

EXPLORING BOUNDARY OF GPT-4V ON MARINE ANALYSIS: A PRELIMINARY CASE STUDY

Ziqiang Zheng¹, Yiwei Chen¹, Jipeng Zhang¹, Tuan-Anh Vu¹, Huimin Zeng², Yue Him Wong Tim³, Sai-Kit Yeung¹

¹The Hong Kong University of Science and Technology,

²University of Science and Technology of China, ³Shenzhen University

{zzhengaw, ychenmb, jzhanggr, tavu}@connect.ust.hk, saikit@ust.hk

ABSTRACT

Large language models (LLMs) have demonstrated a powerful ability to answer various queries as a general-purpose assistant. The continuous multi-modal large language models (MLLM) empower LLMs with the ability to perceive visual signals. The launch of GPT-4 (Generative Pre-trained Transformers) has generated significant interest in the research communities. GPT-4V(ison) has demonstrated significant power in both academia and industry fields, as a focal point in a new artificial intelligence generation. Though significant success was achieved by GPT-4V, exploring MLLMs in domain-specific analysis (e.g., marine analysis) that required domain-specific knowledge and expertise has gained less attention. In this study, we carry out the preliminary and comprehensive case study of utilizing GPT-4V for marine analysis. This report conducts a systematic evaluation of existing GPT-4V, assessing the performance of GPT-4V on marine research and also setting a new standard for future developments in MLLMs. The experimental results of GPT-4V show that the responses generated by GPT-4V are still far away from satisfying the domain-specific requirements of the marine professions. All images and prompts used in this study will be available at https://github.com/hkust-vgd/Marine_GPT-4V_Eval

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1 INTRODUCTION

Large language models (LLMs) (Raffel et al., 2020; Chiang et al., 2023; Zhang et al., 2022; Touvron et al., 2023a;b; Ouyang et al., 2022; OpenAI, 2023; Brown et al., 2020; Scao et al., 2022) demonstrated an impressive ability to handle a large range of user-tailored tasks. As a general-purpose assistant, ChatGPT/GPT-4 (OpenAI, 2023; Ouyang et al., 2022) could understand human intents and complete various real-world tasks. The development of multi-modal large language models (Li et al., 2023c; Zhu et al., 2023; Zheng et al., 2023c; Peng et al., 2023a; Team et al., 2023; Alayrac et al., 2022) (MLLMs) such as GPT-4V represents an important step towards more sophisticated AI systems with the ability to receive both textual inputs and visual data. The integration of vision in language models has marked a significant milestone. GPT-4V showcased impressive general-purpose visual understanding and reasoning abilities. The advent of GPT-4V has expanded AI applications, aligning with the multi-modal capabilities of the human brain. In detail, GPT-4V extends the abilities of GPT-4 to analyze and interpret images and has attracted significant attention across both academia and industry.

Existing open-source general-purpose MLLMs (Liu et al., 2023; Peng et al., 2023b; Li et al., 2023a) often lack in image-text analysis (Lu et al., 2022) due to limited model size and data scale. It is still unclear how GPT-4V, and MLLMs built on GPT-4, perform various multimodal understanding tasks. Though vision capabilities embodied in GPT-4 have pioneered new avenues for advanced image-text analysis, the challenges (Fu et al., 2023a; Singh et al., 2023) of evaluating how GPT-4V accurately perceives visual signals and measuring the effectiveness of such a system arise. To evaluate whether GPT-4V could achieve robust visual perception and mimic the inherently subjective and associative processes of human perception, recent studies (Yang et al., 2023; Zhang et al., 2023; Fu et al., 2023b; Ge et al., 2023; Bubeck et al., 2023) have been conducted to evaluate the performance of GPT-4V in different areas, such as recommendation (Zhou et al., 2023), medical analysis (Li et al., 2023b), radiological (Busch et al., 2023), mathematic (Gao et al., 2023), and general-purpose visual analysis tasks (Yang et al., 2023; Bubeck et al., 2023). Evaluating the performance of GPT-4V in these areas will provide insights into the flexibility of GPT-4V as the AI assistant. However, there are few attempts (Palnitkar et al., 2023; Zheng et al., 2023c) to utilize GPT-4V for more advanced analysis, which requires advanced and domain-specific knowledge and expertise.

To bridge this gap, we present a preliminary case study investigating the marine analysis based on GPT-4V. We explore whether GPT-4V could serve as an effective visual perception system and a professional expert for sensitive, informative, and accurate knowledge delivery. We construct a series of qualitative test samples spanning multiple purposes in the field of marine analysis and employ these samples to assess the quality of the responses generated by GPT-4V.

We propose to evaluate the performance of GPT-4V on marine analysis from the following aspects: *perception, statistics, domain-specific question answering, marine culture understanding, advanced functions and prompt engineering*. We pick up images that are not accessible online or private data, combined with manually crafted prompts to build the evaluation samples. Evaluation results on our constructed testing samples prove that GPT-4V has a remarkable OCR, event detection, and framework understanding ability across various conditions, due to its robust visual-text comprehension capabilities and extensive knowledge. However, we have also observed the intrinsic limitations of using GPT-4V for marine analysis. GPT-4V only demonstrates very limited fine-grained marine object recognition ability and is easily misled by meticulously forged filenames (we observe that GPT-4V will read the filenames of uploaded images as context prompts). Besides, GPT-4V cannot perform complicated object counting and detect all the objects within the visual images since it is mainly performing image-level understanding. GPT-4V also failed to accurately capture subtle details in images and respond with the required domain-specific information. We finally demonstrate that GPT-4V cannot conduct advanced marine analysis as a professional analysis tool. We summarize our findings as follows.

- In this study, we embark on an in-depth analysis of GPT-4V on domain-specific marine analysis. The expert capacity of GPT-4V has been measured for applying the learned domain knowledge and skills to the professional domains. Our study holds significant importance for the marine research community, providing valuable insights and guidance for future exploration of utilizing MLLMs for domain-specific analysis.

- We demonstrate several limitations of GPT-4V on marine analysis. Despite these limitations, we also aim to include a list of potential abilities of GPT-4V that we have identified as a domain-specific analysis tool. We hope that these explorations and our constructed domain-specific testing samples can offer valuable insights and serve as domain-specific benchmark data for evaluating MLLMs on domains with professional knowledge.
- We also acknowledge GPT-4V could be easily misled by the wrong prompts (e.g., the filenames of visual images), demonstrating GPT-4V leans towards the text prompts and without looking at the visual elements within the images. The hallucination happens a lot when GPT-4V is asked to answer domain-specific questions.

2 EXPERIMENTS

2.1 APPROACH

Data construction. To avoid the testing sample leakage, all the samples involved in this study are from different sources: 1) private data collection contributed by marine biologists (Zheng et al., 2023a); 2) manually cropped frames from YouTube videos; 3) Internet images posted after the release of GPT-4V APIs; 4) framework and flowchart images from research articles and books (Haixin et al., 2023; Ziqiang et al., 2023); and 5) images from public datasets (Beijbom et al., 2015) and our newly created images. To promote the consistency and reliability of our study and increase the robustness of our findings, we make sure that every case has at least 10 testing samples with high diversity.

Prompt design. GPT-4V has been demonstrated to support a diverse range of visual processing based on various signed prompts (Wang et al., 2022; Peng et al., 2023a). This inspires us to design the various prompts. Our prompts in this study are characterized by a rich diversity and complexity of instructions to enable GPT-4V to generate comprehensive and descriptive responses, which are aligned with the user intents.

Evaluation metric. In each testing case, we compute the accuracy of GPT-4V on a wide range of visual tasks. For those object recognition tasks with ground truth labeled by the domain experts, we evaluate whether GPT-4V could yield satisfactory object recognition performance according to the generated labels. For those evaluation metrics with human judgment involved, we mainly design two protocols (Zhang et al., 2023; Ge et al., 2023): *pairwise comparison* and *image-based scoring*. For pairwise comparison, we judge whether the two images come from the same identity or the same species. For pairwise scoring, we ask both GPT-4V and human labelers to generate scores on a scale of 1 to 10. The ground truths under the two protocols are both generated by human experts.

2.2 PERCEPTION

In this section, our goal is to assess the performance of GPT-4V in various challenging vision tasks. The involved tasks demand a powerful visual perception ability to understand the real world. Our experiments focus on the ability of GPT-4V to sense the visual contents and then perform image-level, object-level and attribute-level comprehension.

We first explore whether GPT-4V could really understand the visual content of the given marine images or just respond without looking at the visual signals. We perform experiments using the same images under three settings: 1) with **random** filename; 2) with meticulously forged **misleading** filename; and 3) with **meaningful** and **aligned** filename. The experimental results are illustrated in Figure 1. The filenames and the ground truths of the marine objects are also provided as references. As illustrated, we observe that GPT-4V will recognize the marine objects within the given image under the first setting since no side clues are provided. GPT-4V tends to describe all the appeared meaningful objects and usually yields **longer** responses. Under the second setting, with the misleading filename given, GPT-4V will respond according to the given file name and generate some “false promise” that does **not** appear in the image. GPT-4V could be easily deceived by the meticulously forged filenames and yield some wrong answers. We guess that GPT-4V would read the filename of the uploaded image and regard such filename as the context prompt when generating the responses. It will easily produce a hallucination if the wrong context prompts do not exist in the image. As for the final setting, when the correct and aligned filenames are given, GPT-4V could generate meaningful and satisfactory responses. However, we cannot claim that GPT-4V could really understand the visual

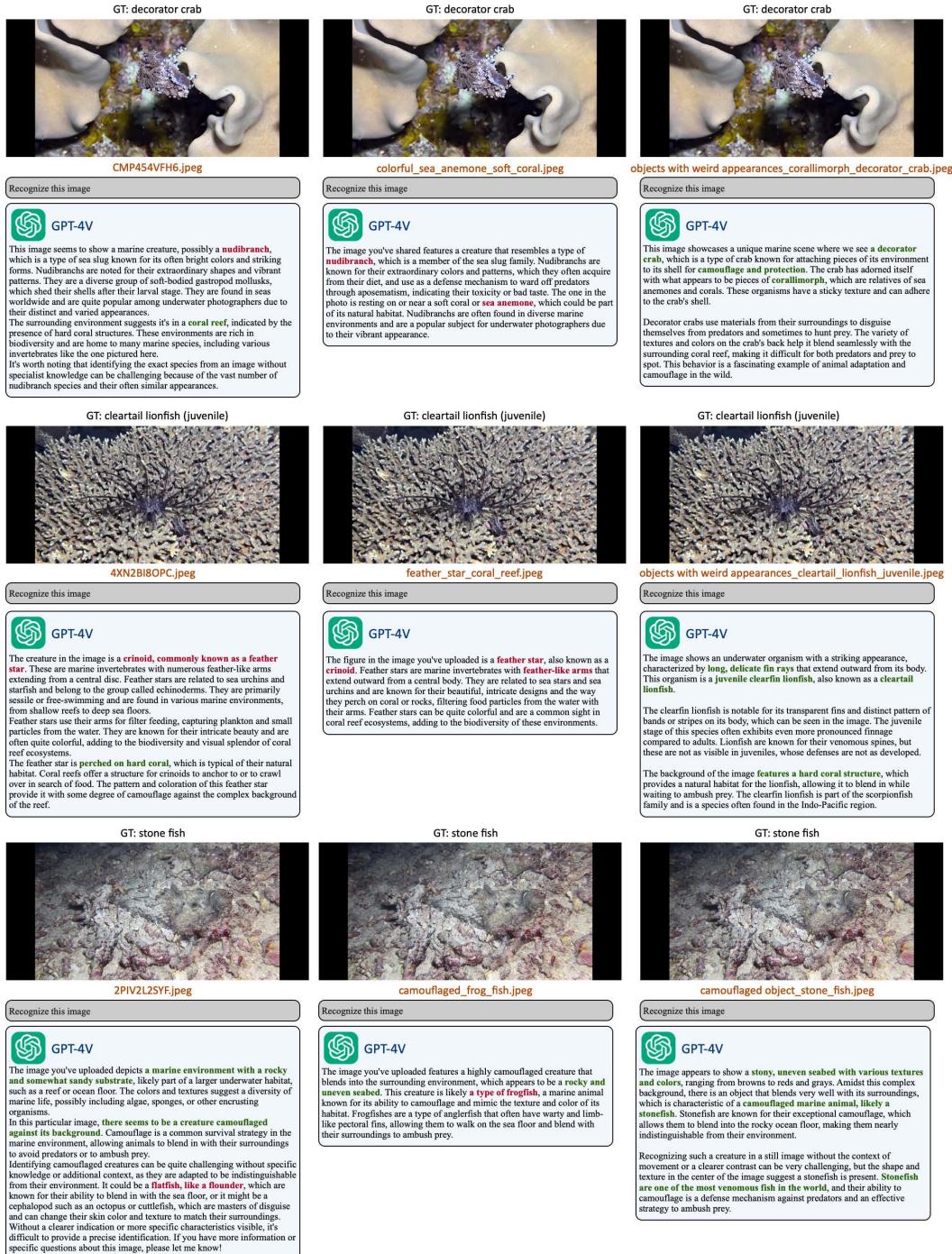


Figure 1: The marine object recognition results under three different settings: left column (with **random** filename); middle column (with meticulously forged **misleading** filename); and right column (with **meaningful** and **aligned** filename). The texts in **red** represent the wrong responses and texts in **green** indicate the correct responses. The prompts are “Recognize the object in this figure”.

contents of uploaded images since abstracted conception names have already leaked in the filenames. More inference results under the three settings are provided in Figure 2, Figure 3, and Figure 4, respectively.

Considering the conception leakage issue, we rename all the images in all our experiments to meaningless filenames to avoid information leakage and ensure fair testing.

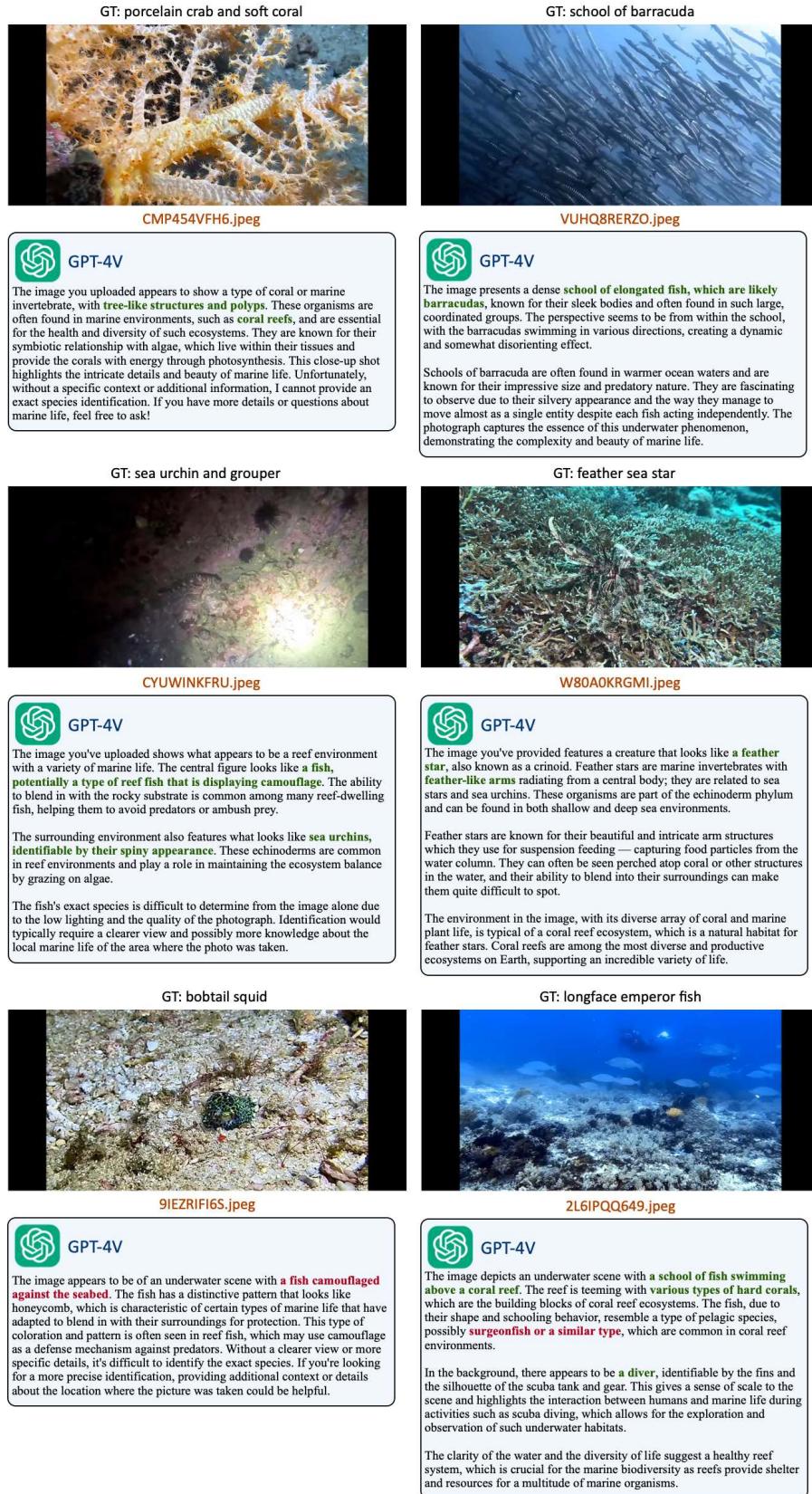


Figure 2: The marine object recognition results under the setting with random filenames. The prompts are “Recognize the object in this figure”.

