
ArtGPT-4: Artistic Vision-Language Understanding with Adapter-enhanced MiniGPT-4

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Abstract

In recent years, large language models (LLMs) have made significant progress in natural language processing (NLP), with models like ChatGPT and GPT-4 achieving impressive capabilities in various linguistic tasks. However, training models on such a large scale is challenging, and finding datasets that match the model’s scale is often difficult. Fine-tuning and training models with fewer parameters using novel methods have emerged as promising approaches to overcome these challenges. One such model is MiniGPT-4, which achieves comparable vision-language understanding to GPT-4 by leveraging novel pre-training models and innovative training strategies. However, the model still faces some challenges in image understanding, particularly in artistic pictures. A novel multimodal model called ArtGPT-4 has been proposed to address these limitations. ArtGPT-4 was trained on image-text pairs using a Tesla A100 device in just 2 hours, using only about 200 GB of data. The model can depict images with an artistic flair and generate visual code, including aesthetically pleasing HTML/CSS web pages. Furthermore, the article proposes novel benchmarks for evaluating the performance of vision-language models. In the subsequent evaluation methods, ArtGPT-4 scored more than 1 point higher than the current **state-of-the-art** model and was only 0.25 points lower than artists on a 6-point scale. Our code and pre-trained model are available at <https://huggingface.co/Tyrannosaurus/ArtGPT-4>.

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1 Introduction

In recent times, the advancements made by large language models (LLMs) in the domains of natural language processing have been truly remarkable [Ouyang et al., 2021, Brown et al., 2020, OpenAI, 2022, Cohen et al., 2022, Du et al., 2022]. The performance of each task has demonstrated improvement with the increase in model size, simultaneously unlocking novel capabilities [Chowdhery et al., 2022]. These models can perform a variety of intricate linguistic tasks in a zero-shot manner, thanks to their exceptional language capabilities. Large multimodal models, such as M6 [Lin et al., 2021], LLaVA [Liu et al., 2023], and GPT-4 [OpenAI, 2023], have shown impressive capabilities in understanding the vision-language. For instance, models like LLaVA and GPT-4 have shown the ability to capture intricate details and understand the meaning of images, thereby producing diverse language outputs.

However, training a model on such a large scale presents a significant challenge to the experimental device. And finding datasets that match the scale of large models like GPT-3, which utilizes up to 45 terabytes of text data, can be a daunting task. As a result, fine-tuning with existing pre-trained models has emerged as a promising approach, as illustrated by ChatGPT’s use of GPT-3 for fine-tuning according to Reinforcement Learning with Human Feedback (RLHF) [Christiano et al., 2017]. Training a model with fewer parameters using a novel training method is also a crucial approach like the Vicuna [Chiang et al., 2023] and Alpaca [Taori et al., 2023]. An example of this is the Alpaca model, which has only 7 billion parameters but can achieve similar performance to the text-davinci-003 model, a GPT-3 variant with 175 billion parameters, on the Self-Instruct evaluation suite for instruction-following [Wang et al., 2022b].

The MiniGPT-4 model [Zhu et al., 2023] achieves comparable vision-language understanding to GPT-4 by leveraging novel pre-training models and innovative training strategies. However, there are still some challenges that need to be addressed. Firstly, the model’s ability to understand images still needs improvement, as it struggles to capture all the details, particularly in artistic pictures. Since Vicuna, the language model used in MiniGPT-4, is only fed image information without any prior training in image understanding, it may not be fully equipped to understand all the information conveyed by the image. Secondly, there are currently no well-defined benchmarks for evaluating the model’s performance. Finally, it is worth noting that the experimental setup employed four Tesla A100s, which is relatively high-end equipment.

