..

Fig. 4 Upload CSV

	Data entry categories		
	Required	**Recommended**	**Suggested**
Collections	Owner's institution	Bibliographic citation	Collection code
	Rights holder (use owner's institution if not specified)	Access rights (for more generous use)	Collection ID
	Contributor's email	Basis of record (manual or machine)	Dataset generalizations
	Record type (images)	Dataset language	Dataset name
	Modified field (upload date)		Dynamic properties
	UUID		Information withheld
	URL		Institution code
	Data format (CSV+)		Institution ID
			References
Images	Image URL	Latitude/Longitude	Group of
	Bounding box coordinates (x, y, width, height)	Depth	Occluded
	Concept name	Timestamp (ISO8601)	Truncated
		Imaging type	AltConcept
		Observer	
		Altitude	

Fig. 5 Required, Recommended, and Suggested Sections for Uploads

Then you will be prompted to input the optional information like access rights, bibliographic citation, a place to upload your JSON file if you made annotations, etc.. Then you can upload your CSV under the header “Select CSV file”, and, finally, submit. You have now contributed to the growing and impactful database, FathomNet.

It's important to note that only select members of the FathomNet community have the ability to verify the submissions that are uploaded, these members being subject-matter experts. This ensures that the database remains accurate and reliable for anyone to use in any field of study or simply for ocean enthusiasts. While anyone can upload images to FathomNet, the verification of these images is limited to certain members who have been granted access to do so.

To search the vast database, you can go on the “Explorer” tab. Images can then be filtered out by “What” (animal, mineral, substrate, etc.), “Where” (area, region, basin, etc.), and “Taxonomy Provider” (organization– i.e. the MBARI, etc.). After searching, you can click on any image to download for your own use. Once you've found an image that speaks to your research or interests you, you can simply click on it to download it for your own use. This download is a JSON file that can be opened with any code/text editor and can be used to create and test machine learning algorithms. The different fields in the JSON file can be filtered out to your liking using the your preferred programming languages.

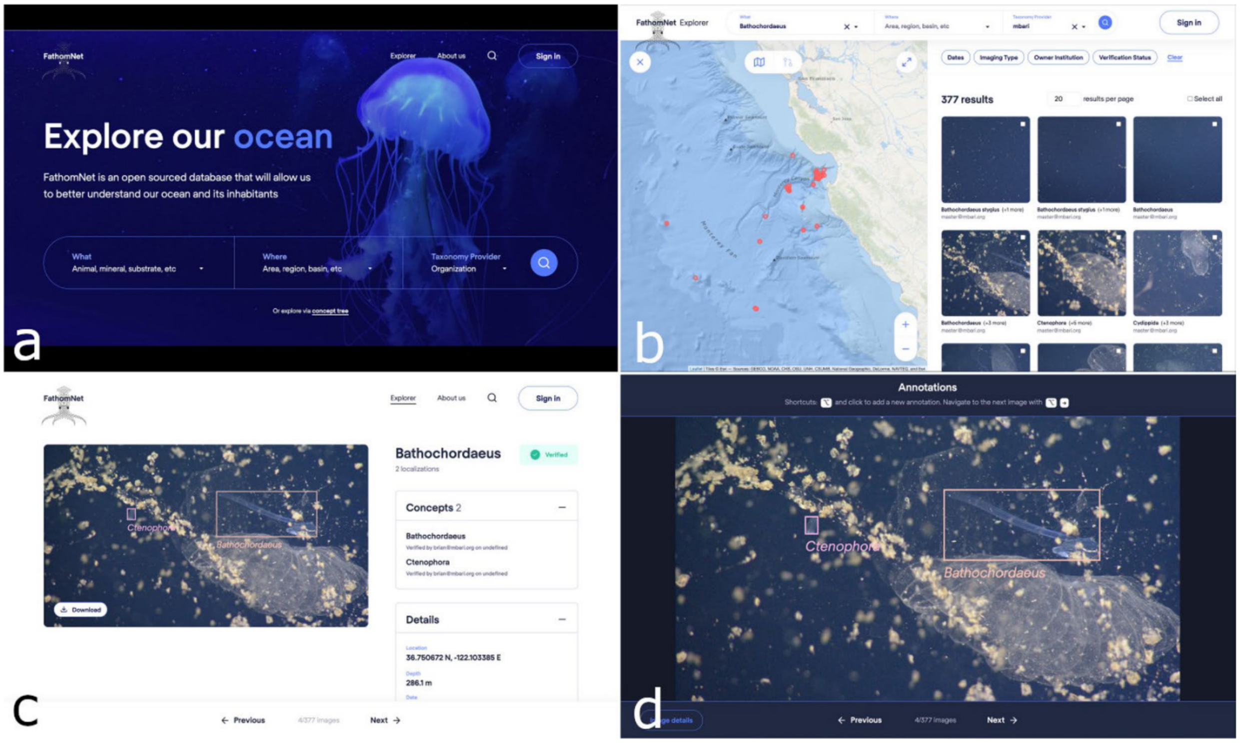

Fig. 6 (a) Home Page of FathomNet (b) Explore Page (c) Image Selection (d) Enlarged Image Selection