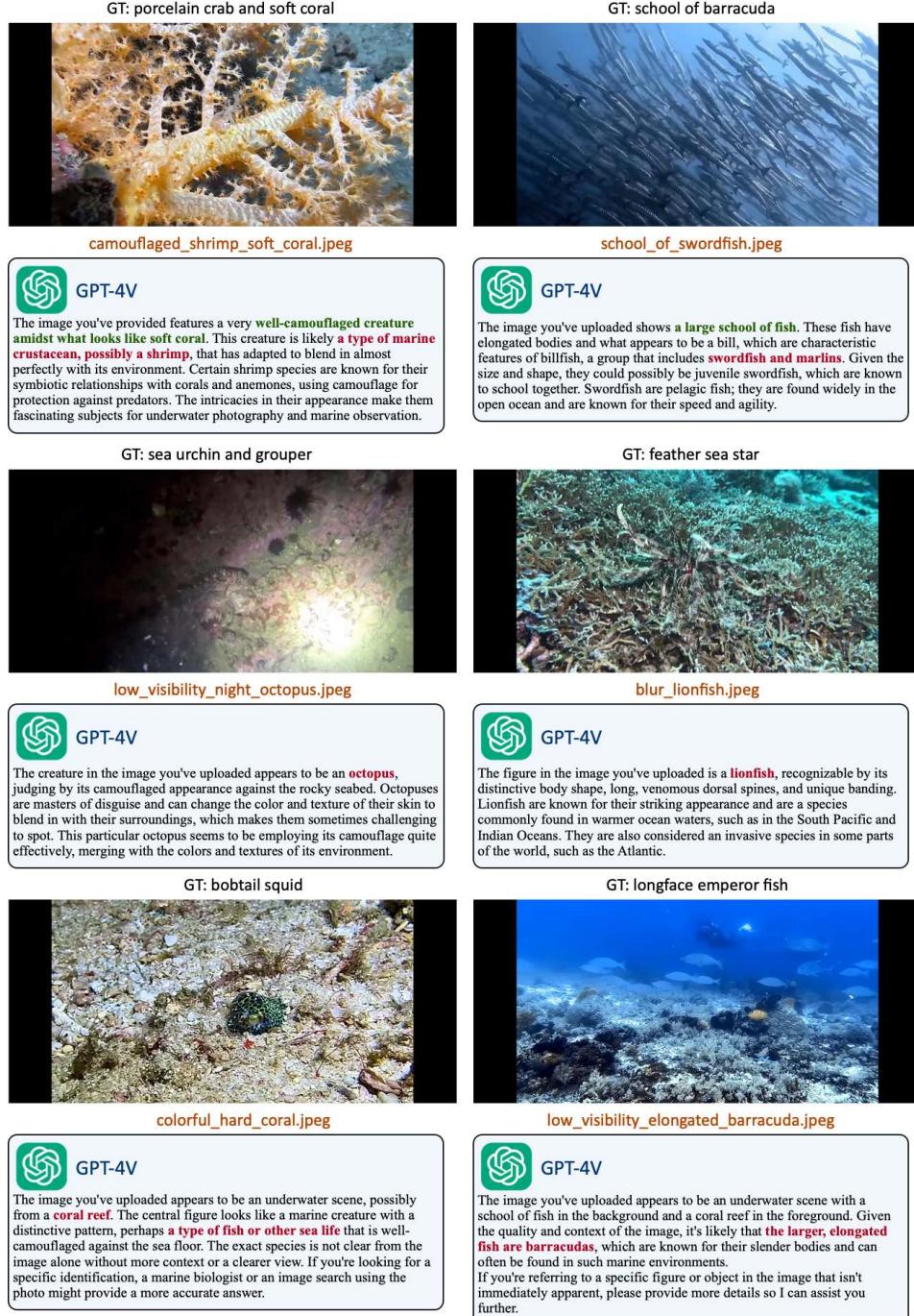


Figure 3: The marine object recognition results under the setting with meticulously forged **misleading** filenames. The prompts are “Recognize the object in this figure”.

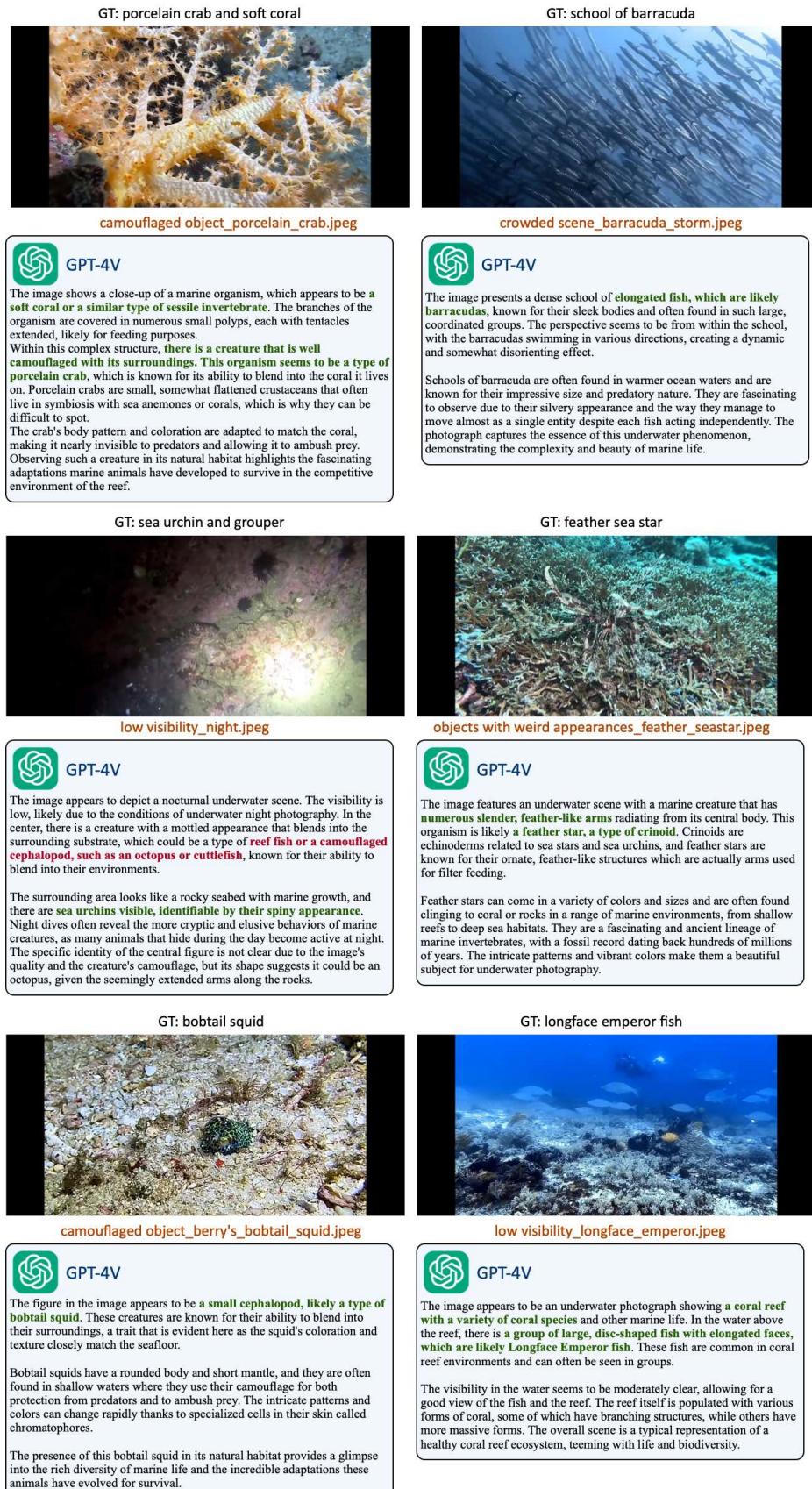


Figure 4: The marine object recognition results under the setting with **meaningful** and **aligned** filenames. The prompts are “Recognize the object in this figure”.

2.2.1 MARINE OBJECT RECOGNITION

Wide spectrum of marine object recognition. We first explore whether GPT-4V could recognize a wide range of marine objects. We pick up 300 different marine images that contain the salient visual elements from one single marine species. In other words, there are 300 different marine species involved in our experiments. These images are manually cropped from the Youtube videos or the MVK dataset (Truong et al., 2023; Zheng et al., 2023a) The ground truth of the appeared marine objects is labeled by domain experts and we manually compared the recognized object names with the ground truth for computing the recognition accuracy. Some marine object recognition results are provided in Figure 5. As illustrated, GPT-4V failed to accurately recognize marine objects that are not relatively common. There is still a very large room to improve the recognition accuracy of GPT-4V on marine object recognition.

Marine object recognition under challenging conditions. We then test whether GPT-4V is capable of depicting the key visual elements under some challenging conditions, including *crowded scene*, *objects with weird appearances*, *fluffy object*, *irregular boundary*, *tiny object*, *camouflaged object*, *object detection under occlusion*, *low visibility*, and *optical artifacts*. All the experimental results are reported in Figure 6 and Figure 7, respectively. For these testing experiments, we make sure there are at least 10 images under each experimental setting. We compute the recognition accuracy under those diverse settings. We observe that GPT-4V has a poor ability to accurately recognize the visual elements under challenging conditions. We guess that such failure of GPT-4V may be subject to the minority training data from the marine field. More training data collected under challenging conditions should be further included to promote the recognition ability of GPT-4V in challenging conditions.

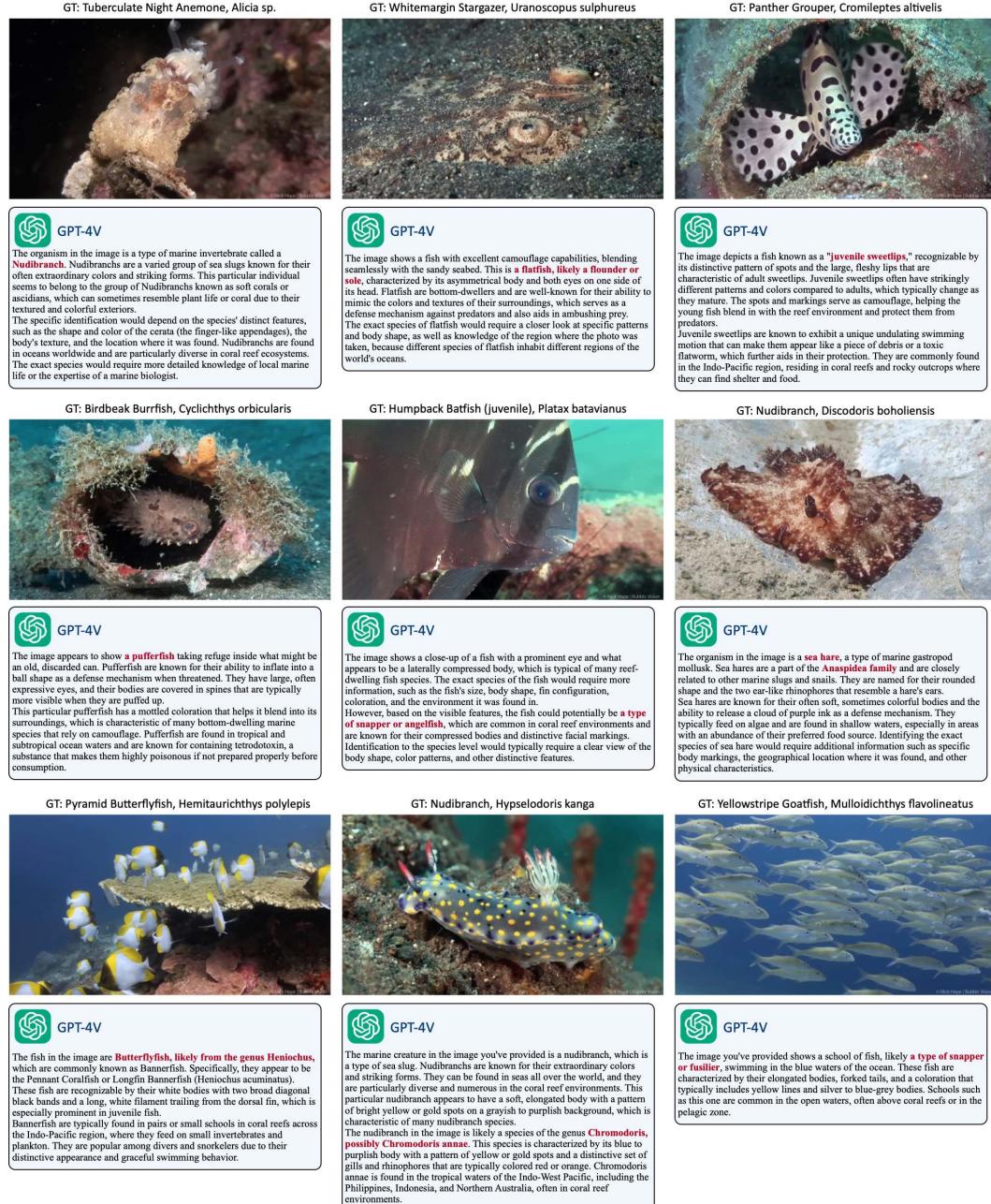


Figure 5: The marine object recognition results of recognizing a wide spectrum of marine objects. The prompts are “Recognize this image and tell me the species name of the recognized objects”. The ground truths are also provided.

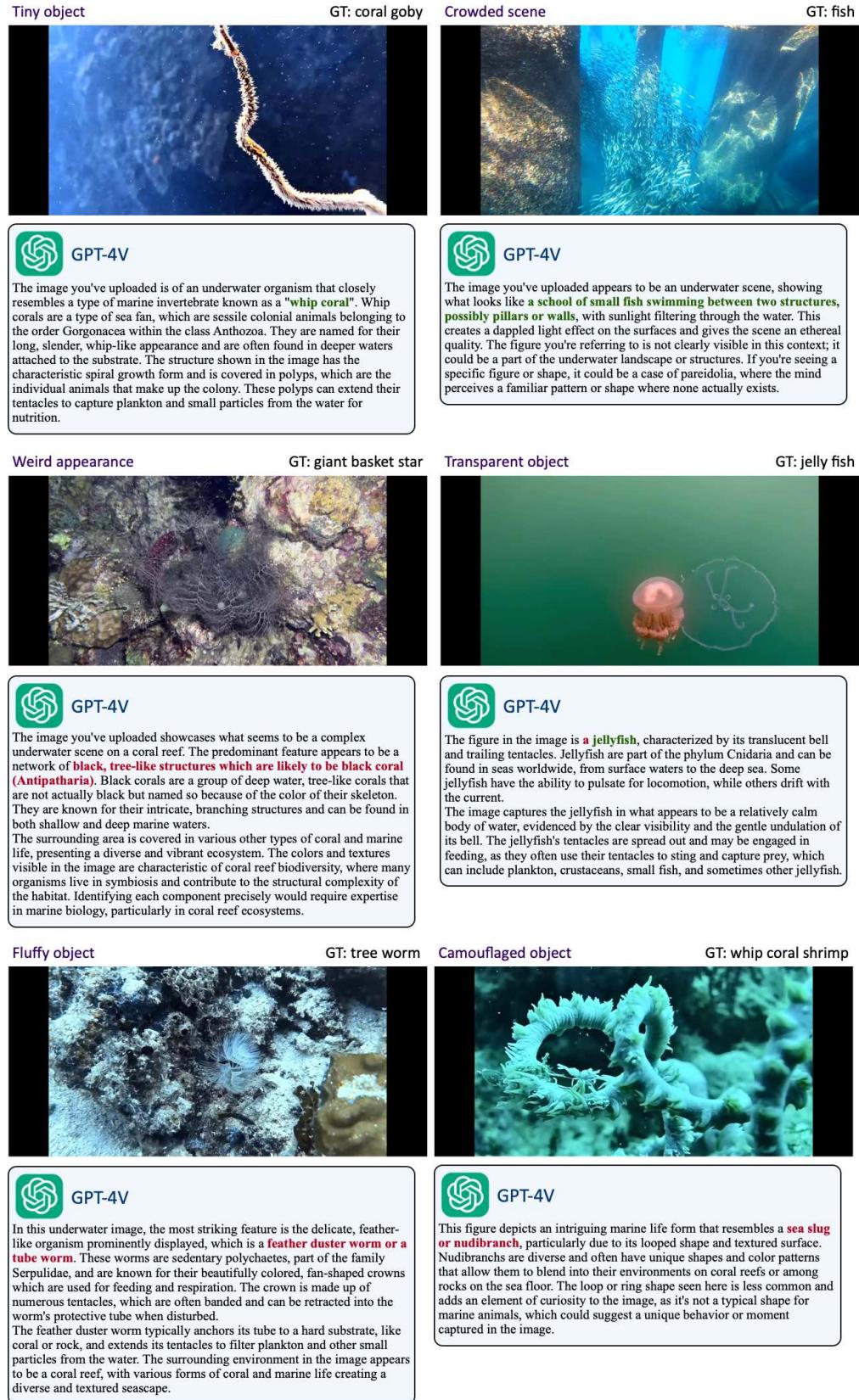


Figure 6: The marine object recognition results under challenging conditions. The prompts are “Recognize the object in this image and tell me the species name of the recognized objects”. The ground truths are also provided.

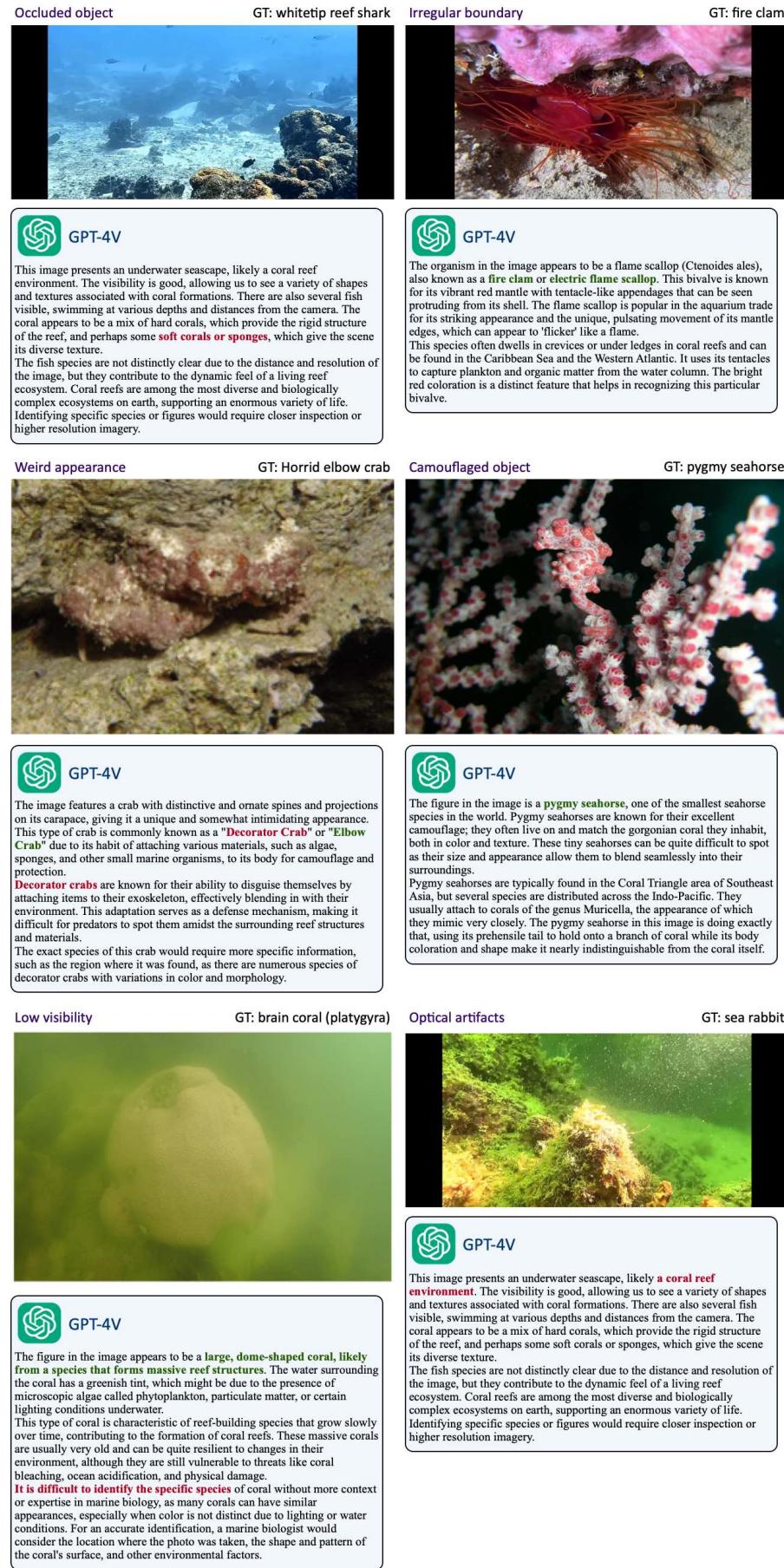


Figure 7: The marine object recognition results under challenging conditions. The prompts are “Recognize the object in this image and tell me the species name of the recognized objects”.