We propose a novel solution to the limitations of MiniGPT-4 by introducing a new model called ArtGPT-4. ArtGPT-4 incorporated tailored linear layers and their corresponding activation functions into Vicuna, in conjunction with activating specific training parameters. Our modifications were designed to optimize the model’s performance and enable it to effectively address the unique challenges posed by vision-language tasks. ArtGPT-4 was trained on a Tesla A100 device in just 2 hours, using only about 200 GB of image-text pairs. ArtGPT-4 can depict images with a more artistic flair and generate visual code, including aesthetically pleasing HTML/CSS web pages. In a subsequent evaluation method, it was shown that ArtGPT-4 outperformed the original MiniGPT-4 model in terms of image understanding.

Our contribution is as follows:

- We are the first to utilize efficient fine-tuning for cross-visual and linguistic domain models and have achieved impressive results.
- We propose a novel multimodal model called ArtGPT-4, and it achieved state-of-the-art performance.
- We propose a novel benchmark for multimodal vision-language understanding models. These proposed benchmarks can serve as a more comprehensive criterion for evaluating the performance of vision-language models.
- We have made all the code and training layer parameters in this article available as open source.

2 Related Work

Language Models: Early language models such as BERT [Devlin et al., 2019], GPT [Radford et al., 2018], GPT-2 [Radford et al., 2019], RoBERT [Liu et al., 2019], ELECTRA [Clark et al., 2020] and

XLNet [Yang et al., 2019] have tended to place greater emphasis on natural language understanding tasks in the field of natural language processing, including language inference, text classification, and named entity recognition. These models leverage large-scale unsupervised pre-training to acquire rich linguistic knowledge and patterns and have achieved impressive performance across a range of NLP tasks. In recent years, the emergence of large-scale language models like T5 [Raffel et al., 2019], GPT-3 [Brown et al., 2020], and LLaMA [Cohen et al., 2022] has yielded impressive results in natural language generation tasks, including chatbots, text generation, and summarization. These models have proven highly effective at producing coherent and contextually relevant language, paving the way for a range of innovative new applications in natural language processing. Furthermore, in order to improve the usability of these large models for humans and enhance their ability to understand natural language commands, researchers have applied Reinforcement Learning with Human Feedback (RLHF) [Christiano et al., 2017]. This approach has yielded impressive results, with models such as ChatGPT [OpenAI, 2022] and GPT-4 [OpenAI, 2023] demonstrating outstanding performance. By leveraging the insights and feedback of human users, these models have become more accurate, efficient, and responsive, opening up new possibilities for natural language processing applications.

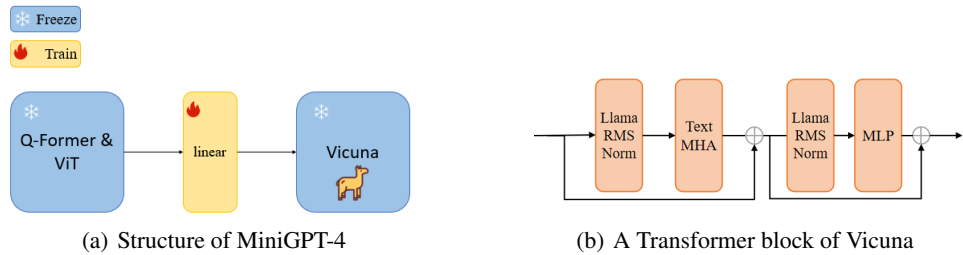


Figure 1: Model structure and training process of MiniGPT-4 and Vicuna models

Vision-Language Model: Recently, some researchers [Chen et al., 2022a, Alayrac et al., 2022, Tsimpoukelli et al., 2021] are exploring models with broader capabilities beyond a single domain, such as enabling language models to understand images. For instance, GPT-4 leverages a vast amount of image-text data to enhance its power not only for linguistic tasks but also for image understanding, allowing it to describe images using language. Remarkably, MiniGPT-4 can equip the Vicuna model with image understanding abilities by employing only a ViT [Dosovitskiy et al., 2020], Q-Former [Zhang et al., 2023], and a linear layer as shown in Figure 1(a). There also exist some efficient training methods for multimodal models, like BLIP-2 [Li et al., 2023], which proposes a generic and efficient pre-training strategy for vision-language tasks. It utilizes off-the-shelf frozen pre-trained image encoders and large language models, along with a lightweight Q-Former to bridge the modality gap.