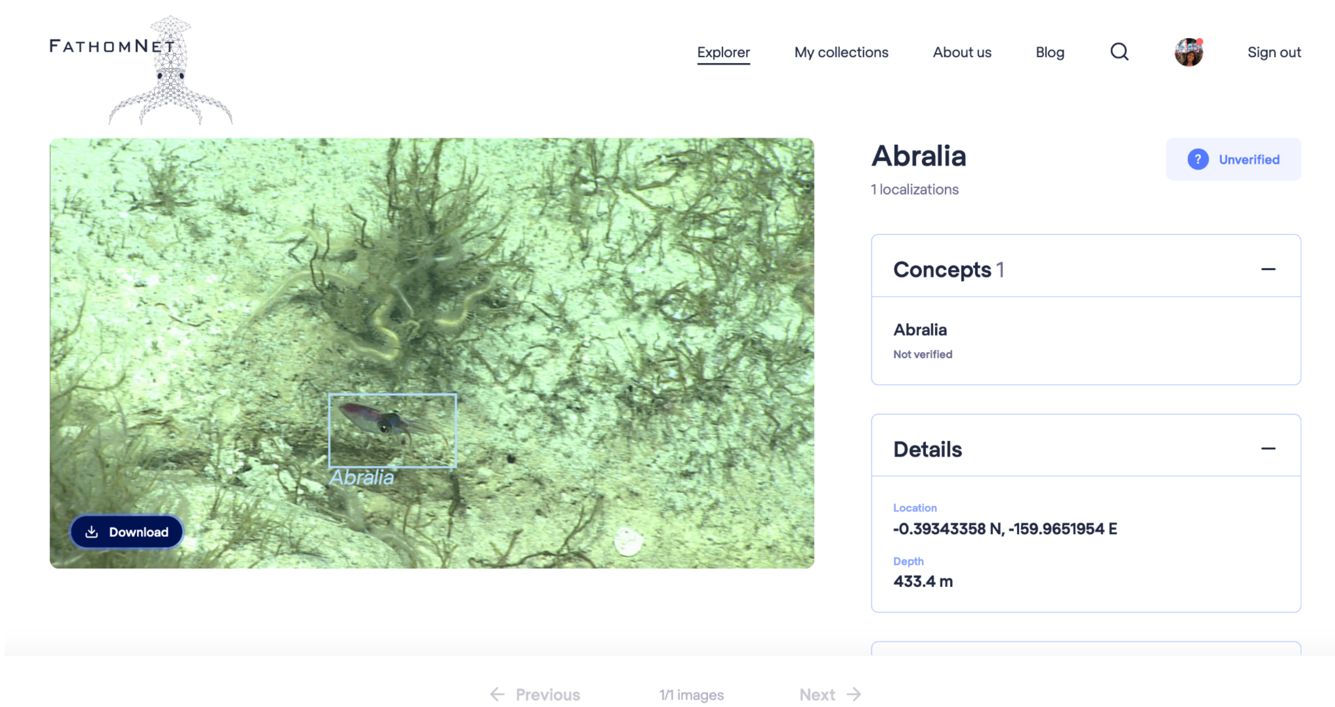

Fig. 7 Image Selection


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Fig. 8 JSON File of Image in Fig. 4

FathomNet and Machine Learning Algorithms– Use Case #1

Deep learning algorithms that are run on labelled datasets have significantly improved the classification of underwater species. This approach requires a large database of labeled images, and FathomNet provides just that. *FathomNet: A global image database for enabling artificial intelligence in the ocean* gave important use-cases of FathomNet, explained below.

The first project that will be explained is called "Midwater Transect Activity Detection Using NOAA (National Oceanic and Atmospheric Administration) Footage and MBARI Training Data." This project used the MBARI's annotated images to train machine learning algorithms to detect underwater activity/motion. Why is this project important? Reviewing footage after collection can be very "costly and tedious" if the reviewer is watching hours of videos just for a few events. By training machine learning algorithms to detect underwater activity, researchers can drastically reduce the time and effort required to analyze the footage and identify important events.

An AR (activity recognition) routine was fine-tuned and tested with FathomNet's underwater annotated imagery and the MBARI's Video Annotation and Reference System.