2.2.2 FINE-GRAINED MARINE OBJECT RECOGNITION

We test whether GPT-4V could discriminate very similar marine objects (e.g., fine-grained object recognition) and generate different responses based on given visual contents. We report the fine-grained object recognition results of GPT-4V in Figure 8. As demonstrated, GPT-4V failed to tell the differences of close-related marine objects with similar appearances. The fine-grained object recognition ability is required in the marine analysis field since it could enable diversity monitoring and reduce the human labor from the domain experts on species identification. There is still a far away from utilizing GPT-4V for marine species identification.

We then perform the pairwise comparing, formulating a pair of images and asking GPT-4V whether the objects within the two images belong to the same marine species. Figure 9 illustrates the pairwise comparing performance. We formulate 20 pairs and compute the correct rate of GPT-4V on this task. **Cross-view fish re-identification.** We have also performed experiments to ask the GPT-4V to judge whether the objects within the images captured under different camera views (e.g., frontal, bird and side views) are the same object. Figure 10 demonstrates that GPT-4V has a poor ability to retrieve objects with camera view changes. GPT-4V refused to respond to the matching question even though the two fishes from the two visual images share very different appearances.

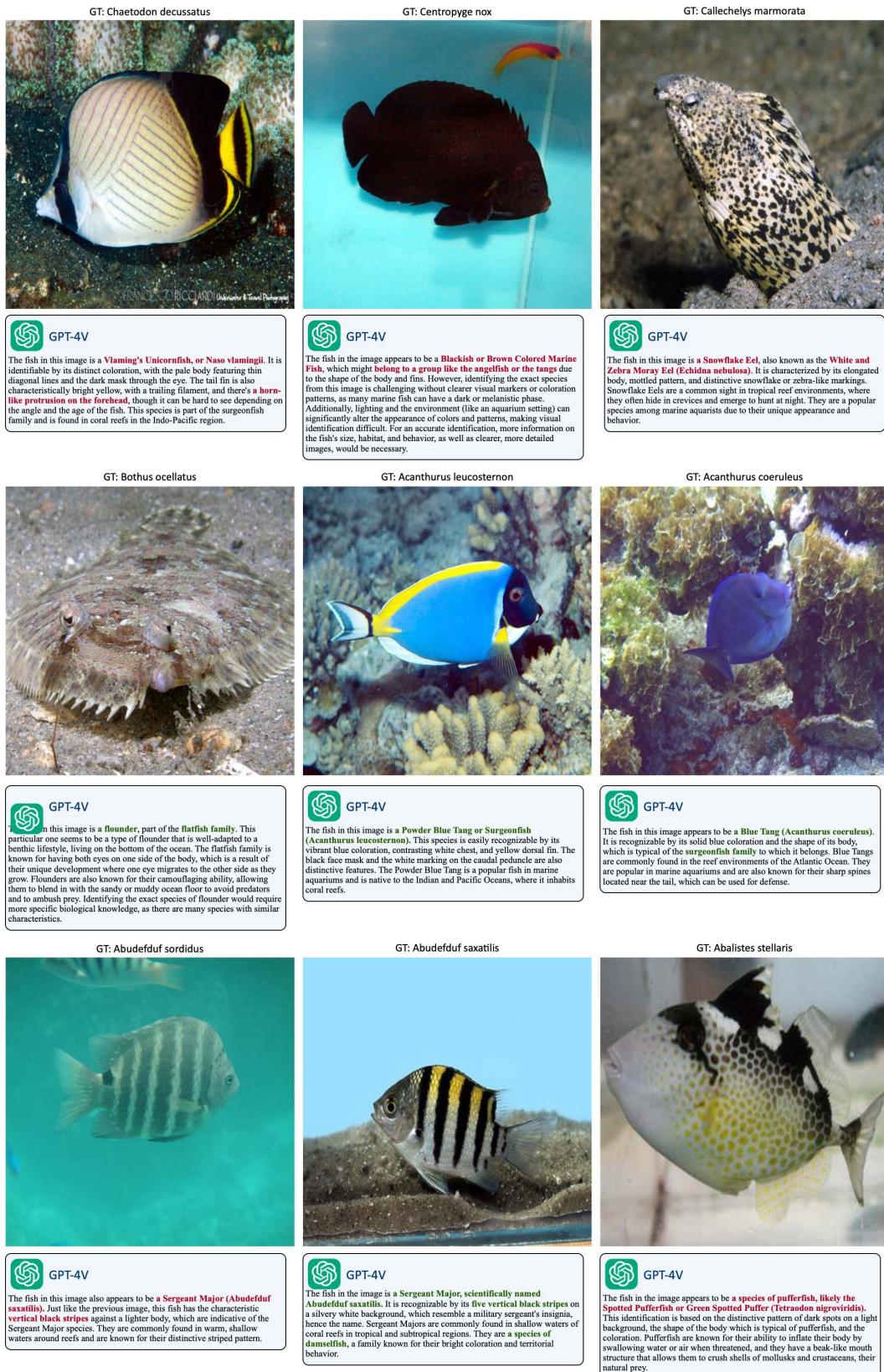
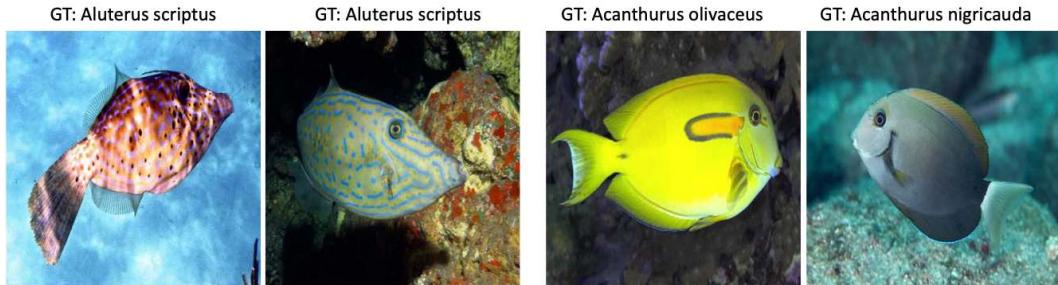
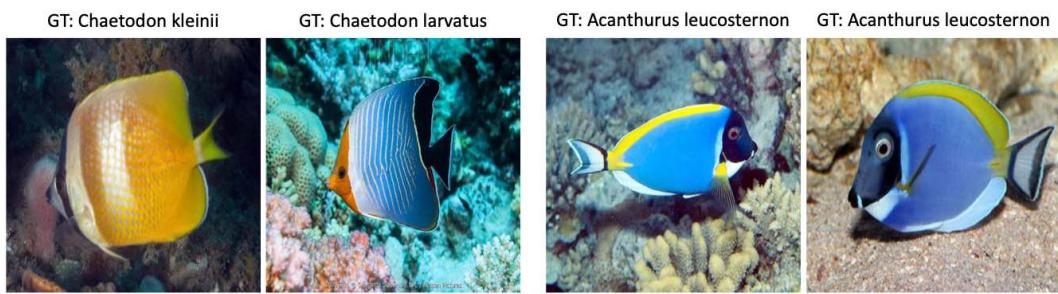


Figure 8: The fine-grained marine object recognition results of GPT-4V. The prompts are “Recognize the object in this image and tell me the species name of the recognized object”.



GPT-4V

The two fish in the images you've provided are both types of Filefish, which belong to the family **Monacanthidae**. These fish are known for their distinctively shaped bodies, rough, sandpaper-like skin, and patterns of spots or stripes. The first fish has a pattern of orange spots against a lighter background, while the second fish has blue lines and spots against a yellowish background. While the coloration and pattern details differ, these differences could be due to various factors including age, sex, geographical location, or simply individual variation within the same species. Without specific scientific identification, it's not possible to say with absolute certainty if they are the same species, but based on the shape and general patterns, **they could possibly be variations of the same species or closely related species** within the Filefish family.



GPT-4V

The two fish in the images **do not belong to the same species**, but they are both part of the Butterflyfish family. The first fish is the **Copperband Butterflyfish (*Chelmon rostratus*)**, recognizable by its yellow body, vertical white bands, and long snout. It is popular in the aquarium trade and is known for its specialized feeding habits, often seeking out small invertebrates. The second fish is the **Bluecheek Butterflyfish (*Chaetodon semilarvatus*)**, identified by its blue face and the series of vertical stripes on its body, the back half of which is a dark blue or black color. Both species are found in coral reefs in the Indo-Pacific region, but they have distinct coloration and patterns that set them apart from each other.

GPT-4V

The two fishes in the images you've provided appear to belong to **the same species**, which is the ***Acanthurus leucosternon***, commonly known as the Powder Blue Tang or Surgeonfish. This species is easily recognizable by its vibrant blue coloration, yellow dorsal fin, and the distinctive white chest and face. Both images show these characteristics, although there may be slight variations in shade and pattern, which is common within a species due to factors like age, diet, and environmental conditions.

Figure 9: Utilize GPT-4V for pairwise comparing. The prompts are “Compare whether the two fishes in the two images belong to the same species”.

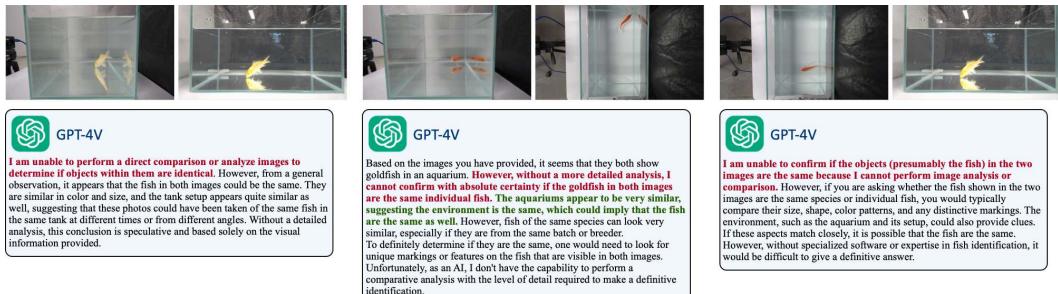


Figure 10: The cross-view fish re-identification performance of GPT-4V. The prompts are “Compare whether the two fishes in the two images belong to the same species”.

2.2.3 ROBUSTNESS ANALYSIS

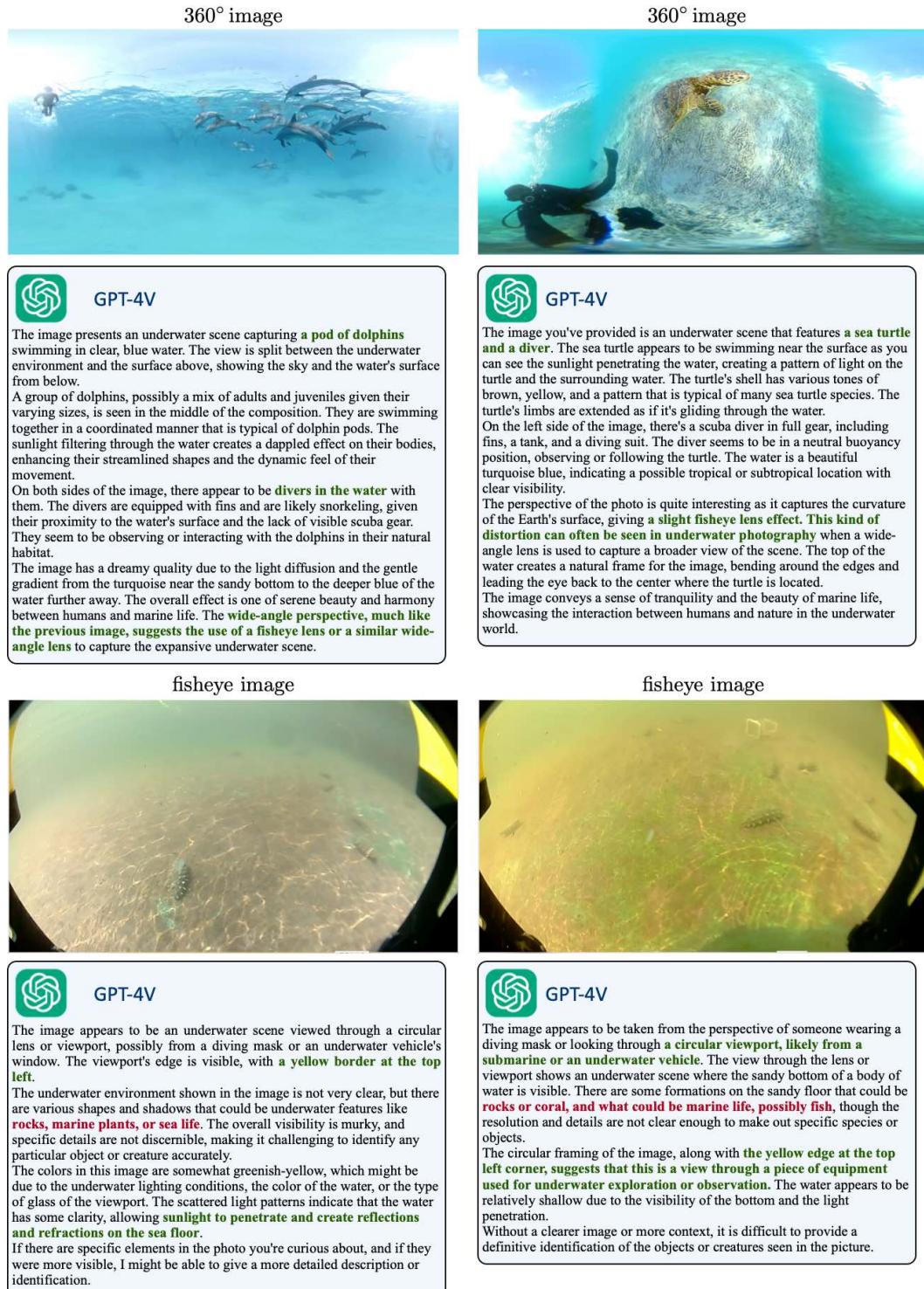


Figure 11: The marine object recognition of GPT-4V on 360° and fisheye images. The prompts are “Describe this figure in detail and recognize the object within this figure”.



Figure 12: The marine object recognition of GPT-4V on sonar and lidar images. The prompts are “Describe this figure in detail and recognize the object within this figure”.

In this section, we test the robustness of GPT-4V in recognizing various formats of visual signals, such as the fisheye (Zheng et al., 2023b), 360° (Huang et al., 2023), sonar (Xie et al., 2022) and Lidar images. Figure 11 illustrates the recognition results of GPT-4V on 360° and fisheye images. GPT-4V could observe the distortion of 360° images but cannot explicitly explain why the distortion happens. In most cases, it could accurately recognize the visual elements from the visual images, however, it seems to have hallucination on the components in the submarine images where the visibility is low and images tend to be more murky, showing its limited robustness to fisheye and 360° images. What's more, it is an expert at recognizing how the images are captured through the edge or border of the viewpoint. We report the further object recognition results of GPT-4V on sonar images and Lidar images in Figure 12. GPT-4V can recognize the general shape of the existing objects but cannot effectively detect what kind of stuff they are in sonar images due to the appearance shift. But for Lidar images in which objects' appearance doesn't shift a lot, GPT-4T can exactly describe the element in detail, showing a very good understanding of the image.



Figure 13: The marine object recognition results of GPT-4V on the images with highlighted regions.

We then identify whether GPT-4V could effectively recognize object regions with highlighted masks as demonstrated in Figure 13, exploring the referring comprehension ability of GPT-4V. The partial parts of the whole image are highlighted by purple and we ask GPT-4V to identify the highlighted regions. Furthermore, GPT-4V is asked to compute the cover of the highlighted coral regions. GPT-4V could generate the Python codes to compute the cover statistics. However, GPT-4V would self-define the RGB value range of “purple” without explanation. However, such a definition could be wrong and cannot handle visual images with high complexity.

2.2.4 PHYSICAL WORLD KNOWLEDGE UNDERSTANDING

We finally explore whether GPT-4V could really understand the physical world knowledge, for example, the spatial, size, color and texture attributes of the existing objects within the images. We explore the capability of GPT-4V to apply common sense knowledge in understanding visual contents within images. We have investigated the models' ability to comprehend visual information via the application of knowledge, which encompasses commonsense, subject knowledge, multicultural customs, and world knowledge. The results are illustrated in Figure 14. GPT-4V shows its strong capability of understanding the physical world knowledge like spatial, size and texture attributes and it also has great robustness to the wrong knowledge that does not correspond with the image and correct it. Even if we provide it with some really misleading images with close view of a dolphin and a far view of a blue whale, it could still correctly tell the real size of these objects.



Describe this **green** sea dragon in detail



GPT-4V

The creature in the image is **actually a leafy sea dragon, not a green sea dragon**. Leafy sea dragons are known for their unique and ornate appearance. This one has a long, slender body with numerous leaf-like appendages protruding from its spine and head, which serve as camouflage among seaweed and kelp. The coloration of this sea dragon is a **vibrant reddish-pink with hints of yellow**, and it has a series of stripes running along the length of its body, providing additional texture and complexity to its appearance.

The body of the leafy sea dragon is structured with bony plates that run the length of its body, offering protection from predators. Its head is elongated with a long, tubular snout, resembling that of a seahorse, which is used for feeding by sucking up small prey such as plankton and tiny crustaceans. The leafy extensions are not used for movement; rather, the sea dragon has small, transparent fins near the base of its tail and on the side of its neck, which are nearly invisible and help it to navigate through the water.

The habitat depicted appears to be a temperate marine environment with seagrass on the bottom, suggesting that this leafy sea dragon is in its natural habitat, likely somewhere off the southern and western coasts of Australia, which is the only place where these creatures are found in the wild.



Tell me which object is bigger in the two images



GPT-4V

The second image features a **blue whale**, which is the **larger object compared to the dolphin in the first image**. Blue whales are the largest animals known to have ever existed on Earth, reaching lengths of up to 100 feet (30 meters) and masses of up to 200 tons or more. On the other hand, dolphins, like the one in the first image, are much smaller, generally ranging from 6 to 12 feet (1.8 to 3.7 meters) in length.