Efficient Fine-tuning: Efficient fine-tuning strategies can enhance the performance of large language models (LLMs) on specific tasks. For instance, the LoRA [Hu et al., 2022] method utilizes low-rank projection of model weights to adapt large language models to new domains with limited training data. For example, Vicuna and Alpaca models based on the LLaMA model utilizing the LoRA method with ChatGPT dialogue data have demonstrated impressive performance. Parameter-efficient fine-tuning methods [Houlsby et al., 2019, Zaken et al., 2022, Li and Liang, 2021, He et al., 2021, Qing et al., 2023] are also a promising approach in the field of NLP, with the goal of reducing the number of learning parameters and computational resources required to adapt to downstream tasks while achieving comparable results to full fine-tuning. There has also been recent work in the field of computer vision on efficient learning, such as the work by Jia et al. [Jia et al., 2022], Bahng et al. [Bahng et al., 2022], and Chen et al. [Chen et al., 2022b] on visual adaptation using methods similar to those used in NLP. It is worth noting, however, that these works are based on the same modality (such as text to text, image to image, video to video), or the same domain [Yang et al., 2023] (such as visual image to visual video).

Benchmark for Vision-Language Tasks: To improve the evaluation benchmarkss for multimodal models, several works have proposed new benchmark tests and datasets [Lin et al., 2014, Young et al., 2014, Antol et al., 2015]. These datasets have limitations such as a lack of diversity in image types, a bias towards certain cultural references, and limited size. While they provide a useful benchmark

for evaluating vision-language models, it’s important to keep in mind their potential limitations. By tackling these challenges, we leverage the conference paper review process and the exceptional multimodal model GPT-4 to establish a novel benchmark for evaluating multimodal models.

3 ArtGPT-4

In this section, we will provide a brief overview of MiniGPT-4 and its baseline model (Section 3.1). Next, we will detail the Image Adapter (Section 3.2), and the training of ArtGPT-4 (Section 3.3), illustrating how we use the Adapter layer to construct visual-verbal multimodal models step-by-step.

3.1 MiniGPT-4

MiniGPT-4 is a model that aims to combine visual information from a trained vision encoder with an advanced large language model (LLM) to perform a wide range of complex linguistic tasks. The model uses the Vicuna language decoder, which is constructed upon LLaMA, and a visual encoder consisting of a ViT backbone coupled with a pre-trained Q-Former as shown in Figure 1. MiniGPT-4 is trained in two stages: pretraining on a large collection of aligned image-text pairs to acquire vision-language knowledge, and fine-tuning on a smaller but high-quality image-text dataset with a designed conversational template to enhance the model’s generation reliability and usability. During the initial pretraining stage, MiniGPT-4 acquires vision-language knowledge from a large dataset of aligned image-text pairs. However, it may still struggle with generating coherent and human-friendly responses, similar to ChatGPT before its fine-tuning and reinforcement learning stage. The second stage alignment process is essential to enhance the model’s naturalness in generated language. A carefully curated image-text dataset is used to fine-tune the MiniGPT-4 and post-processing is employed to refine the generated descriptions, resulting in approximately 3,500 high-quality image-text pairs for the alignment process.