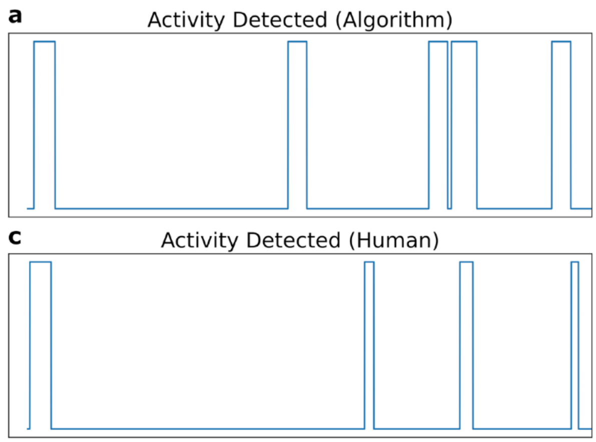

Fig. 9 Human vs. Algorithm Activity Detection

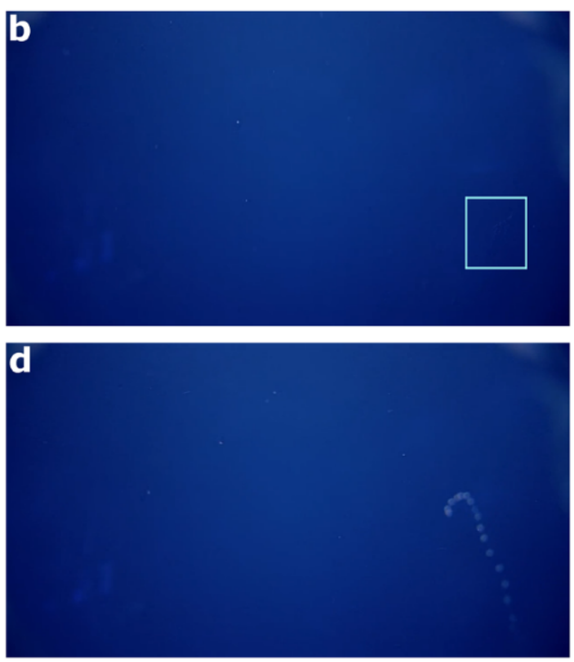

Fig. 10 Continued

(a) Activity detected by algorithm for video collected by NOAA ROV Deep Discover (c) Activity detected by human expert for same video. (b) Algorithm correctly identifies an animal for activity detection (c) Algorithm cannot distinguish image because image is blurred.

Although the algorithm isn't perfect due to camera angles, inability to distinguish blurred images, etc., having an algorithm create some form of annotations for activity detection at least gives the human reviewer a place to start when they begin their reviewing process. The potential applications of this technology are vast: Identifying new species simply because the human eye can not detect all motion in a video, identifying potential threats to researchers in specific diving areas before going in, etc..

FathomNet and Machine Learning Algorithms– Use Case #2

Similarly, *Low-Cost, Deep-Sea Imaging and Analysis Tools for Deep-Sea Exploration: A Collaborative Design Study* discusses how the images on FathomNet can be used to train species classification machine learning algorithms for metadata, for humans can not possibly classify the species in millions of images of the ocean. This is yet another use-case for FathomNet. This use-case was elaborated on in the project “Benthic Animal Detection Using NOAA Footage and MBARI’s Training Data,” described below.