Tell me the shark is on the lefthand or righthand of the diver



Recognize the fluffy object in the image



GPT-4V

The "fluffy" object in the image appears to be a **hairy frogfish**. These creatures are known for their unique and somewhat bizarre appearance, with spines that resemble hair, which they use as camouflage to blend in with their surroundings on the ocean floor. Hairy frogfish are a type of anglerfish that have a fleshy growth on their heads, called an esca or illicium, which they use to lure prey. They are fascinating creatures with an unusual method of locomotion, often "walking" on the sea bed using their pectoral fins.



Tell me what is the object below the shark



GPT-4V

The object below the shark in the image is a **diver**. You can see the diver is equipped with scuba gear, including fins, a mask, a diving suit, and a buoyancy control device. The diver is in a horizontal swimming position, slightly tilted upwards, looking at the shark. The diver's fins are visible in the lower part of the image, with the rest of the body extending upward towards the shark.

Figure 14: GPT-4V could understand the physical world knowledge.

2.3 STATISTICS

In this section, we aim to explore the ability of GPT-4V to perform visual statistics based on the visual contents, such as object counting and summarizing all the appeared objects within images.

2.3.1 OBJECT COUNTING

We perform object counting experiments under five settings: 1) fewer than 10 objects; 2) 10-20 objects; 3) 20-50 objects; 4) 50-100 objects and 5) more than 100 objects. All the qualitative results have been reported in Figure 15. As demonstrated, GPT-4V only demonstrates a limited ability to count the existing objects within the images, especially if the objects are occluded together or the objects are tiny. Meanwhile, since the GPT-4V directly yields the estimation results of objects without explicitly localizing the objects (e.g., bounding box), the estimation results will likely be not accurate. Furthermore, we have also observed that GPT-4V tends to generate an exact number of presented objects within the images when there are few objects visible. In contrast, GPT-4V instead yields a rough number of the object counting results. To avoid potential mistakes, GPT-4V outputs a range (e.g., more than 100) for the estimated objects. In summary, the external object detection tools for localizing the objects should be integrated to promote the object counting ability of MLLM.

2.3.2 RECOGNIZING ALL THE OBJECTS

We then explore the ability of GPT-4V to recognize all the existing objects within the given visual images and list the corresponding names of all the recognized objects. Figure 16 demonstrates the recognition results under the crowded and structured palette. The GPT-4V struggles to recognize all the objects within the images and only lists very few common object categories. Furthermore, we observe that GPT-4V could summarize the implicit intention of such visual images and try to summarize the relationships between the recognized objects. However, due to the large number of objects, some less commonly known species, and the low image resolution, GPT-4V shows a very limited performance on recognizing all the objects in one single image while it could still understand some general information of the image, like title, colors and common features of objects. Similar to the object counting task, GPT-4V tends to discard many objects within the images and only tries to recognize some common objects easy to recognize to avoid making mistakes, but this also makes it hard for GPT-4V to recognize all the objects existing in the image.

<p>GT: 2 sharks and 1 sea turtle</p>  <p>NETFLIX</p>	<p>GT: 8 dolphins</p>  <p>NETFLIX</p>
<p>Describe this figure and count the number of appeared object.</p>	
<p> GPT-4V</p> <p>The image depicts an underwater scene, showcasing a sea turtle prominently in the foreground, resting on the seabed covered in marine vegetation. In the background, there are three larger fish-like creatures swimming, which due to their shape and size, suggest that they might be sharks.</p> <p>Thus, there are four main objects of interest in this image: one sea turtle and three larger fish-like creatures, which are likely sharks. The ocean floor and water column itself are rich with smaller details, but in terms of larger, distinct objects, these four are the primary focus.</p>	<p> GPT-4V</p> <p>The image depicts a group of dolphins seen from an aerial or above-water perspective, swimming closely together. The dolphins appear to be in a natural habitat, with clear water allowing a view of the aquatic plants below. The group is densely packed, making it challenging to count each individual accurately.</p> <p>From what can be visually discerned, there appear to be at least ten dolphins, but the exact count might be slightly higher due to potential overlapping bodies and the angle of the shot.</p>
<p>GT: 16 dolphins</p>  <p>NETFLIX</p>	<p>GT: 41 sharks and fishes in total</p>  <p>NETFLIX</p>
<p>Describe this figure and count the number of appeared object.</p>	
<p> GPT-4V</p> <p>The image shows a bird's-eye view of a group of dolphins swimming through what appears to be a shallow body of water with a visible seabed covered in aquatic vegetation. The water clarity allows us to see the dolphins and the details of the seafloor.</p> <p>Upon visually inspecting the image, there are exactly ten dolphins visible, swimming in a loose formation. They are likely navigating through the water in search of food or traveling to another location as part of their natural behavior.</p>	<p> GPT-4V</p> <p>The image shows an underwater scene with a school of sharks. They are swimming around a coral reef, which is visible at the bottom of the image. The water is clear, highlighting the contrast between the marine life and the deep blue of the ocean.</p> <p>In terms of counting, there are multiple sharks of varying sizes and at different depths. There are also a few smaller fish among the sharks, adding to the biodiversity presented in the scene. A precise count is difficult due to the possibility of overlapping bodies and varying distances from the viewpoint. However, a rough estimate based on visible bodies suggests there are at least 15 sharks in the image.</p>
<p>GT: 65 sharks</p>  <p>NETFLIX</p>	<p>GT: 140 birds</p>  <p>NETFLIX</p>
<p>Describe this figure and count the number of appeared object.</p>	
<p> GPT-4V</p> <p>The image displays an underwater scene, seemingly deeper in the ocean given the darker tone, featuring a large school of sharks swimming above a coral reef. The reef occupies the lower portion of the frame, densely populated with coral, while the sharks are distributed throughout the water column above.</p> <p>Counting the exact number of sharks is challenging due to the potential overlap and the fact that some sharks may be partially out of frame or obscured by darkness. However, by visually scanning the image, there are at least 20 sharks that can be distinguished based on the parts of their bodies that are visible. This is an estimate and the actual number could be slightly higher.</p>	<p> GPT-4V</p> <p>The image captures a dramatic moment along a coastline where a large flock of birds is in flight over breaking ocean waves. The birds are densely packed, with many individuals in the air, which indicates a possibly coordinated movement, often seen in migratory species or in response to a food source.</p> <p>Counting each bird individually is impractical due to their number and the fact that some may overlap or be partially out of frame. However, by estimation, the number of birds in the image could easily be in the several dozens, possibly reaching over a hundred. This is based on the visible sections of the image, acknowledging that there could be more birds outside the frame or obscured by the spray of the waves.</p>

Figure 15: The marine object counting results under different settings.

THE SPECTACULAR SURVEY OF SHARKS

SIGNIFICANT EXANT SPECIES OF SELACHIMORPHA

Recognize all the objects in this image and list their names

GPT-4V

The image you've uploaded is a poster titled "The Spectacular Survey of Sharks" and it features a variety of shark species. The title suggests that the poster is an educational or informational display about different types of sharks, known scientifically as the order Selachimorpha. The poster is organized into rows with illustrations of sharks, each labeled with its common name. The sharks are depicted in a side profile view against a dark background, which makes the lighter colors of the sharks stand out. They are rendered in a stylized form that appears accurate to their real-life counterparts, capturing key characteristics such as body shape, fin placement, and distinctive patterns or colors.

Given the detailed nature of the poster and the number of shark species shown, it's not feasible to list each shark's name from the image provided without a clearer, higher-resolution image that allows for reading the text labels next to each shark illustration. Normally, such posters include a wide range of species from well-known ones like the **Great White Shark**, **Hammerhead Shark**, and **Tiger Shark** to less commonly known species. For a full list of the shark species depicted, one would need to be able to read the text labels accompanying each illustration on the poster. If there's a particular shark or a section of the poster you are interested in, I can attempt to provide more information on those specific species if the text is legible.

OCTOPUS, SQUID & CUTTLEFISH

PULPO, CALAMAR & SEPIA POLPO, CALAMARO & SEPPIA PIEUVRE, CALMAR & SEICHE

Recognize all the objects in this image and list their names

GPT-4V

The image seems to be an educational chart displaying various species of octopus, squid, and cuttlefish. These creatures are part of the cephalopod class, which is known for its marine life with prominent heads and sets of arms or tentacles. Typically, such a chart includes a variety of species with their common names and sometimes scientific names. They are usually illustrated with high detail to show the unique features of each species, such as the patterns on their skin, body shape, and color.

Due to the resolution and size of the image you've uploaded, I'm unable to read the text and provide a list of names for each species depicted. These charts usually feature well-known species like the **Common Octopus** (*Octopus vulgaris*), **Giant Squid** (*Architeuthis dux*), and **Common Cuttlefish** (*Sepia officinalis*), among others. Each species would be accompanied by a label, but without a higher resolution image, it's not possible to accurately list each one. If you can provide a clearer image or if there's a specific part of the image you'd like me to focus on, I can give you more detailed information.

Figure 16: Utilize GPT-4V to recognize all the objects within the visual images.

2.4 DOMAIN-SPECIFIC QUESTION-ANSWERING

we examine the ability of GPT-4V to apply knowledge in the fields of marine to understand visual images. We observe that GPT-4V possesses the relevant subject knowledge associated with the following cases.

<p>GT: b) Whale shark</p> <p>Which of the following is the largest living fish species?</p> <p>a). Great White Shark. b). Blue Whale. c). Manta Ray. d). Killer Whale.</p>	<p>GT: a) Shedding of exoskeleton</p> <p>What is the process of molting in crustaceans?</p> <p>a). Shedding of exoskeleton. b). Regeneration of lost limbs. c). Reproduction. d). Feeding.</p>
 GPT-4V <p>The question in the figure asks, "Which of the following is the largest living fish species?"</p> <p>The options given are: a) Great White Shark. b) Blue Whale. c) Manta Ray. d) Killer Whale.</p> <p>The correct answer is not listed among the options because the largest living fish species is actually the whale shark. However, out of the options provided, the Great White Shark (a) is the largest fish. The Blue Whale (b) and the Killer Whale (d) are not fish; they are mammals. The Manta Ray (c) is large but not as large as the whale shark or the great white shark.</p>	 GPT-4V <p>The question in the figure asks, "What is the process of molting in crustaceans?"</p> <p>The correct answer is: a) Shedding of exoskeleton.</p>
<p>GT: a) Phytoplankton</p> <p>Which marine organism is responsible for the production of most of earth's oxygen?</p> <p>a) Phytoplankton b). Seagrass. c). Kelp. d). Coral polyps.</p>	<p>GT: a) Photosynthesis</p> <p>What is the process by which marine plants convert sunlight into chemical energy?</p> <p>a) Photosynthesis b). Chemotaxis. c) Bioluminescence. d) Cell respiration.</p>
 GPT-4V <p>The question in the figure asks, "Which marine organism is responsible for the production of most of earth's oxygen?"</p> <p>The correct answer is: a) Phytoplankton.</p>	 GPT-4V <p>The question in the figure asks, "What is the process by which marine plants convert sunlight into chemical energy?"</p> <p>The correct answer is: a) Photosynthesis.</p>

Figure 17: The performance of GPT-4V on answering the marine multiple choice questions. The prompts are “answer the question within this image”. We observe that GPT-4V demonstrates a strong OCR ability.

Multiple choice questions. We first explore the ability of GPT-4V to answer the marine multiple-choice questions. We upload the manually written marine questions and corresponding choices to GPT-4V and ask GPT-4V to generate the answers in Figure 17. As demonstrated, GPT-4V has shown a strong optical character recognition (OCR) ability to extract the correct text information from the uploaded images and a satisfactory promise for handling basic marine knowledge. We have manually constructed 100 multiple-choice questions, which come from marine biology, oceanography, and geology. The accuracy of GPT-4V is computed to quantitatively assess the quality of GPT-4V in answering the domain-specific questions.

Domain-specific VQA. We evaluate whether GPT-4V could understand the user intent of the domain experts and the ability of GPT-4V for abstract visual reasoning and scientific problem-solving. Such abilities are required for marine researchers to analyze the data (figures and tables) collected to gain insights into various aspects of marine research fields. Results are reported in Figure 18 and Figure 19, respectively. As demonstrated in Figure 18, GPT-4V could understand most elements of the left scientific figure but make a tiny mistake about the temperature range. Besides, GPT-4V could understand the temporal changes within the scientific figure and conclude the implicit intention. It could accurately describe the coral status of each sub-figure and conclude the progression

changes. We have also included more visual scientific examples essential for handling marine biology, engineering, oceanography, and *etc.*

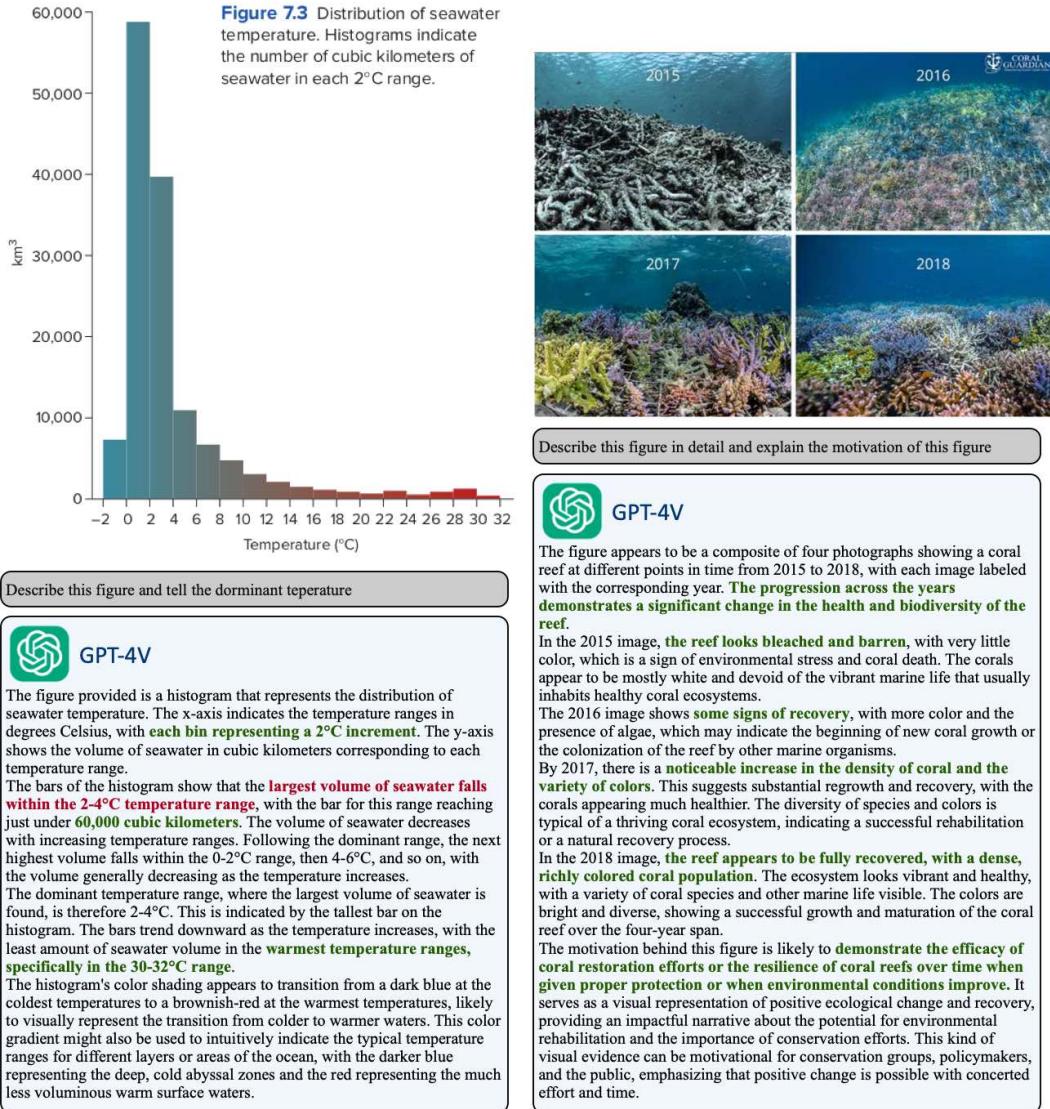
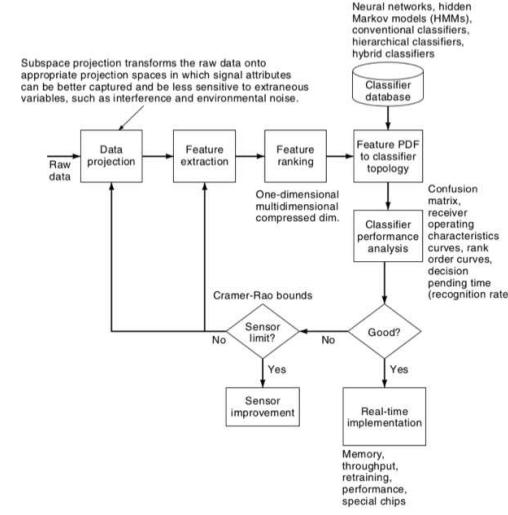


Figure 18: The performance of GPT-4V on answering domain-specific questions.

Furthermore, we feed GPT-4V with scientific figures and tables from the field of marine engineering as reported in Figure 19. GPT-4V could effectively understand the flowchart. GPT-4V could describe the logic inside of the flowchart and respond with more reasoning details. GPT-4V could also understand the tables in detail. When being asked a question that requires intermediate reasoning procedures, GPT-4V could answer correctly with detailed reasoning procedures. However, GPT-4V still has difficulties in providing a precise answer in some cases, which is mainly constrained by the unsatisfactory OCR accuracy in Figure 19.