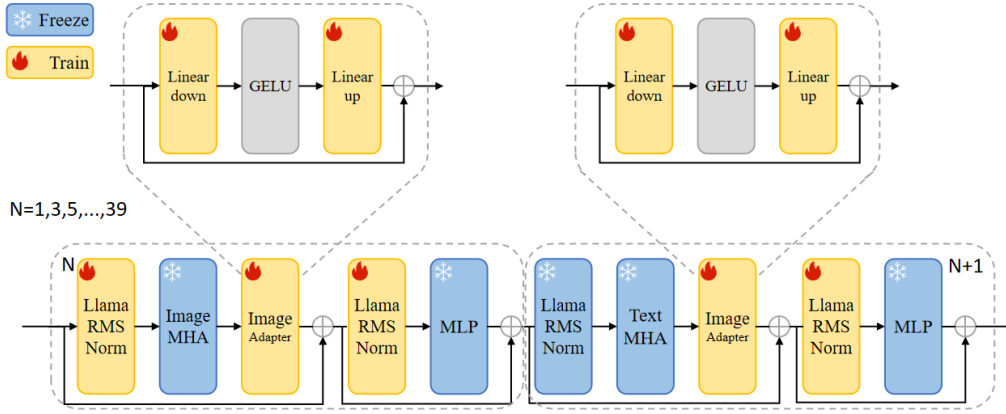


Figure 2: Transformer block of Vicuna with image adapter

3.2 Image Adapter

While MiniGPT-4 has demonstrated impressive image understanding capabilities, it still falls short in understanding all the image content, particularly in cases where the image contains artistic coloration. We draw inspiration from two sources: the Parameter-efficient fine-tuning technique [Houlsby et al., 2019] in NLP and the training of AIM models (image-to-video) [Yang et al., 2023]. As depicted in Figure 2 and Equation (1), we incorporated an image adapter layer into the MiniGPT-4’s original Vicuna model to enhance its ability to understanding images.

$$Y = Linear_2(GELU(Linear_1(X))) + X \quad (1)$$

where $Linear_1$ and $Linear_2$ denote the Linear down (hidden size to $\frac{1}{4}$ hidden size) and Linear up ($\frac{1}{4}$ hidden size to hidden size) layers in the graph, respectively, GELU represents the activation

function [Hendrycks and Gimpel, 2016], X represents the data calculated after the Multi-Headed Attention (MHA) mechanism, and Y represents the data after the image adapter layer and Y represents the output data after the image adapter layer.

Furthermore, in the training process of ArtGPT-4, the parameters of the RMS Norm layer in front of the MLP are also enabled. This is done to regulate the output of data from the image adapter layer, preventing it from causing gradient explosion and making it difficult to update the model parameters.

To further enhance the Vicuna model’s understanding of image information, we also activated the RMS Norm training parameters in the base layer ($N=1,3,5,\dots$) of the Transformer block of Vicuna. As we think it’s not ideal to directly input image information into the original Text MHA layer, we named the MHA layer with the activated training parameters as Image MHA, to distinguish it from the original Text MHA.

3.3 Training

Our goal remains to enable Language Models to understanding visual information using pre-trained models. We still follow the parameters of the original MiniGPT-4, and its training steps. Only we use different training data.

Training Data: We use Laion-aesthetic from the LAION-5B [Schuhmann et al., 2022] dataset, which amounts to approximately 200GB for the first 302 tar files. Laion-aesthetic is a large-scale dataset of images used primarily for training models to evaluate image aesthetics. The dataset includes over 500,000 images sourced from Flickr, each of which has been manually rated for aesthetic quality and affective polarity. Aesthetic quality is rated on a scale from 1 to 10, while affective polarity is rated as positive, neutral, or negative. In addition to image ratings, the dataset also includes metadata such as EXIF information, image tags, and image descriptions.

The First Training Processes: We trained our model using the following hyperparameters: a linear warmup cosine learning rate scheduler with an initial learning rate of $1e-7$, the minimum learning rate of $8e-7$, and a warmup learning rate of $1e-8$. The weight decay was set to 0.05, and the maximum number of training epochs was 2. We used a batch size of 32 for both training and evaluation, with 4 workers. The warmup steps were set to 5000, and there were 5000 iterations per epoch. We only trained on a Tesla A100 for less than 2 hours.