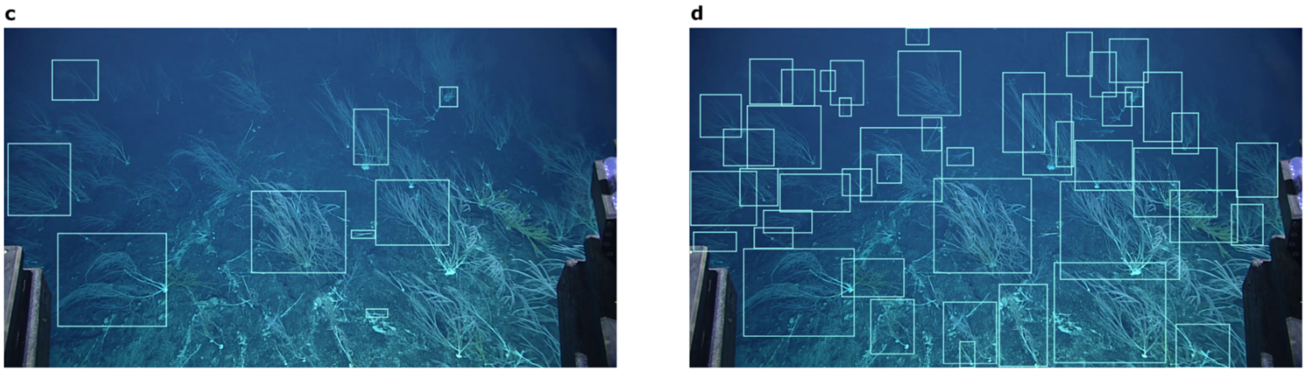

Fig. 11 Algorithm annotations vs. Human annotations

The MBARI's training data was used to train an image detection machine learning algorithm– It had to identify the following organisms: "Urchin, fish, sea cucumber, anemone, sea fan, sea star, worm, sea pen, crab, glass sponge, shrimp, ray, flatfish, squat lobster, gastropod, eel, soft coral, feather star, sea spider, and stony coral." The algorithm performed relatively well in identifying these creatures in images from Monterey Bay in comparison to the human annotations, but there were some things that confounded the algorithm. If there were too many organisms in a frame, if there were subtle changes to the angle of the underwater camera, or if there were organisms in the frame that were not in the training data, the algorithm misidentified or did not identify animals correctly.

Again, although the algorithm is not perfect in identification, it at least gives a human a starting point to begin annotating images vs. starting from scratch. With only less than 5% of the ocean explored, image recognition software can help identify new organisms we have not seen yet– It can help put new organisms into a known species category, allowing researchers to have a starting point to describe the origins of an unknown animal. Further, identifying organisms on a large scale far surpasses a human's ability to manually annotate ocean images and identify organisms in millions of ocean images.

FathomNet and Machine Learning Algorithms– Use Case #3

Another project that highlights the importance of FathomNet is "Machine Learning-Integrated Tracking (ML Tracking) of Animals for Vehicle Navigation and Control." At times researchers need to track animals or ocean data for long periods of time with non-invasive, autonomous vehicles. "Tracking-by-detection" is a new machine learning technology that is being explored. This technology allows the vehicle to be moved by an algorithm according to the motion it detects, and does not have to be manned by human, making it much easier to have 24+ hour deployments of these machines. Katija Kakani, one the main researchers that contributed to the creation of FathomNet, "... developed a Machine Learning-integrated Tracking (ML-Tracking) algorithm that incorporates a FathomNet-trained multi-class RetinaNet56 detection model47, 3D stereo tracker subroutines, and a supervisor module that sends commands to a vehicle controller."

This ML algorithm tracked 50 hours worth of data. This level of continuous tracking is unprecedented and would have been impossible without the help of machine learning algorithms. In comparison, the longest continuous tracking of a gelatinous animal by humans is only 5.27 hours, highlighting the stark difference in the capabilities of technology versus humans.

The use of machine learning algorithms in ocean research has greatly expanded our tracking abilities, allowing us to collect data on a larger scale and over longer periods of time.

This has allowed researchers to uncover new insights about the behavior and distribution of marine organisms, and to better understand how they interact with their environment. By analyzing this data, we can gain a deeper understanding of the complex ecosystems that exist in our oceans, and how they are being impacted by human activities such as pollution and climate change.

The data collected by these machine learning algorithms can also be used to inform conservation efforts and policy decisions related to ocean management. For example, by tracking the movements of endangered species, researchers can identify areas where conservation efforts should be focused and develop strategies to protect these species from further harm. In this way, machine learning algorithms are not only expanding our knowledge of the oceans but also helping us to protect them for future generations.

Conclusion

The field of computer vision has seen a lot of progress due to the advancement of deep learning algorithms. These algorithms have significantly improved the accuracy and speed of image recognition, making it possible to automatically identify objects and patterns in large, vast datasets. As this paper has been dissecting, one application of this technology is in the field of marine biology, where the classification of underwater species can be challenging due to the vast diversity of marine life and the difficulty of capturing clear images in an underwater environment.

Traditional methods for identifying marine species involve manual observation, identification, and annotations by subject-matter experts, which can be time-consuming and expensive. However, with the help of deep learning algorithms, automated identification of marine species from images has become possible, making the process much faster and more efficient.

To train these deep learning algorithms, a large database of labeled images is required. FathomNet provides such a database, containing a vast collection of underwater images that have been labeled with information about the species and habitats depicted. This enables computer scientists to create machine learning algorithms for ocean research without being subject matter experts. With the help of FathomNet, researchers can develop and train deep learning models that can automatically identify different species of marine life, their habitats, and other important features of the underwater environment.

The availability of such a rich dataset has been a game-changer for marine biology research, allowing scientists to study marine ecosystems in great detail. Researchers can now use FathomNet to answer more questions about the distribution of different species, changes in marine ecosystems over time, and the impacts of human activities on marine life. With the help of this platform, we can gain a deeper understanding of our oceans and take steps to preserve these critical ecosystems for future generations.

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