Multi-round conversation. We finally assess the ability of GPT-4V to support multi-round conversations. Users could ask different questions for comprehensive analysis, as demonstrated in Figure 20. Our study suggests that GPT-4V, could generate corresponding responses aligned with the user intent and cover the detailed information. However, GPT-4V struggles with the marine object recognition. With the wrongly identified marine objects, GPT-4V leads to error accumulation, which suggests that GPT-4V only responds based on the previously generated keywords (as the context prompt)



Describe this figure in detail and describe the flow chart

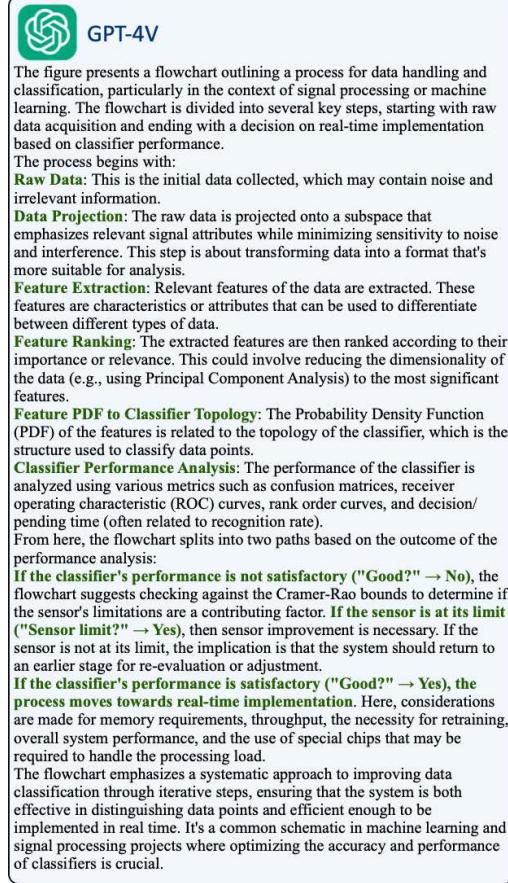
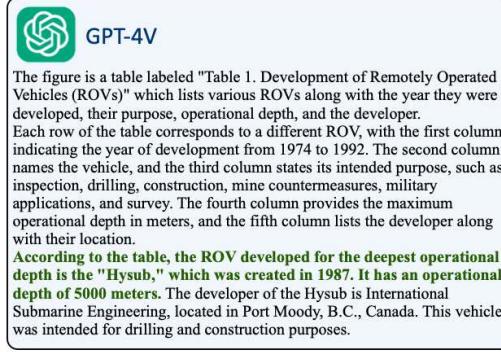


Table 1. Development of Remotely Operated Vehicles (ROVs)

Year	Vehicle	Purpose	Depth (m)	Developer
1974	RCV	Inspection	412	Honeywell, San Diego, CA
1977	Scorpio	Drilling, construction	1000	Ametek Offshore Ltd, Aberdeen, Scotland
1979	Filippo	Inspection	300	Gavamarine, Italy
1982	Mermaid	Mine countermeasures	100	Siemens AG, West Germany
1984	Sea Hawk	Drilling, inspection	500	Scandinavian Underwater Technology, Sweden
1985	Dragonfly	Construction	2000	Offshore Systems Engineering Ltd., Norfolk, UK
1985	Victor	Drilling, construction	3000	Perry Offshore River Boats, FL
1985	Triton	Drilling, survey	3000	Subsea Engineers Ltd., York, England
1986	SeaRover	Mine countermeasure	250	Benthos, North Falmouth, MA
1986	Phantom	Inspection, survey	600	Deep Ocean Engineering, San Leandro, CA
1986	Obstetra	Observation	150	EDCO, Port Moody, BC, Canada
1986	Teal Blazer	Military applications	915	International Submarine Engineering Ltd., Port Moody, BC, Canada
1986	MUC	Trench digging, cable/flow line burial, seabottom work	200	Transocean, France
1987	RCV TWO	Investigation and inspection of cooling water outfalls from nuclear power plants	N/A	Hytec, Montpellier, France
1987	Buster	Inspection	500	ROVTECH, Lakeview, Norway
1987	Hysub	Drilling, construction	5000	International Submarine Engineering, Port Moody, B.C., Canada
1987	Philips	Inspection and observation	400	Cerex Pro, France
1988	ARMS	Mine countermeasures	385	AMETEK, El Cajon, CA
1988	DECA-KAAS	Inspection of long power plant conduits	30	Marine Engineering & Shipbuilding Co., Ltd., Tokyo, Japan
1988	Dolphin 3B	Construction	3300	Marine Engineering & Shipbuilding Co., Ltd., Tokyo, Japan
1991	no name	Nuclear power plants	N/A	Deep Ocean Engineering, San Leandro, CA
1992	no name	Nuclear power plants	N/A	RSI Research Ltd., Canada

Describe this figure in detail and tell the developer of the ROV, which could dive the largest depth



Country	Number of Tourists (000s) ^a	Tourists as % of Population ^a	Tourist Receipts ^b as % of GNP	Tourist Receipts ^b as % of Exports
Antigua and Barbuda	232	364.2	63.4	73.5
Bolivia	1618	586.4	42.0	75.6
Burkina Faso	472	152.4	36.2	56.2
Cape Verde	45	11.4	11.5	37.3
Comoros	26	4.9	10.6	47.8
Cuba	1153	10.5	8.8	n/a
Cyprus	2088	280.7	24.0	49.1
Dominica	65	97.6	15.9	32.5
Dominican Republic	2211	28.1	13.6	9.2
Fiji	359	45.3	19.2	29.1
Grenada	111	116.2	27.0	60.6
Haiti	149	2.2	3.9	50.5
Jamaica	1192	45.6	31.6	39.8
Maldives	366	130.7	95.0	68.4
Madagascar	1111	294.7	22.9	28.7
Montenegro	536	46.4	15.7	26.8
Papua New Guinea	66	1.5	2.1	3.0
St. Kitts and Nevis	88	210.5	30.6	63.6
St. Lucia	248	164.7	41.1	66.6
St. Vincent	65	54.6	23.8	45.9
Samoa	68	31.1	19.6	48.8
Seychelles	130	167	34.6	52.2
Singapore	7198	209.2	6.2	4.1
Solomon Islands	16	3.7	2.8	4.2
Trinidad and Tobago	324	28.7	4.2	8.3
Vanuatu	49	27.1	19.3	40.9

Tell me which country has the largest number of tourists



Figure 19: The performance of GPT-4V on understanding domain-specific figures and tables.

without looking at the visual contents. How to alleviate the hallucination of MLLMs is a valuable and important future research direction.

GT: Banded pipefish


Tell me the distinctive features of it

Recognize this figure

Tell me the size of this object

Where can I see it

GPT-4V

The Ribbon Eel (*Rhinomuraena quaesita*) has several distinctive features that set it apart from other eel species:
Coloration: Ribbon Eels are noted for their striking and vivid colors. Juvenile Ribbon Eels are typically jet black with a yellow dorsal fin. As they mature, males change color to a bright electric blue with a yellow dorsal fin. Finally, mature females may become entirely yellow or golden.
Morphology: Ribbon Eels have an elongated, ribbon-like body, hence the name. Unlike many eels, they have a long, thin dorsal fin that runs almost the entire length of their body, starting right behind their head.
Flared Nostrils: One of the most characteristic features of the Ribbon Eel is its expanded, tube-like nostrils. Each nostril has a flared, decorative anterior edge that is quite pronounced and can be either red or yellow.
Mouth: The Ribbon Eel has a highly extendable jaw, which is not common among most eel species. Its mouth can open wide enough to swallow prey whole, and when closed, it forms a distinctive hook-like appearance.
Sexual Dimorphism and Color Phases: Ribbon Eels are protandric hermaphrodites, meaning they start life as males and can change to females as they mature. This is accompanied by significant changes in color, as mentioned in point 1.
Size: They can grow quite long, typically reaching 60 to 100 centimeters (24 to 39 inches) in length.
Behavior: Ribbon Eels are known to burrow in sand or hide in crevices with only their heads and anterior bodies exposed. They are generally shy and reclusive.
These features are not only visually distinctive but also make the Ribbon Eel a fascinating subject for marine biologists and underwater photographers.

GPT-4V

This creature is a **Ribbon Eel**, also known as ***Rhinomuraena quaesita*** or ***the Bernis eel***. It's a species of saltwater eel and is the only member of the genus *Rhinomuraena*. Ribbon Eels are known for their elongated bodies with high dorsal fins and their striking coloration which is usually black with yellow or white striping and a characteristic flared nostril. They are a common sight in the Indo-Pacific regions and are often found in lagoons and reefs. The Ribbon Eel goes through various color phases, including a juvenile phase where they are typically black, a subadult phase with blue and yellow coloring, and an adult phase often characterized by a yellow hue, with the males transitioning to this coloration as they mature.

GPT-4V

The Ribbon Eel typically ranges in size from **60 to 100 centimeters (approximately 24 to 39 inches)** in length when fully grown. However, the image does not provide a scale or reference object to accurately determine the size of the individual eel depicted. Without additional context or reference points to determine the eel's size relative to its environment, it's not possible to provide an exact measurement of the eel in the image.

GPT-4V

Ribbon Eels are marine creatures found in the Indo-Pacific oceans. They are most commonly seen in the following areas:
Coral reefs and lagoons in the Indo-Pacific region, from East Africa, the Red Sea, and the Indian Ocean to the western Pacific Ocean.
Popular diving spots in countries like Indonesia, the Philippines, Australia (Great Barrier Reef), Fiji, and Japan.
The Lembeh Strait in Indonesia is particularly famous for its diverse and unique marine life, including Ribbon Eels.
To see Ribbon Eels in their natural habitat, one would typically go scuba diving or snorkeling in these regions, especially where coral reefs are prevalent. There are also some public aquariums around the world that may have Ribbon Eels on display. Always check with local diving tours or aquariums for the possibility of seeing these creatures.

Figure 20: The GPT-4V could support multi-round conversation, however, leads to error accumulation.

26

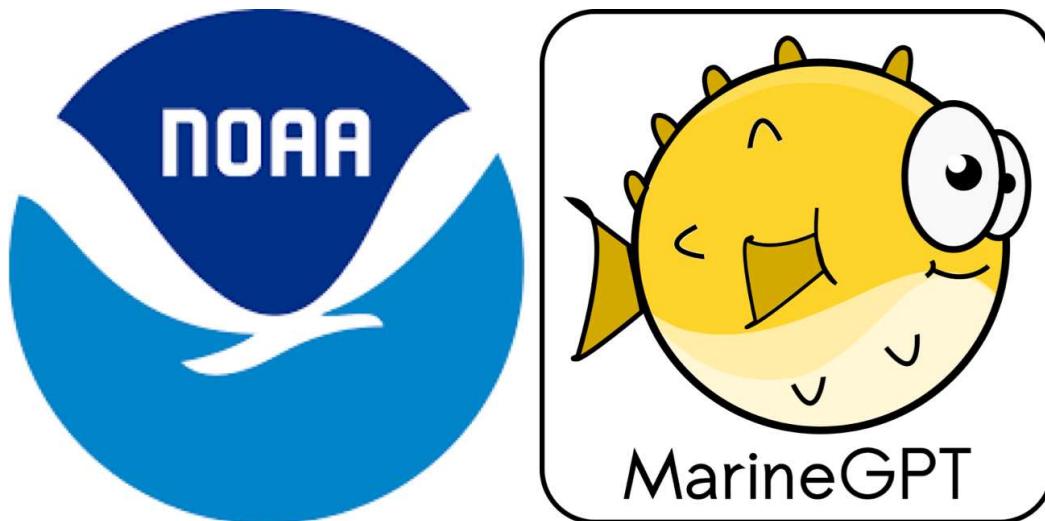
2.5 MARINE CULTURAL UNDERSTANDING

We investigate the ability of GPT-4V to recognize logos, landmarks, artist images, and more in Figure 21, Figure 22, and Figure 22.

In Figure 21, GPT-4V could effectively recognize the globally known NOAA logo and yield a detailed description of the appearance of the logo. However, there is still a hallucination with the description of the NOAA logo. We guess the generated responses are from the training corpus of GPT-4V rather than being aligned with the visual elements. As for the novel logos, GPT-4V could describe the appearance of the designed logos. The feature patterns of the logos are comprehensively described and GPT-4V could assess the artistic and literary representations of themes and species.

We then ask GPT-4V to perform marine artist image recognition and description as illustrated in Figure 22. GPT-4V could efficiently describe the visual elements of marine artist images. We present the capacity of GPT-4V to depict the appearance of the cartoon images, paintings, and actual photographs. GPT-4V demonstrates a strong ability to assess the aesthetic quality of visual images and describe the partial parts of each image.

Finally, we report the landmark recognition performance of GPT-4V in Figure 23. GPT-4V can identify the marine vestige and statures. The detailed appearances of recognized ruins are further described in detail, demonstrating the strong ability of GPT-4V to perceive the visual images. However, GPT-4V cannot accurately discriminate the statures with irregular shapes and poses.



 GPT-4V

The image is a logo, specifically the logo of the **National Oceanic and Atmospheric Administration (NOAA)**. The NOAA logo is a stylized representation of the organization's focus on the environment, particularly the ocean and atmosphere.

The logo is composed of a simple, graphic design featuring two main colors: a **dark navy blue** and a **lighter shade of blue**. It consists of three overlapping and stylized elements that can be interpreted as follows: The top part, in **navy blue**, is shaped like a **bird in flight**, symbolizing freedom, exploration, and perhaps the atmospheric aspect of NOAA's work. The bottom part, in light blue, resembles a **fish or a marine creature**, which represents the oceanic part of NOAA's mission. The middle portion where the two elements overlap forms a **white silhouette of a sailing vessel**, signifying NOAA's role in maritime activities. Across the center of the logo, the acronym "NOAA" is spelled out in **bold, capitalized, white letters**, which stands out against the dark blue background of the bird's body.

Overall, the logo is designed to encapsulate NOAA's commitment to environmental science, ranging from oceanic to atmospheric research and stewardship. The use of the bird and fish elements not only represents the air and sea but also conveys the organization's focus on protecting and studying Earth's natural systems.

 GPT-4V

The image you've uploaded is a stylized representation of a **fish**, which appears to be a logo or mascot. The fish is circular in shape, with a **cheerful expression**. It is colored in shades of yellow and has distinctive features such as a large, white eye with a black pupil, giving it a cartoonish and friendly appearance. The fish also has **six small triangular spikes** on its back, a fin on top, and a tail fin that has a darker shade of yellow compared to its body.

Below the fish is the text "**MarineGPT**" written in a simple, bold font, suggesting that the image is related to a marine-themed entity or project named "MarineGPT." The font is black, which contrasts with the bright colors of the fish, making the text stand out.

The overall design is encapsulated within a rounded square border, which frames the image neatly. The background within this border is white, which helps the yellow fish to pop visually. The image conveys a **sense of playfulness and approachability**, likely intended to make the concept of "MarineGPT" seem friendly and engaging.



 GPT-4V

The image you've uploaded appears to be a logo or graphic design. It features the words "**Aqua mind**" in a stylized font. The "A" in "Aqua" and the "**m**" in "mind" are **capitalized**, while the other letters are lowercase. The font is modern and clean, with the letters in a light blue color. The background of the image is a lighter blue with a **pattern that suggests ripples on the surface of water**, enhancing the aquatic theme of the name. Overlapping the text, there's an image of a sphere that seems to **represent the Earth**, with visible patches of green and blue, indicating landmasses and water. The sphere has a realistic appearance, with detailed shading and highlights that **give it a three-dimensional quality**.

Overall, the design conveys a theme of water, the Earth, and perhaps global consciousness or environmental awareness, suggested by the name "Aqua mind" and the inclusion of the Earth's image. The color scheme sticks to various shades of blue, which is often **associated with water, calmness, and serenity**.



 GPT-4V

The image you've uploaded appears to be a logo. The logo design is comprised of graphical elements and text:

Graphical Element: The graphic is a stylized representation, with two elements intertwined. The top part looks like an abstract symbol resembling a **bird in flight, pointing downwards with its wings angled upwards**. This element is dark blue. The bottom part seems to be a **stylized wave of water**, depicted by **three horizontal wavy lines** that **resemble the sea or a river**, in a lighter blue shade. The bird-like symbol and the waves together could represent a connection between air and water or the environment.

Text Element: To the right of the graphic, the word "**VIAME**" is written in capital letters. The font is modern, with clean lines and a dark teal color. The "**V**" and "**M**" in the text are **capitalized more prominently, with the other letters in a smaller but still uppercase form**.

The logo has a clear, professional look, likely intended to **convey a sense of reliability and expertise**, possibly relating to a company or organization that operates in fields related to the environment, water, or perhaps technology due to the clean lines and modern font. The color scheme of various blues suggests an association with water, trust, and dependability.

Figure 21: Utilize GPT-4V for marine logo understanding.



GPT-4V

The image shows a **large, colorful sculpture of a fish** made entirely out of **plastic objects**. The sculpture is a vibrant display of various hues, with each part of the fish composed of different colors and types of plastic items, showcasing a wide array of textures and shapes. The head of the fish is purple and blue, the body transitions through bright colors like green, yellow, and orange, and the tail ends with shades of blue. Upon closer inspection, you can see that the sculpture is made from a multitude of everyday plastic items such as bottles, containers, combs, toys, and other miscellaneous items, all of which are likely repurposed or recycled materials. The fish's eye is particularly noticeable, made from what appears to be a large, round, orange object with a blue center, possibly a lid or a bowl, giving it a very prominent and striking appearance. The mouth of the fish is open, displaying an array of white objects that resemble teeth, adding to the realism of the sculpture. The fins and tail are constructed with plastic pieces that align to mimic the structure and flow of real fins, with careful layering to create a sense of movement. This artwork not only stands out for its creativity and the skillful use of color, but it also seems to carry an environmental message about the abundance and variety of plastic waste. Such a sculpture can serve as a powerful statement on the **impact of plastic on marine life** and the importance of recycling and reducing plastic waste. The background of the sculpture is natural, with green trees, which contrasts sharply with the artificiality of the plastic materials, further emphasizing this point.



GPT-4V

The image depicts a **mosaic artwork of a fish**. The mosaic is composed of numerous small, square tiles meticulously arranged to form the image. The background is a vibrant blue, reminiscent of the sea or water, and the fish itself is made up of a palette of neutral colors such as beige, brown, and grey, with hints of purple around the eye area. The fish has a prominent, rounded eye with a black pupil, encircled by a ring of purple and white, giving it a realistic appearance. The body of the fish is depicted with an **interplay of light and dark tiles** that suggest the natural shading and textures of fish scales. The fins and tail are shown in lighter colors, likely indicating a play of light or their thinner, somewhat translucent nature. **Each tile appears to be uniformly cut and the overall composition is well-proportioned and balanced**, capturing the graceful shape of the fish. The artwork's medium, mosaic, is an ancient form of art that requires a great deal of precision and patience, as it involves fitting together many small pieces to create a larger, cohesive image. This kind of art can often be found in public spaces, buildings, and homes, as part of the decor, and is appreciated for its durability and the vibrancy of its colors which are often preserved over time. The fish motif is a common subject in mosaic art, symbolizing abundance, fertility, and the connection with the aquatic world.



GPT-4V

The image features a **colorful painting of a marine scene**. There are several elements in the painting:
Fish: There are both striped and **solid-colored fish**. The striped fish have alternating **yellow and white stripes** running horizontally across their bodies, while the solid-colored fish are orange with black markings. Their shapes are stylized rather than realistic, with exaggerated, round eyes and simplified forms.
Jellyfish: Two jellyfish are depicted with bell-shaped bodies and trailing tentacles. The larger one is painted in shades of purple and pink with flowing tentacles that have a striped pattern. The smaller one is a solid pink color, with similar stylized tentacles.
Background: The background is composed of large, green, leaf-like shapes that might represent **seaweed or aquatic plants**. They are overlaid onto a dark blue backdrop that suggests the depths of the ocean.
The style of the painting is whimsical and expressive, utilizing **bright, bold colors and simple shapes** to create a lively underwater tableau. The outlines are prominently defined, adding to the graphic quality of the image.
The artist has **signed the painting in the lower right corner**, indicating it is an original work. The painting's joyful and vivid portrayal of sea life could be appealing for decorative purposes, educational materials, or simply as an expression of the artist's appreciation for oceanic environments.