The Second Training Processes: We fine-tuned the ArtGPT-4 using a set of MiniGPT-4’s image-text pairs. We employed the same template containing a prompt with a randomly sampled instruction, which allowed our model to generate more natural and reliable responses. We only trained on a Tesla A100 for less than 10 minutes.

4 Quality Comparison

Image Description: Both MiniGPT-4 and ArtGPT-4 provide detailed descriptions of the images they are given as shown in Figure 3, describing a traditional Chinese ink painting of a landscape scene. First, ArtGPT-4 provides more detailed and specific information about the subject matter of the painting, including details about the rocks, trees, and grasses depicted in the image. Second, ArtGPT-4 makes use of more specialized language to describe the painting, including terms such as "Chinese calligraphy brushstrokes" and "shading and texture of the rocks." This indicates a greater level of expertise and familiarity with the subject matter, which can help to lend credibility and authority to the description. Finally, ArtGPT-4 uses language that emphasizes the emotional and aesthetic impact of the painting, describing it as having a "tranquil" and "beautiful" effect that emphasizes the rugged, wild beauty of the natural landscape. This suggests that ArtGPT-4 is better able to understand and convey the emotional and aesthetic impact of visual art, which could be particularly useful in fields such as art criticism or curation.

Aesthetics: Both MiniGPT-4 and ArtGPT-4 recognized the artistic qualities of the image as shown in Figure 4, but ArtGPT-4’s response is more detailed and descriptive. ArtGPT-4 not only describes the image but also provides an interpretation of it, highlighting the beauty in decay and evoking emotions such as sadness, loneliness, and desolation. In addition, ArtGPT-4 provides a more technical analysis

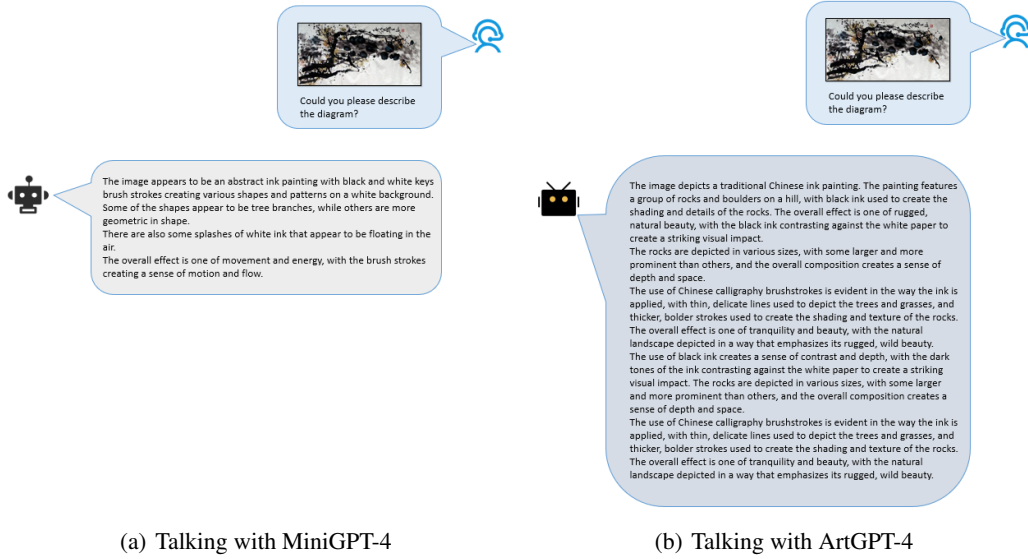


Figure 3: Description of traditional Chinese painting

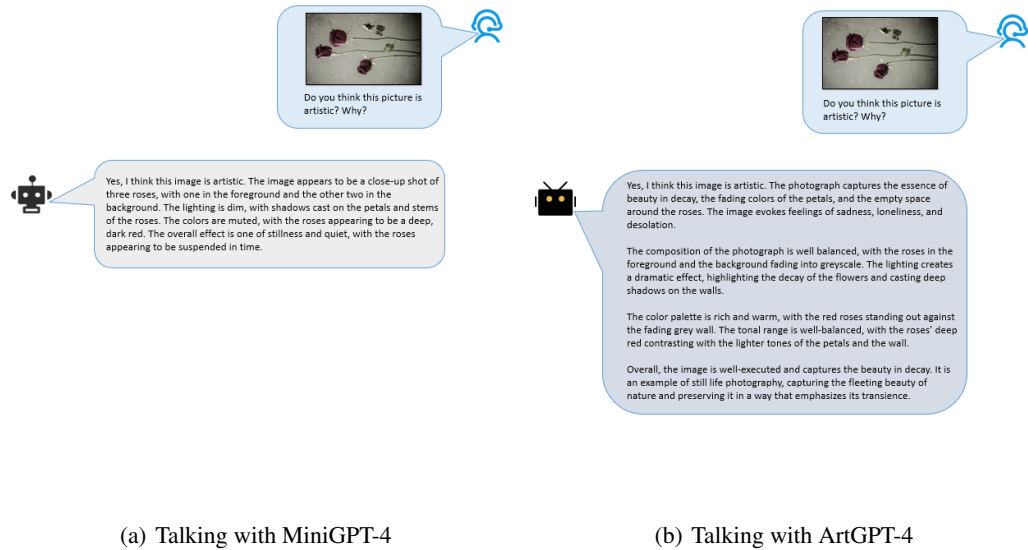


Figure 4: Appreciation of judgments about aesthetics

of the image, discussing the composition, lighting, color palette, and tonal range. These details demonstrate a deeper understanding of the elements of visual arts and photography. Overall, ArtGPT-4’s response is more nuanced and insightful, showcasing its superior capacity for understanding and analyzing art.

Better-Looking Websites: ArtGPT-4’s response includes an image that serves as a visual representation of the joke website as shown in Figure 5. The use of the image adds an extra layer of creativity to the website and can help to attract visitors. Additionally, the CSS styling used in ArtGPT-4’s response is more comprehensive, providing more visual appeal to the website. In comparison, MiniGPT-4’s response uses a more basic CSS styling and does not include an image. The website still looks functional and readable, but it lacks the same level of visual interest that ArtGPT-4’s response provides. Overall, ArtGPT-4’s response demonstrates a more sophisticated understanding of web design and has more visual appeal than MiniGPT-4’s response.



Figure 5: About the generation of better-looking websites

5 Evaluation Benchmarks

Similar to how the TOEFL and IELTS tests are used to measure English language proficiency, we were enthusiastic about establishing a reliable standard for evaluating the ability to understand multimodal images. We implemented four scoring criteria and a five-point scoring scale to evaluate the model's capacity for understanding images.

Image Depiction Capability (IDC): We selected 10 various types of graphs, such as paintings, photographs, AI-generated images, etc., for the model to provide descriptions for. Each image is scored according to the following criteria:

- 0: No image description capability
- 1: Description does not match real image representation
- 2: Partial image description
- 3: Complete image description without appreciation information
- 4: Complete image description at the human level of appreciation
- 5: Complete image description surpassing the human level of appreciation, such as an artist.

Image Sentiment Analysis Capability (ISAC): We chose 10 images of individuals and instructed the participants to "Analyze the emotions expressed by the individuals in the images as well as the emotions felt by the viewer observing them." Each image is scored according to the following criteria:

- 0: Can't describe the feelings about the picture
- 1: Can describe the relevant emotion but no logical proof (e.g.: the picture is seen... So people will have a kind of... emotion)
- 2: Can describe the relevant emotion and justify it. But the description is not perfect
- 3: The individuals in the images or the viewer's emotions can be described perfectly and justified.
- 4: Can describe all the emotions as an ordinary person and justify them.
- 5: Can describe all emotions perfectly and justifiably and full of art.