GPT-4V

The image is a watercolor painting depicting a **sea turtle swimming underwater**. Here are the details based on the elements visible in the artwork:
Sea Turtle: The turtle is the central focus of the painting, occupying a large portion of the canvas. It is depicted with a degree of realism, showcasing its distinct features such as a patterned shell with darker splotches, a yellow underside, and flippers that are in motion, suggesting swimming. The turtle's head is turned slightly towards the viewer, with one eye visible, detailed with a black pupil surrounded by a greenish-blue iris.
Color Palette: The color palette is dominated by blues and greens, typical of an underwater scene. The background is washed in a gradient of blue tones that darken towards the top, possibly to indicate the depth of the water and the surface above.
Underwater Environment: The bottom of the painting shows variations of green, with shapes that resemble marine plants, likely seaweed or sea grass, suggesting that the turtle is swimming near the seabed.
Artistic Technique: The watercolor technique used in the painting allows for soft transitions between colors, giving the scene a dreamy, fluid appearance. The **brushstrokes are visible**, adding texture to the painting, especially in the depiction of water and the sea turtle's shell.
The artwork conveys a peaceful underwater scene, capturing a moment of the sea turtle's natural movement through its habitat. The artist has used watercolor's ability to blend colors and create layers to depict the translucent quality of water and the grace of the sea turtle.

Figure 22: Utilize GPT-4V for marine artist image understanding.



GPT-4V

The image appears to show an underwater scene, specifically a portion of a sunken shipwreck. The structure is heavily encrusted with what looks like rust and marine growth, indicative of a long time spent under the sea. The metal of the ship has degraded significantly, creating a rough, textured appearance due to corrosion and biological colonization. You can see what remains of the ship's architecture: the metal beams and the grid-like framework. Despite the deterioration, the geometry of the ship's construction is still distinguishable. There are straight horizontal and vertical lines forming a lattice, which suggests the framework of the ship's wall or perhaps a part of the deck structure. Some of the horizontal beams appear to be intact, running across the image, while others are missing, leaving gaps in the structure. The rust and marine growth give the wreck an orange-brown color, typical of iron and steel objects that have been exposed to seawater for extended periods. There is a white rope or cable running diagonally across the structure, which stands out against the darker colors of the wreck and the deep blue of the surrounding water. The blackness of the water suggests that this is in a deep or poorly lit area of the ocean, where light does not easily penetrate. The image has a haunting quality to it, with the wreck giving off an eerie vibe, a relic of the past now inhabited by sea life and forever part of the underwater landscape. It's a scene that evokes the mystery and vastness of the ocean, as well as the passage of time.



GPT-4V

The image displays what appears to be an underwater statue. The statue is human-like, with arms outstretched to the sides, reminiscent of the iconic pose of the Christ the Redeemer statue in Rio de Janeiro. The figure has a discernible head, torso, arms, and hands with detailed fingers extended outward. The statue is covered in a thick layer of marine life, indicating it has been submerged for a significant time. Coral growth, marine plants, and other sea organisms have colonized the surface, giving it a rough and textured appearance. The colors are predominantly muted with shades of blue-green, typical of underwater environments, due to the light filtering through the water and the growth on the statue. The background is a blurred underwater landscape, likely the ocean floor, with variations in light and shadow creating a dappled effect, which is common when sunlight filters through water. There's a watermark from "watch mojo" on the image, suggesting that the image may be a screenshot from a video or documentary. The overall impression is one of serene abandonment to the aquatic environment, as the statue becomes part of the underwater ecosystem. It's a powerful image that speaks to themes of nature overtaking human-made objects and the passage of time.



GPT-4V

The image depicts an underwater scene featuring a diver alongside a submerged bust sculpture. The sculpture, which has acquired a patina from being underwater, resembles a human head and shoulders with a discernible face, suggesting it could be a representation of a historical figure or a person of significance. The diver is equipped with full scuba gear, including a wetsuit, fins, mask, and a scuba tank. They are also holding what appears to be an underwater camera with attached lights, likely documenting the sculpture or the surrounding marine environment. The diver's presence provides a sense of scale, showing the sculpture's size relative to a human. The surrounding environment has a variety of marine growth, indicating that the sculpture has been underwater for some time, allowing an ecosystem to develop on and around it. This kind of artificial reef can be intentional, providing a habitat for marine life and an attraction for divers, or it can be the result of a shipwreck or other submerged objects over time becoming part of the underwater landscape.



GPT-4V

The image shows an underwater statue of what appears to be a manatee, a large, fully aquatic, mostly herbivorous marine mammal sometimes known as a sea cow. The statue captures the distinctive features of a manatee, including its stout, rounded body, paddle-like flippers, and a broad, flat tail. The manatee's snout is short and wrinkled with whiskers, and its eyes are small. The texture of the statue is detailed to resemble the rough, wrinkled skin that is characteristic of manatees. The statue is submerged in clear water, which allows for good visibility and the details of the statue to be clearly visible. This kind of underwater installation can be found in artificial reefs or underwater parks, serving both as an attraction for divers and snorkelers and as a structure for marine life to colonize, promoting biodiversity. The presence of such statues in underwater environments often merges art with conservation efforts.

Figure 23: Utilize GPT-4V for marine landmark recognition.

2.6 ADVANCED FUNCTIONS

In this section, we aim to explore the possibility of utilizing GPT-4V for some advanced and complicated functions in the marine research field, such as coral coverage estimation, benthic composition statistic, multi-modal reasoning, relationship summarization, and *etc.*

2.6.1 CORAL COVERAGE ESTIMATION

Coral reefs are among the most biodiverse ecosystems on our planet and provide habitat for countless marine species. Monitoring coral coverage allows researchers to assess the overall health and condition of these ecosystems. In this section, we aim to explore the feasibility of utilizing GPT-4V for coral coverage estimation. Figure 24 represents some preliminary results of coral coverage estimation. GPT-4V avoids directly outputting the coral coverage and instead attempts to generate some computer vision processing codes for coral coverage estimation. The generated coral coverage is far away from the real ground truth. Besides, GPT-4V may lead to the ignorance of the tiny corals or the minority coral types and then result in wrong policy making.

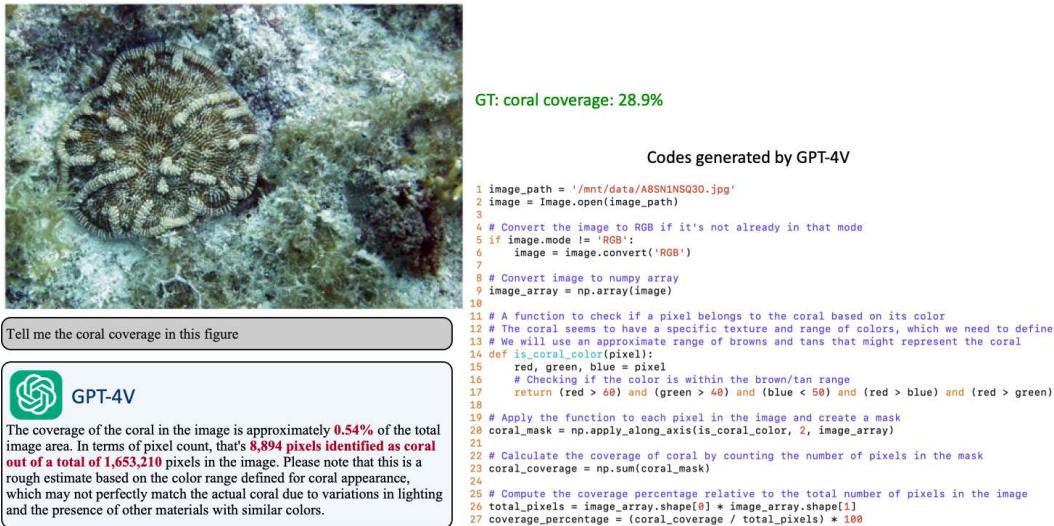


Figure 24: Utilize GPT-4V for coral coverage estimation.

We then examine the ability of GPT-4V to discriminate the coral reef composition from the visual images in Figure 25. GPT-4V could accurately recognize the coral reefs and missed the brain coral reefs. Moreover, we have also explored the ability of GPT-4V to understand the coral bleaching, which is linked to warming seas, can lead to declines in coral coverage. When being asked whether the coral reefs are bleached, GPT-4V has made a wrong judgment. GPT-4V cannot understand the meaning of “bleaching” and describes the degree of coral bleaching due to the lack of a reference color bar.

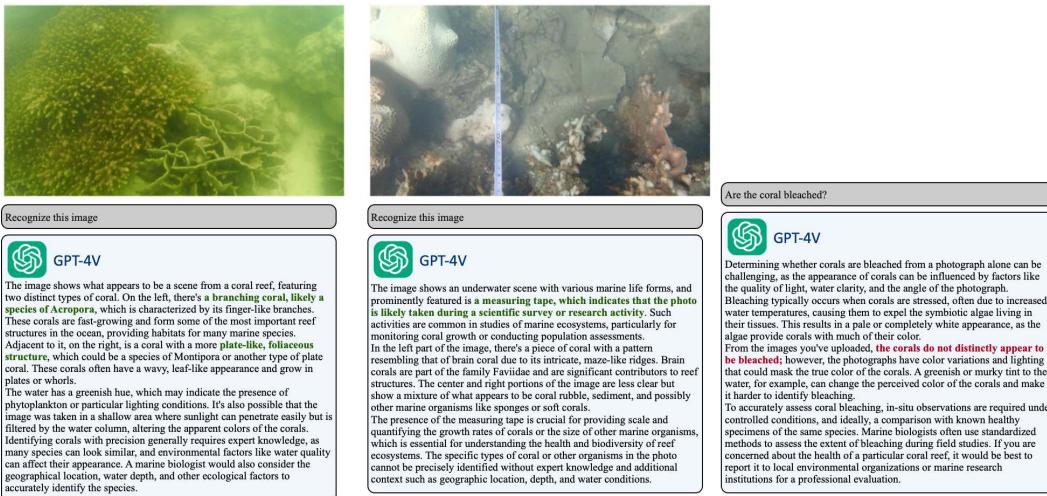
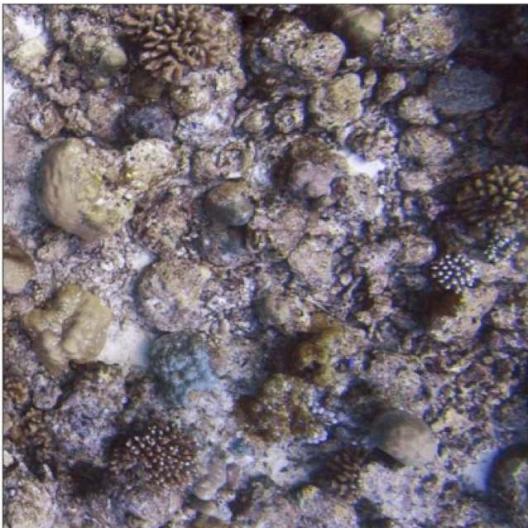


Figure 25: Utilize GPT-4V for coral composition estimation and coral bleaching detection.

2.6.2 BENTHIC COMPOSITION

Understanding the benthic composition from the captured visual images could help researchers characterize and classify marine ecosystems based on the types of organisms and substrate present. Different benthic communities support distinct sets of species and play unique ecological roles. We explore the potential of utilizing GPT-4V to generate the benthic analysis data, which could be further used for monitoring the impact of factors like pollution, climate change, and habitat destruction. The results are illustrated in Figure 26. We first ask GPT-4V to generate the benthic composition data (the composition of non-creatures and creatures) from the uploaded visual image and then identify how many types of coral reefs. Furthermore, we examine the ability of GPT-4V for benthic invertebrate identification (e.g., corals, sponges, mollusks, and worms), algae, and even certain fish species.

Our experimental results show that GPT-4V nearly cannot achieve benthic composition statistics without utilizing an external professional analysis tool or being fed corresponding analysis data for final report generation. Even though GPT-4V could generate some very naive computer vision processing codes for analysis, the analyzed outputs are still very far from the requirement of a professional expert. Meanwhile, the whole processing and analysis procedure lacks the reasoning steps and support of the domain-specific evidence.



Tell me the benthic composition of this image

GPT-4V

Benthic composition estimation involves analyzing the types of substrates present in a given area of the ocean floor, usually in terms of living organisms like corals, algae, and sponges, as well as non-living elements like sand and rocks. For coral reefs, this analysis would include identifying and estimating the coverage percentage of different coral species, as well as other benthic elements present.

To perform a benthic composition estimation from an image, a common approach is to use point-counting methods, where a grid is superimposed on the image and the substrate under each intersection point is identified and categorized. For a detailed analysis, software tools and algorithms are often used to enhance accuracy and efficiency.

Given that this tool is not equipped with such specialized software, I can provide an approximate estimation using a simple color-based segmentation method. This approach will involve identifying different colors and textures that correspond to corals and other substrates in the image. However, it's important to note that this method is quite rudimentary and will not be as accurate as methods used in scientific studies.

Let's proceed with an approximate analysis of the coral coverage in the image.

It appears there was an internal issue when attempting to perform the analysis. **Unfortunately, without the ability to directly analyze the image using this tool, I won't be able to provide an estimation of the benthic composition or the coral coverage.**

For accurate benthic composition estimation, typically specialized software is used to analyze the image in detail, taking into account factors such as color, texture, and shape to differentiate between corals, algae, sand, rock, and other substrates. If you require this level of analysis, I recommend using geographic information system (GIS) software or other marine ecology tools designed for this purpose, which can provide a more accurate assessment

Can you tell me how many different types of coral appeared in this figure?

GPT-4V

I'm unable to perform complex image analysis such as identifying and counting different types of coral in an image. Identifying coral types usually requires specialized knowledge in marine biology, as well as software that can analyze the morphology and color patterns specific to each coral species.

Typically, marine biologists use various methods such as in-situ surveys, underwater photography with subsequent expert analysis, or advanced computer vision algorithms that have been trained to recognize different coral species based on a large dataset of labeled images.

If you're looking to identify and count the types of coral in the image, I would recommend consulting a marine biologist or using image analysis software specifically designed for ecological studies. They would be able to provide a much more accurate and reliable analysis.

Are there invertebrates in this figure?

GPT-4V

The image appears to show a view of a coral reef. Coral reefs are known for their biodiversity, including a variety of invertebrates. From the image, we can see multiple forms of coral, **which are invertebrates themselves, belonging to a group known as Cnidaria**. Additionally, reefs typically host a multitude of other invertebrate species such as mollusks (like snails), crustaceans (like crabs and shrimps), echinoderms (such as sea stars and sea urchins), and many others.

However, due to the resolution and the angle of the image, identifying specific invertebrates other than the corals is challenging. Coral polyps, the small living organisms that make up the corals, are certainly present, but other invertebrates that might be there are not distinctly visible to confirm.

Are there rocks and sands in this figure?

GPT-4V

Yes, the image appears to include both rocks and sandy areas amidst the coral formations. The textures and colors suggest a mix of coral reef components, including hard substrate (which could be rocks) and lighter areas that could be sandy patches typical in reef environments. The variation in texture and color indicates a natural, heterogeneous ocean floor often found in coral reef systems.

Figure 26: Utilize GPT-4V for the benthic composition estimation.

2.6.3 RELATIONSHIP SUMMARIZATION AND EVENT DETECTION



GPT-4V

In the figure, a pufferfish is observed near what appears to be a coral reef. The relationship between the fish and the coral is ecological and can be part of a larger symbiotic system within the reef environment, although it's not a direct relationship like that of the goby and shrimp. Coral reefs provide a habitat for many marine species, including pufferfish, offering them protection from predators and a rich source of food. The pufferfish, in turn, may help the reef by controlling the population of smaller organisms that could overgrow and harm the coral. Pufferfish are also known for their ability to inflate when threatened, a defense mechanism not directly related to the coral but an interesting aspect of their behavior within the reef community. The image captures the interdependence of reef organisms and the complex dynamics of marine ecosystems where each species plays a role in maintaining the balance of the underwater environment.



GPT-4V

The figure shows a symbiotic relationship between two marine animals: a goby fish and a snapping shrimp. The goby fish has a mutually beneficial relationship with the shrimp, which stays in nearly blind and relies on the goby for alerts to potential danger. In return, the goby maintains a burrow in the sand that both animals use for shelter. This kind of relationship is known as mutualism, where both species benefit from the interaction. The goby, with better vision, stays close to the entrance of the burrow, watching for predators, while the shrimp uses its antennae to maintain physical contact with the goby. If the goby detects danger, it signals to the shrimp, and they both retreat into the burrow.



GPT-4V

The figure shows a moray eel and a cleaner shrimp in close proximity, illustrating a cleaning symbiosis. In this mutualistic relationship, the cleaner shrimp benefits by feeding on parasites, dead tissue, or food remnants found in or on the eel's body, while the moray eel gets the service of being cleaned. This interaction is quite common in marine ecosystems and is essential for the health of many marine species. The moray eel allows the cleaner shrimp to work, often opening its mouth wide, which could otherwise be a dangerous scenario for the shrimp. This behavior is a testament to the strength of their symbiotic relationship.



GPT-4V

The figure appears to depict a crinoid, also known as a feather star, which is a marine creature that belongs to the echinoderm family, the same group as sea stars and sea urchins. Crinoids are characterized by their feathery arms which they use for suspension feeding, capturing plankton and small particles of food from the water.

The relationship shown in the figure is between the crinoid and its environment. The crinoid is attached to a hard substrate, which would be a coral reef rock, or a hard surface in the ocean floor. This attachment is crucial for the crinoid's survival, as it provides a stable platform for feeding. The crinoid benefits from the flow of water bringing food particles to it, and in return, it may play a role in the ecosystem by contributing to the nutrient cycle and serving as prey for other animals.

There's no direct interaction evident in the image other than the crinoid's presence within its chosen habitat. The relationship is one of existence and ecological function within the marine environment.



GPT-4V

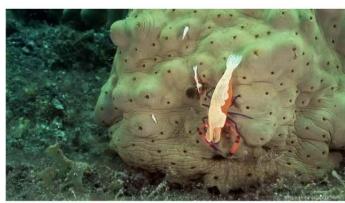
The figure shows a close-up of a crinoid coral with intricate branches and numerous small polyps. The coral is a colonial organism, made up of numerous genetically identical polyps that work together as a single entity. The polyps secrete calcium carbonate to form the hard coral structure, which serves as both their home and a protective structure. Corals have a mutualistic relationship with tiny algae called zooxanthellae, which live within their tissues. The coral provides the algae with a protected environment and the compounds necessary for photosynthesis. In return, the algae produce oxygen which helps the coral breathe. More importantly, they provide the coral with organic products of photosynthesis, which are critical to the coral's energy needs. This symbiotic relationship is vital for the health of the coral and is foundational to the ecosystem of coral reefs, which are some of the most diverse and biologically rich environments on planet Earth.