Image Content Recognition Capability (ICRC): We selected 5 images with a variety of objects and scenes, such as animals, landscapes, and household items, for the model to recognize and label. Each image is scored according to the following criteria:

- 0: No image content recognition capability
- 1: Some objects/scenes are recognized but with significant errors or omissions
- 2: Most objects/scenes are recognized with some errors or omissions
- 3: All objects/scenes are recognized with few errors or omissions
- 4: All objects/scenes are recognized with high accuracy and speed, comparable to a human observer
- 5: All objects/scenes are recognized with high accuracy, speed, and contextual understanding, surpassing the performance of a human observer.

Multi-round Dialogue Image Understanding Capability (MDIUC): We randomly select 2 images and conduct five rounds of dialogue with the model for each image to assess its multi-round image understanding capability. Each image-dialogue pair is scored according to the following criteria:

- 0: No image understanding capability in the dialogue
- 1: Partial image understanding, but unable to carry on the dialogue smoothly
- 2: Able to understand the image to some extent and carry on the dialogue with some coherence, but lacks understanding of some key points

- 3: Can understand the image and carry on the dialogue smoothly, but with some minor misunderstandings or mistakes
- 4: Can understand the image and carry on the dialogue smoothly, with accurate understanding and good coherence
- 5: Can understand the image and carry on the dialogue smoothly, with accurate understanding, good coherence, and creative responses.

We incorporated these scoring criteria into the state-of-the-art GPT-4 model to establish a comprehensive multimodal model evaluation system.

6 Evaluation

We separately scored each response based on the benchmarks presented in Section 5. Due to space limitations, we could not include the responses in the text. However, the responses generated by MiniGPT-4 and ArtGPT-4 can be found on Huggingface at <https://huggingface.co/Tyrannosaurus/ArtGPT-4/tree/main/Evaluation> as open-source reporters.

Items	1	2	3	4	5	6	7	8	9	10	Average
Human	4	4	4	4	4	3	4	5	4	5	4.1
GIT [Wang et al., 2022a]	2	2	2	2	2	2	2	2	2	2	2
ViLT [Kim et al., 2021]	1	1	2	1	1	2	1	1	1	1	1.2
MiniGPT-4	2	3	3	1	2	2	4	3	3	3	2.6
ArtGPT-4 (Ours)	4	4	3	4	4	3	4	5	3	4	3.8

Table 1: IDC benchmarks based on GPT-4 scores.

Items	1	2	3	4	5	6	7	8	9	10	Average
Human	3	4	3	3	3	3	3	3	3	3	3.1
GIT [Wang et al., 2022a]	1	1	1	1	1	1	1	1	1	1	1
ViLT [Kim et al., 2021]	0	0	0	0	0	0	0	0	0	0	0
MiniGPT-4	2	3	2	3	2	2	2	2	3	2	2.3
ArtGPT-4 (Ours)	3	3	1	3	3	3	3	3	3	3	2.8

Table 2: ISAC benchmarks based on GPT-4 scores.

We enlisted 10 artists (5 male, 5 female) to interpret the images according to the same instructions we provided to the model. We then used GPT-4 to score their interpretations, selecting the highest score for each image and presenting the results in a table. According to Table 1, Table 2, and Table 3 show, ArtGPT-4’s image understanding ability is significantly superior to that of the original MiniGPT-4 and even approaches that of Artists. ArtGPT-4 outperformed all multimodal models in all four benchmark tests. According to the four benchmark scores average, ArtGPT-4 scored 3.4 points while MiniGPT-4 scored 2.35 points, indicating a difference of more than 1 point on a 6-point scale. Notably, ArtGPT-4’s final score of 3.4 was only 0.15 points below that of the artists.