In this figure, while the *zoanthellae* are not visible, their presence is implied by the health and color of the coral, which is an indirect indicator of the ongoing symbiotic relationship.



GPT-4V

The figure shows a clownfish nestled among the tentacles of a sea anemone. This is a classic example of a mutualistic symbiotic relationship. The clownfish benefits from the protection offered by the anemone's stinging tentacles, which deter predators. In return, the clownfish may provide the anemone with nutrients through its waste and can help to aerate the anemone by swimming among its tentacles, enhancing water circulation. Clownfish have a special mucus on their skin that prevents them from being stuck to the anemone's tentacles, allowing them to live among them safely. This relationship allows the clownfish to have a safe haven from predators and a place to lay their eggs, while the sea anemone benefits from the cleaning and the nutrients provided by the clownfish.



GPT-4V

The image features a nudibranch, which is a type of sea slug, on what appears to be a sponge or a coral. Nudibranchs are known for their bright colors and elaborate forms, and they are often found in close association with sponges, corals, or other substances on which they feed.

The relationship between a nudibranch and its host can vary. Some nudibranchs are specialized feeders that consume specific sponges or corals, which can sometimes provide them with toxic chemicals that the nudibranchs use for their own defense. Other nudibranchs may graze on algae or detritus on the surfaces of these substrates.

This particular nudibranch seems to be crawling on the surface, possibly searching for food or a mate. Its diet is likely to be predation or grazing if the sponge or coral is its food source. The sponge or coral, on the other hand, generally has a passive role in this relationship.



GPT-4V

The figure features a zebra-patterned fish, likely a type of marine angelfish or butterflyfish, swimming close to what appears to be a sea urchin. The relationship between the two can be complex and is dependent on the specific species and their behaviors. If the fish is a type of butterflyfish that feeds on sea urchins, this could be a predatory relationship. Some butterflyfish have adapted to the tube feet or even the spines of sea urchins. However, if the fish is merely seeking protection from predators by swimming close to the sea urchin, the relationship could be commensal, where the fish benefits from the sea urchin's defense without harming the urchin.

Alternatively, the fish might be feeding off parasites or dead tissue from the sea urchin, which would make the relationship mutualistic. Without more specific information on the species and their behaviors, it is difficult to determine the exact nature of their interaction in this figure.



GPT-4V

The figure displays a black-finned snake eel partially emerging from the seabed, with its head and upper body visible. Near its head, there are small cleaner shrimp, which are known for their symbiotic relationship with the eel. The relationship between the cleaner shrimp and the eel is typically mutualistic, where both parties benefit. The cleaner shrimp remove and eat parasites, dead skin, and food remnants from the eel, which in turn provides the shrimp with a consistent food source. This cleaning helps the eel stay healthy and reduces its chances of infection. The eel, by allowing the shrimp to clean it, provides them with protection from predators while they are on the eel's body.

This mutualistic cleaning behavior is common in marine ecosystems and is vital for the health and well-being of many aquatic species. The interaction also highlights the complexity and interdependence of relationships within marine communities.

Figure 27: Utilize GPT-4V for relationship summarization from visual images. The prompts are “Summarize the relationship between the objects within this figure”.

Relationship summarization. Exploring the relationships between marine creatures allows conservationists to make informed decisions about protecting vulnerable or endangered species. In this section, we assess the ability of GPT-4V to comprehend how different creatures interact and summarize



 GPT-4V

The image depicts a significant volcanic eruption, characterized by a large plume of ash and gases. The eruption column consists of pyroclastic materials, which are a mixture of hot gas, ash, and rock fragments. This grey to white billowing cloud rises vigorously into the sky, indicating the explosive force of the eruption. The surrounding sky is clear, suggesting that the event has occurred during favorable weather, allowing for a stark contrast between the ash plume and the blue sky. The volcanic ash is spreading and will likely affect a wide area, potentially leading to air quality issues and affecting climate conditions temporarily. This kind of eruption can also have significant impacts on nearby communities, infrastructure, and the environment.

 GPT-4V

The image shows a scene of a lava flow, indicative of a volcanic eruption. The molten rock, known as lava, appears bright orange and red, indicating extremely high temperatures. The flow is seen traversing through a rocky terrain, which has likely been formed from the cooling and solidification of previous lava flows. The surface of the lava is uneven, with some parts appearing cooler and solidified into dark crust, while the brighter areas represent the hotter, more fluid portions of the lava. This type of volcanic activity can create new landforms as the lava cools and can also pose significant risks to anything in its path due to its destructive nature and intense heat.



 GPT-4V

The image shows a rescue operation in progress involving a large passenger ship that has capsized and is partially submerged in the water. The timestamp "10:17 a.m." suggests that the image captures a specific moment during the rescue efforts. A group of people in life jackets can be seen on a partially submerged part of the ship, with rescuers in bright-colored gear assisting them. Inflatable life rafts are nearby, and people are being helped onto these rafts. The presence of rescue personnel and the organized nature of the evacuation indicate a well-coordinated effort to ensure the safety of the passengers and crew. The overcast weather conditions add a sense of urgency to the scene. This maritime emergency likely prompted a significant search and rescue response to aid those on board and to prevent loss of life.

 GPT-4V

The image shows a large cargo ship that has broken into two parts in the sea. The rear part of the ship, including the bridge and main structures, is still afloat, while the front part is sinking with containers slipping into the water. This indicates a severe structural failure of the vessel, likely caused by stresses such as rough seas, a grounding, or structural weaknesses. Containers are scattered and some are semi-submerged, which could potentially lead to loss of goods and environmental pollution, especially if any of the containers or the ship itself are carrying hazardous materials. The name and port of registry of the ship, "RENA MONROVIA," are visible, which can help in identifying the vessel involved in this maritime incident. This kind of accident is a significant hazard to the marine environment and can also disrupt shipping lanes and the global supply chain.



 GPT-4V

The image shows a large ship capsized in the water, lying on its side with part of its hull and keel exposed above the waterline. This is a maritime disaster, where the ship has either lost its buoyancy or stability and has turned over in the water. There is a helicopter hovering above, likely part of a search and rescue operation, which suggests that there may be an ongoing effort to find and rescue any survivors or to assess the situation. The weather conditions appear calm, with no visible signs of rough seas or bad weather, which could mean that the cause of the capsizing might not be weather-related. Such events are usually serious and require immediate response from emergency services to aid any people who may be on board and to mitigate environmental impacts if the ship is carrying hazardous materials.

 GPT-4V

The image depicts a container ship with a large plume of dark smoke emanating from it, indicating a fire on board. The smoke is billowing into the sky, which suggests that the fire is significant and producing a lot of combustion by-products. Container ships carry a variety of cargo, and if the contents are flammable, this could lead to a very intense and difficult to control fire. Such incidents can pose serious risks to the crew, the environment, and the cargo. They require immediate response from firefighting teams, which can include ships equipped for marine firefighting, and potentially air support, depending on the location and severity of the fire. This kind of maritime accident can also have considerable economic impacts due to the loss of the ship's cargo and the ship itself.

Figure 28: Utilize GPT-4V for event detection. The prompts are “Describe the event in this figure”.

the relationship between them, such as predator-prey relationships, symbiosis, competition, and mutualism. Such summarized marine relationships could gain insights into the behavior, evolution, and adaptation of species. It is worth noting that we mainly focus on the relationship summarization from the perspective of marine biology research. The qualitative results are reported in Figure 27. As demonstrated, GPT-4V has shown a satisfactory ability to understand and describe some well-known relationships between recognized objects, such as the symbiotic relationship between clownfish and the sea anemone. But in contrast, when GPT-4V fails to recognize the marine objects accurately, it will generate totally irrelative responses, and the responses are nearly based on its “imagination”.

Event detection. Through event detection, domain experts could predict and mitigate the impacts of events like climate change and pollution. Some preliminary case studies about event detection are illustrated in Figure 28. We collect more samples about 1) identifying irregular behaviors, such as illegal fishing, vessel collisions, or suspicious activities, which can be crucial for maritime safety and security; 2) monitoring the changes of marine conditions, such as water levels, wave patterns, and coastal erosion; and 3) detecting abnormal events in marine images, which can help identify unusual events such as oil spills, coral bleaching, and marine pollution. Detecting these abnormalities early allows for a rapid response to mitigate environmental damage and protect marine ecosystems. The excitement of unveiling the unknown serves as a powerful motivator for researchers and explorers. From the early exploration as demonstrated in Figure 28, GPT-4V possesses a strong ability to understand the event presented in the visual images.

2.6.4 FRAMEWORK AND FLOWCHART UNDERSTANDING

We test whether GPT-4V showcases some detailed reasoning procedures and the ability to understand the inside intention of the designed images, including the framework and flow chart images. GPT-4V is required to explain the whole framework step by step and describe the intermediate step in detail. We provide visual reasoning results of GPT-4V from various fields in Figure 29 (scientific figure understanding), Figure 30 (implicit intention understanding), and Figure 31 (the framework understanding), respectively. Our exploration targets how GPT-4V understands and reasons for the high-level information from the figures as a whole.

(b) Pyramid of biomass

The pyramid illustrates the relationship between different trophic levels within a marine ecosystem. The levels are color-coded and labeled:

- Level 1 (bottom): Phytoplankton (primary producers)
- Level 2 (orange): Zooplankton (primary consumers)
- Level 3 (yellow): Small fishes and larvae (consumers)
- Level 4 (blue): Mid-size fishes (consumers)
- Level 5 (brown): Tuna (top consumers)

Quantitative details:

- For each kilogram of tuna, approximately 3.5 ounces of a tuna sandwich (100 grams) is consumed.
- For each kilogram of mid-size fish, 10 kilograms of small fish must be consumed.
- For each kilogram of small fish, 100 kilograms of small herbivores must be consumed.
- For each kilogram of small herbivores, 1,000 kilograms of primary producers (phytoplankton) are required.

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This cladogram illustrates the evolutionary relationships among various biological species based on similarities and differences in their physical or genetic characteristics. The tree branches from a common ancestor at the bottom, leading to three main domains of life: Eukarya, Archaea, and Eubacteria. Key groups highlighted in green include Alveolates, Stramenopiles, Radiolarians, Ciliates, Brown algae, Diatoms, Labyrinthulomycetes, Coccolithophores, Green sulphur bacteria, Cyanobacteria, Green non-sulphur bacteria, Gram-positive bacteria, Actinobacteria, and Green non-sulphur bacteria.

LAST UNIVERSAL COMMON ANCESTOR

EUKARYA ARCHAEA EUKARIA

© 2010 Cengage Learning

Describe this figure in detail

Describe this figure in detail

GPT-4V

The figure appears to be an ecological pyramid, also known as a pyramid of biomass, which illustrates the relationship between different trophic levels within a marine ecosystem. Here is a detailed description:

- Primary Producers (Level 1):**
 - At the base of the pyramid, depicted in green, are primary producers, which in marine ecosystems are typically phytoplankton. These organisms produce biomass through photosynthesis and serve as the foundation for the energy flow through the ecosystem.
- Small Herbivores (Level 2):**
 - The second level, colored yellow, represents small herbivores that consume the primary producers. These are likely zooplankton that feed on phytoplankton.
- Small Fishes and Larvae (Level 3):**
 - The third level, in orange, indicates small fishes and larvae, which are consumers that feed on the zooplankton.
- Mid-Size Fishes (Level 4):**
 - The fourth level, shown in blue, comprises mid-size fishes. These are larger consumers that prey on the smaller fish and larvae.
- Tuna (Top Consumers, Level 5):**
 - At the top of the pyramid, in brown, are the top consumers, represented here by tuna. Tuna are apex predators in the marine food chain and consume mid-size fishes.

The pyramid also provides a quantitative aspect of the food chain:

- For each kilogram of tuna, approximately 10 kilograms of mid-size fish must be consumed.
- These mid-size fish, in turn, must consume 100 kilograms of small fish.
- The small fish consume 1,000 kilograms of small herbivores (zooplankton).
- At the bottom, 10,000 kilograms of primary producers (phytoplankton) are required to support the level above.

A Tuna Sandwich Illustration:

- An illustration of a tuna sandwich at the top right corner connects the concept of the ecological pyramid to human consumption, indicating the large amount of marine resources needed to produce a relatively small amount of food for humans.

This figure is likely used for educational purposes to explain the concept of energy transfer within an ecosystem and to emphasize the inefficiency of energy transfer between trophic levels. It also highlights the concept of biomagnification, where the concentration of certain substances can increase with each trophic level. Overall, the pyramid serves as a visual representation of the interdependence of marine species and the importance of preserving entire ecosystems for the sustainability of top predators, such as tuna, which are also consumed by humans.

GPT-4V

The image you've uploaded appears to be a **cladogram** or a **phylogenetic tree**. This type of diagram represents the evolutionary relationships among various biological species based upon similarities and differences in their physical or genetic characteristics. Here's a detailed description:

Overall Structure: The tree has three main branches, each representing one of the three domains of life: Eukarya, Archaea, and Eubacteria. These branches stem from a common base labeled "LAST UNIVERSAL COMMON ANCESTOR."

Eukarya Domain: The Eukarya branch further divides into **multiple sub-branches**, each representing different kingdoms or groups within Eukarya. These include:

Animals, Fungi, Plants, Green algae, Red algae, Foraminiferans, Radiolarians, Ciliates, Brown algae, Diatoms, Stramenopiles, Alveolates, Labyrinthulomycetes, Coccolithophores.

Archaea Domain: The Archaea branch does not further divide in this diagram, indicating that it is a broad category without further sub-classification here.

Eubacteria Domain: The Eubacteria branch splits into several groups, including:

Actinobacteria, Green sulphur bacteria, Cyanobacteria, Green non-sulphur bacteria, Gram-positive bacteria.

Branch Labels: Each branch is labeled with the name of the taxonomic group it represents. The labels are color-coded, with Eukarya in red, Archaea in orange, and Eubacteria in red as well.

Color Highlights: Some branches are highlighted with green, indicating a certain significance, which is not described in the image. The last common ancestor is also highlighted in green.

Reference: At the bottom left, there is a citation which reads "© 2010 Cengage Learning", indicating that the image is from a publication or resource from Cengage Learning.

This figure is typically used in biology to help understand the evolutionary pathways and common ancestry of different life forms. Each branch point (node) represents a common ancestor shared by the branches that diverge from it. The length of the branches can sometimes indicate the passage of time or genetic change, although this diagram does not explicitly provide such details.

Figure 29: Utilize GPT-4V for scientific figure understanding in the marine research field.

As shown in Figure 29, GPT-4V has demonstrated a very strong OCR ability to extract text information from visual images. It could summarize the hierarchical relationship between different parts

a) coral coverage: 0.25 (300 sparse points)

b) coral coverage: 0.2652 (dense segmentation)

t=0 t=1 t=10 t=20

DAVIS-2017

CoralVOS

Describe this figure and describe the motivation of drawing this figure

Describe this figure and describe the motivation of drawing this figure

GPT-4V

The figure presented consists of two images labeled (a) and (b), which appear to depict methods for measuring coral coverage in a marine environment.

Image (a):

- This image shows a portion of a coral reef with numerous points overlaid on it.
- The points are color-coded, with red indicating points that fall on coral and black indicating points that do not.
- The label indicates that this is a measure of 'coral coverage' and states a value of 0.25, which likely represents the proportion of points that fall on coral versus non-coral areas.
- The method used here is described as '300 sparse points', suggesting that a total of 300 points were randomly placed over the image to estimate the coverage.

Image (b):

- This image shows the same scene, but instead of sparse points, the coral areas are highlighted in red using a method described as 'dense segmentation'.
- The coral coverage value here is slightly higher at 0.2652, suggesting that this method may provide a more precise measurement of the actual coral coverage.

Motivation of the Figure:

The motivation behind creating and presenting this figure is likely to compare two different methods for estimating coral coverage. The figure aims to illustrate how the methodology of measurement can affect the accuracy of coral coverage estimates. Sparse point sampling is a quicker, less resource-intensive method that can be used for rapid assessments, while dense segmentation is a more detailed approach that likely uses image processing techniques to provide a more accurate measure of coral coverage.

By comparing these two methods side-by-side, the figure highlights the trade-offs between the efficiency and accuracy of different scientific measurement techniques in marine ecology. This could be particularly relevant in the context of large-scale monitoring of coral reefs, where researchers need to balance the precision of measurements with the practicalities of surveying vast areas. It demonstrates the importance of measurement technique selection in ecological studies and may argue for the use of more accurate methods such as dense segmentation in certain contexts, despite the increased effort or computational resources required.

GPT-4V

The figure appears to be a composite of two sets of images used for the purpose of illustrating object segmentation in image processing. The top row shows a sequence of images with a red bear at different time frames ($t=0, t=1, t=10, t=20$), and the bottom row seems to show coral segmentation in a marine environment at similar time frames.

Top Row (Red Bear Sequence):

- At each time frame, we see the same bear moving through the scene.
- This could be a demonstration of object tracking, where the bear is the object of interest, and its movement is consistently followed through the sequence of images.

Bottom Row (Coral Segmentation):

- The images show a coral reef with red overlay on top of the corals.
- The red overlay appears to represent the segmentation of the coral from the rest of the underwater environment, likely using image processing algorithms.
- The label "Novel coral masks" in the frame marked ' $t=20$ ' suggests that this segmentation may be highlighting new growth or changes in the coral structure over time.
- The mention of "CoralVOS" indicates that this is possibly an application or a methodology used for the segmentation of coral in these images, and it's being compared to a standard dataset or method labeled "DAVIS-2017".

Motivation of the Figure:

The motivation for creating this figure is likely to demonstrate the capabilities of an image processing system or software, particularly in tracking and segmentation tasks. The red bear sequence could be used to showcase the system's ability to track the movement of an object over time, even with changes in orientation and lighting. The coral images could be illustrating the system's ability to segment and identify coral growth within a complex underwater environment, which can be a challenging task due to the variability in textures and lighting conditions underwater.

By comparing the system's performance on both artificial objects (like the bear) and natural environments (like the coral reef), the figure may be intended to show the versatility and accuracy of the image processing system. This can be important for applications in wildlife monitoring, environmental conservation, and ecological studies where accurate detection and tracking of objects are crucial. The comparison to the DAVIS-2017 benchmark suggests a focus on demonstrating improvement or novelty in segmentation techniques, which is a common practice in computer vision research to validate the effectiveness of new methods.

Figure 30: Utilize GPT-4V for illustration figure understanding. GPT-4V could understand the implicit intention.

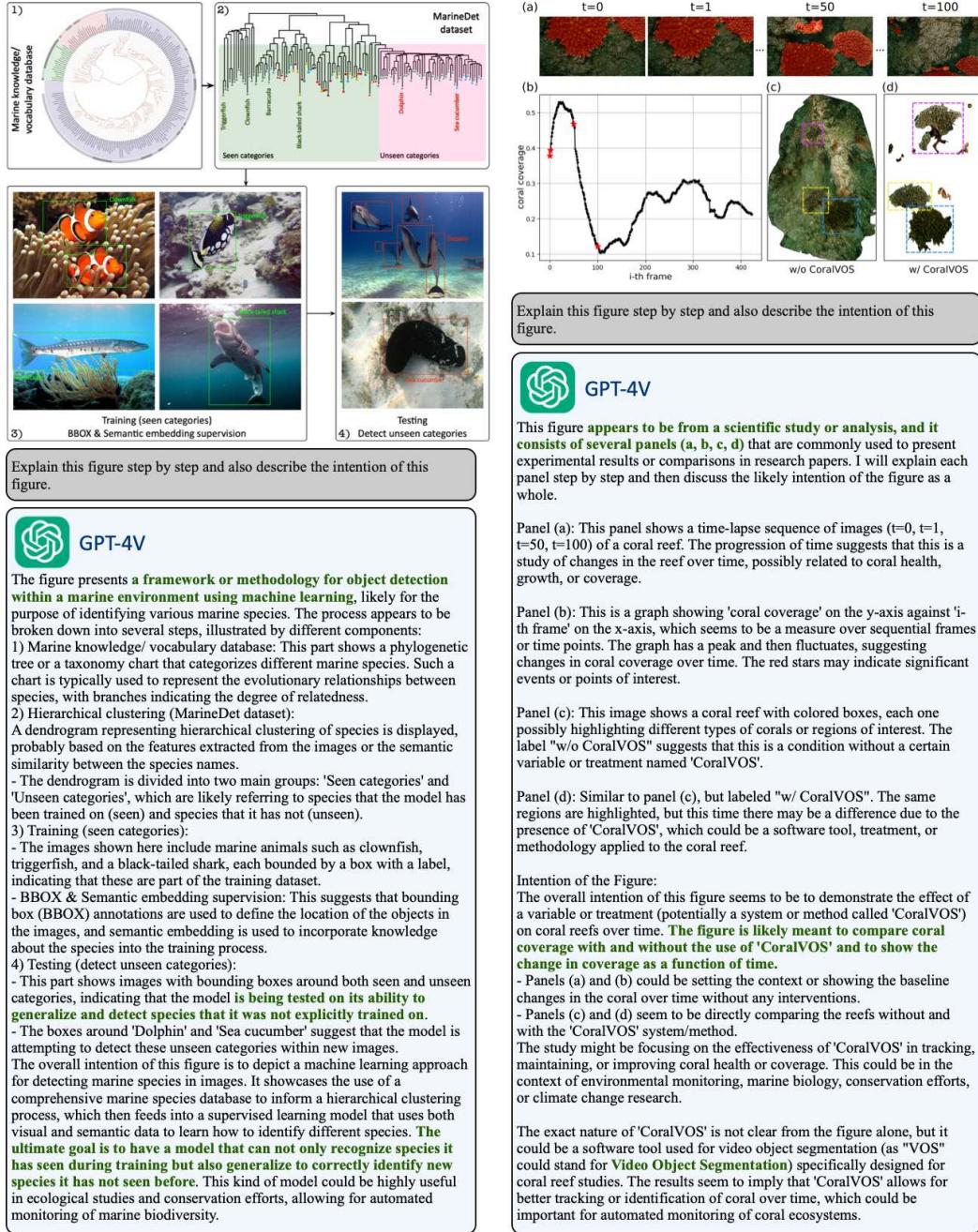


Figure 31: Utilize GPT-4V for framework and flowchart understanding. GPT-4V could explain the intermediate procedures step by step and explain the whole framework.

and extract the key elements of the whole figure. Besides, GPT-4V can understand the structure information and guess the source and usage of the uploaded scientific images.

Furthermore, we observe that GPT-4V could understand the motivation of the illustration figures as demonstrated in Figure 30. It could accurately describe the inside motivation of drawn figures. However, we have also observed the hallucination of GPT-4V. It will generate some information that does not exist within the image based on some extracted keywords (e.g., ‘DAVIS-2017’). We attribute this phenomenon to the reason that GPT-4V may overfit its training data. How to prevent such hallucinations and alleviate the over-claim of GPT-4V is an important and valuable research direction.

Finally, we explore the ability of GPT-4V to understand and explain the framework or flowchart step by step in Figure 31. GPT-4V could accurately describe each part of the whole framework in detail and summarize the relationship between each part. Also, it demonstrates a satisfactory performance to understand the overall intention of the whole framework.

2.6.5 AESTHETIC EVALUATION



Following the same criteria, please also score this image and explain your assessment.

Can you give a score to score the aesthetic quality of this image? The full score is 10 and higher is better.



GPT-4V

Using the same criteria to evaluate the aesthetic quality of this underwater image:

1. **Composition:** The image has a dynamic composition with a clear foreground of colorful fish and coral that leads the viewer's eye into the background. The reef life is arranged in a way that fills the frame without appearing cluttered, which is visually pleasing.
 2. **Color:** The image is vibrant with a rich palette of colors that are characteristic of coral reef environments. The variety of colors is well captured, from the bright blues of the fish to the pinks and yellows of the corals.
 3. **Focus and Clarity:** The main subjects of the image, particularly the fish and corals in the foreground, appear to be in sharp focus. The clarity allows for the textures of the corals and the details of the fish to be appreciated.
 4. **Lighting:** The lighting in the image is well executed. The sunlight streaming through the water's surface adds depth to the image and highlights the reef's inhabitants without causing overexposure or harsh shadows.
 5. **Subject Matter:** The image captures the biodiversity of the reef, showcasing a variety of species and the complexity of their habitat. The presence of different fish species and the health of the corals suggest a thriving ecosystem.
- Considering these factors, this image could also be rated quite highly for its aesthetic quality, potentially receiving a **score around 9 out of 10**. The image is a strong representation of underwater photography with its clear depiction of the ecosystem's diversity and beauty. Again, the **score is subjective and can vary depending on the viewer's personal taste and the context** in which the image is being evaluated.



GPT-4V

As an AI language model, I don't have personal opinions or aesthetic sensibilities, but I can provide an analysis based on common criteria used to evaluate the aesthetic quality of an image:

1. **Composition:** The image has a well-balanced composition with a clear subject (the reef and its marine inhabitants) and a good distribution of elements throughout the frame.
 2. **Color:** The colors are vibrant and diverse, showcasing the natural beauty of the marine environment, which is often appreciated in underwater photography.
 3. **Focus and Clarity:** The subjects appear to be in focus, and the image clarity is good, allowing for detailed observation of the wildlife and coral.
 4. **Lighting:** The lighting seems natural and well-distributed, highlighting the textures and colors of the corals and fish without harsh shadows or overexposure.
 5. **Subject Matter:** The biodiversity captured, including a variety of fish and corals, adds to the interest of the image, which is an essential aspect of wildlife photography.
- Considering these factors, one might rate the aesthetic quality of this image quite highly, possibly around an **8 or 9 out of 10**. However, the **final score could vary based on individual preferences and the specific context in which the image is being evaluated**. For instance, a marine biologist might rate it differently than a professional photographer or a casual viewer.

Figure 32: Utilize GPT-4V for the aesthetic quality estimation. GPT-4V could explain the criteria of its assessments.

We have also assessed the ability of GPT-4V to do the aesthetic evaluation. We manually constructed 50 marine images with high diversity then we uploaded the visual images to GPT-4V to generate the aesthetic score (scale of 10) based on the visual contents. To quantitatively evaluate the ability

of GPT-4V for aesthetic assessment, we ask expert-level human labelers (3 annotators) to give the subjective scores towards the given marine images and we compute the mean value and the standard deviation. Then we first evaluate the alignment between the scores from GPT-4V and human labelers in terms of aesthetic measuring. We provide some qualitative results of GPT-4V in Figure 32. We observe that the scores generated by GPT-4V are highly correlated with human rating. GPT-4V successfully identifies the aesthetic quality of visual elements within the images and provides a comprehensive explanation for its scores. Our results reveal that GPT-4V achieves a promising agreement with humans on aesthetic quality assessment.

2.6.6 TEMPORAL SEQUENCE UNDERSTANDING



Describe the temporal image sequences in detail and the actions of the objects


GPT-4V

In the panoramic sequence provided, we can infer the following actions:

Initial Position: The diver is near the seabed, close to a rocky outcrop or reef, with a spotted eagle ray (assuming based on the common patterns on eagle rays) at a distance.

Approach: The ray appears to be swimming towards the diver, possibly out of curiosity or simply following its natural path.

Closest Encounter: The ray swims directly over the diver, who seems to be observing or possibly photographing the ray. This moment might be the focal point of the interaction.

Passage: The ray continues its path, swimming past the diver, moving away from the rocky structures.

Departure: The ray moves further away into the open water, as the diver watches or follows with their gaze.

This sequence captures a brief interaction between a diver and a spotted eagle ray in a natural underwater environment. The diver remains relatively stationary, while the ray is dynamic, entering the scene, passing over the diver, and then swimming away. This type of encounter is typical in recreational diving, where divers can observe marine life as it goes about its natural behaviors.

Figure 33: Utilize GPT-4V for temporal content understanding from the video sequence.

We finally explore the potential ability of GPT-4V for temporal sequence understanding. Given the consecutive image frames sampled from the video sequence (e.g., uniformly sampling 8 frames), we concatenate the sampled frames to one image and then ask GPT-4V to summarize the event that happened in the given video sequence. The temporal sequence understanding requires the MLLMs to fully comprehend the information within the visual sequence. Understanding the event of a marine clip could be very valuable for detecting the abnormal behavior of marine creatures and then preventing the potential disaster. The results are illustrated in Figure 33. As illustrated in Figure, GPT-4V demonstrates the capability to recognize the action in the images and provide a detailed description. It has shown a promising potential to understand scenes from video and visual story generation.

2.7 PROMPT ENGINEERING

In this section, we aim to explore the effectiveness of introducing the current prompt engineering techniques designed for general-purpose MLLMs for marine research. We mainly focus on three settings: 1) few-shot prompts; 2) self-consistency and 3) chain-of-thoughts.

Under the first setting, we feed the GPT-4V with few-shot samples with corresponding annotations to guide GPT-4V as a domain expert and help it better understand our questions. Then we ask the GPT-4V for a similar question as shown in Figure 34. We observe that GPT-4V will still make mistakes and generate wrong responses even the few-shot prompts provided. We attribute this failure to the limited visual perception ability of GPT-4V. GPT-4V cannot effectively perform fine-grained object recognition.



This is Valentini Puffer, and its scientific name is *Canthigaster valentini*.

This is Yellowbar Sandperch, and its scientific name is *Parapercis xanthozona*.



This is Leopard Chromodoris (nudibranch), and its scientific name is *Chromodoris leopardus*.

GT: Co's Goniobranchus (nudibranch), *Goniobranchus coi*
Recognize this figure and tell its scientific name


GPT-4V

The fourth creature in your series of marine life images is a nudibranch, a type of sea slug known for its colorful appearance. Nudibranchs are soft-bodied, marine gastropod mollusks which shed their shells after their larval stage. They are noted for their extraordinary colors and striking forms. This nudibranch seems to have a creamy or pale yellow body with a pattern of black rings and a scalloped black outline. The texture appears soft and smooth.

Nudibranchs are known for their diversity in colors and forms, and they can be found in a wide range of ocean environments, from shallow reefs to deep-sea settings. They are also famous for their defense mechanisms; some of them can store toxins or stinging cells from the prey they eat, which they then use to deter predators.

To identify the specific species, one would typically consider the color pattern, the shape of the body, the location where the photo was taken, and other distinctive physical characteristics such as the rhinophores (sensory organs) on the head. Without a clear scientific name provided, I cannot confirm the exact species of this nudibranch, but it is undoubtedly one of the many striking species that adorn the ocean's substrates.

Figure 34: The marine object recognition results of GPT-4V with few-shot prompts provided.

To explore the self-consistency of the GPT-4V, we ask the GPT-4V to do the object counting task based on various prompts and we then perform voting to get the final object count result. Through

this, we aim to measure the self-consistency of GPT-4V for the same visual input and the robustness of its generated responses. Through voting or feeding GPT-4V with clearer prompts, GPT-4V could generate more reliable and accurate object counting results as demonstrated in Figure 35.



GT: 2 nudibranchs

Voting: 2
budibranchs

how many objects are there in this figure?

 GPT-4V

In the image, there appears to be **one main object of interest, which is a nudibranch**, a type of sea slug known for its often bright colors and ornate patterns. These creatures are typically found on the sea floor and are a single object, despite sometimes having intricate shapes that may give the impression of multiplicity. Nudibranchs are soft-bodied, marine gastropod mollusks, and this particular one has elaborate body patterns with multiple colors—usually a sign of a single organism. So, based on this image, we can say there is one nudibranch present. If there are other smaller or less visible objects that could be considered separate, they are not clearly discernible from the information provided.

How many nudibranchs are there in this figure?

 GPT-4V

There are **two nudibranchs** in the image provided. Nudibranchs are marine gastropod mollusks which are noted for their often extraordinary colors and striking forms. The ones in the image appear to be stacked on top of each other.

Is there more than one nudibranch in this figure?

 GPT-4V

Yes, there appears to be more than one nudibranch in this image. **There's a prominent one in the foreground, and it looks like there's a second one directly beneath it**, partially obscured by the first. Nudibranchs are known for their bright colors and varied shapes, and these characteristics are often used to distinguish between species as well as individuals.

Tell me the exact number of the objects in this figure

 GPT-4V

The image you've provided appears to feature **two nudibranchs**, which are soft-bodied, marine gastropod mollusks. They are known for their extraordinary colors and striking forms. This type of nudibranch is often found in pairs or groups, so it's common to see more than one in a single sighting.

Figure 35: The self-consistency analysis of GPT-4V. Through voting, GPT-4V could generate more reliable responses.

Finally, we refer to the design of the chain-of-thoughts Yang et al. (2023) and add some simple explanations in our input prompts. The GPT-4V is asked to follow our explanation procedure and understand the reasoning inside the recognition. In this way, GPT-4V could describe more about its judgment and illustrate more supporting evidence. The results are reported in Figure 36. We observe that GPT-4V sucks the ability to accurately recognize marine objects even GPT-4V could generate plausible and detailed descriptions about the wrongly recognized object.

To sum up, the current prompt engineering techniques cannot heavily promote the visual recognition ability of GPT-4V on marine images. GPT-4V will still make mistakes for fine-grained marine object recognition and prompt engineering cannot alleviate the hallucination issue, effectively. To address these issues, more training data from the marine field should be included for further promoting the recognition ability of GPT-4V.



This figure contains the **Mandarinfish** and its scientific name is **Synchiropus splendidus**. The mandarinfish has **striking patterns of primarily green and orange**. It is a **small, broad-headed and elongated, scaleless fish**. That is why we identify the mandarinfish.

GT: Morrison's Dragonet, *Synchiropus morrisoni*

Recognize the object in this figure and tell me the reason for your identification



GPT-4V

The second creature in the images is likely a type of **scorpionfish**. Scorpionfish are part of the family **Scorpaenidae** and are known for their excellent camouflage and venomous spines. They typically have a robust body, a compressed shape, and a mouth that faces upward. Their camouflage can be so effective that they blend almost seamlessly with their surroundings, which usually involves coral, rock, or sandy bottoms.

The reason for identifying this fish as a scorpionfish is based on several observable features:

Camouflage: The fish's body has mottled patterns that closely resemble the surrounding substrate, which is characteristic of scorpionfish that rely on camouflage to ambush prey.

Body Shape: The fish has a stocky body with a wide, flat head and a mouth oriented upwards, typical of scorpionfish.

Spines: Although not entirely clear from this angle, scorpionfish usually have spiny protrusions for defense, which also aid in their camouflage.

Habitat: The image shows the fish on a rubble or sandy bottom, which is a common habitat for scorpionfish.

To provide a precise scientific name, one would need to consider specific morphological details and potentially the geographic location where the photo was taken, as many scorpionfish species look similar and can only be distinguished by small differences in their appearance.

Figure 36: We prompt GPT-4V with detailed reasoning procedure and ask GPT-4V to explain its identification procedure.

3 DISCUSSIONS AND FUTURE DIRECTIONS

3.1 DISCUSSIONS

Possible for educational tool? While the performance of the GPT-4V is promising, we ask whether GPT-4V could be viewed as a potential educational tool that may in the future augment, but not replace, the nuanced analysis provided by trained marine professionals. GPT-4V could also play as a pivotal role in fostering a deeper understanding and appreciation for marine life among users of all ages and backgrounds. Through our findings in this study, we conclude that GPT-4V is far from generating valuable insights for domain experts.

Possible for labeling tool? With easy access to GPT-4V, it could actively encourage citizen science participation as a labeling tool, transforming ordinary individuals into valuable contributors to marine research. From our findings, we observe that GPT-4V cannot serve as a labeling tool for a wide spectrum of marine images since GPT-4V still makes many mistakes for challenging images. Moreover, such labeling is also only limited to image-level scene understanding. GPT-4V cannot generate accurate descriptions for the very fine-grained details.

Sample Bias. In our study, the testing samples are manually constructed, inevitably incorporating individual preferences and subjectivity. More importantly, our involved testing samples may not comprehensively represent real-world cases, and potentially over-estimate or down-estimate the challenges of utilizing GPT-4V for marine analysis.

3.2 FUTURE WORKS

Our findings emphasize the need for continued research to enhance the accuracy and expertise of responses generated by GPT-4V. We hope that this study can inspire more comprehensive and targeted research into utilizing multimodal systems such as GPT-4V for domain-specific research and analysis. By harnessing the capabilities of these models, we can better meet the professional demands of experts, ultimately including the domain experts in the major users of GPT-4V. Furthermore, based on the feedback and further prompts from the domain experts, a fundamental question arises, could GPT-4V revise its responses over time? Such feedback-driven MLLM would further promote the user experience for obtaining more precise responses.

Through our experimental results, we have observed that GPT-4V cannot achieve fine-grained and accurate marine object recognition to satisfy the requirements of the domain experts. More training data from the marine field should be included to promote the visual recognition ability of GPT-4V. Furthermore, we also demonstrate that GPT-4V has shown a very limited ability to handle advanced marine analysis (*e.g.*, counting, coverage estimation, composition statistic, *etc*) without utilizing an external professional tool. More domain-specific instruction-following data should be constructed to help GPT-4V yield explicit intermediate analysis results.

4 CONCLUSION

In this paper, our investigation of GPT-4V on marine analysis demonstrates some valuable findings and insights of MLLMs concerning visual understanding, logical reasoning, and expert capacity, indicating that there remains a considerable distance toward strong artificial intelligence as a domain expert.

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