Benchmark Items	ICRC						MDIUC		
	1	2	3	4	5	Average	1	2	Average
Human	3	3	3	3	3	3	4	4	4
GIT [Wang et al., 2022a]	1	1	1	1	1	1	0	0	0
ViLT [Kim et al., 2021]	1	1	1	1	1	1	0	0	0
MiniGPT-4	1	2	2	2	2	1.8	3	2	2.5
ArtGPT-4 (Ours)	3	4	2	3	3	3	4	4	4

Table 3: ISAC and MDIUC benchmarks based on GPT-4 scores.

7 Conclusion and Future Work

Our ArtGPT-4 model demonstrates significant progress in the field of vision-language understanding, showing superior performance to its predecessor, MiniGPT-4. Our proposed modifications, including added adapter image layers, have optimized the model’s performance and addressed the unique challenges posed by vision-language tasks. Additionally, we have introduced a novel benchmark for evaluating the performance of vision-language models, which provides a more comprehensive criterion for assessing these models. Our model was trained in just 2 hours, using a relatively small dataset, and achieved state-of-the-art performance.

While we have successfully addressed many challenges, a couple of issues remain. First, our training dataset is limited, particularly in the second phase where we utilize the original MiniGPT-4 dataset. Secondly, our benchmarks only evaluate image understanding in English and do not account for other languages.

References

- Jean-Baptiste Alayrac, Jeff Donahue, Pauline Luc, Antoine Miech, Iain Barr, Yana Hasson, Karel Lenc, Arthur Mensch, Katherine Millican, Malcolm Reynolds, et al. Flamingo: a visual language model for few-shot learning. *Advances in Neural Information Processing Systems*, 35:23716–23736, 2022.
- Stanislaw Antol, Aishwarya Agrawal, Jiasen Lu, Margaret Mitchell, Dhruv Batra, C Lawrence Zitnick, and Devi Parikh. Vqa: Visual question answering. In *Proceedings of the IEEE International Conference on Computer Vision*, pages 2425–2433, 2015.
- Hyojin Bahng, Ali Jahanian, Swami Sankaranarayanan, and Phillip Isola. Visual prompting: Modifying pixel space to adapt pre-trained models. *arXiv preprint arXiv:2203.17274*, 2022.
- Tom B Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, et al. Language models are few-shot learners. *arXiv preprint arXiv:2005.14165*, 2020.
- Jun Chen, Han Guo, Kai Yi, Boyang Li, and Mohamed Elhoseiny. Visualgpt: Data-efficient adaptation of pretrained language models for image captioning. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 18030–18040, 2022a.
- Shoufa Chen, Chongjian Ge, Zhan Tong, Jiangliu Wang, Yibing Song, Jue Wang, and Ping Luo. Adaptformer: Adapting vision transformers for scalable visual recognition. *arXiv preprint arXiv:2205.13535*, 2022b.
- Wei-Lin Chiang, Zhuohan Li, Zi Lin, Ying Sheng, Zhanghao Wu, Hao Zhang, Lianmin Zheng, Siyuan Zhuang, Yonghao Zhuang, Joseph E Gonzalez, et al. Vicuna: An open-source chatbot impressing gpt-4 with 90%* chatgpt quality, 2023.
- Aakanksha Chowdhery, Sharan Narang, Jacob Devlin, Maarten Bosma, Gaurav Mishra, Adam Roberts, Paul Barham, Hyung Won Chung, Charles Sutton, Sebastian Gehrmann, Parker Schuh, Kensen Shi, Sasha Tsvyashchenko, Joshua Maynez, Abhishek Rao, Parker Barnes, Yi Tay, Noam Shazeer, Vinodkumar Prabhakaran, Emily Reif, Nan Du, Ben Hutchinson, Reiner Pope, James Bradbury, Jacob Austin, Michael Isard, Guy Gur-Ari, Pengcheng Yin, Toju Duke, Anselm Levskaya, Sanjay Ghemawat, Sunipa Dev, Henryk Michalewski, Xavier Garcia, Vedant Misra, Kevin Robinson, Liam Fedus, Denny Zhou, Daphne Ippolito, David Luan, Hyeontaek Lim, Barret Zoph, Alexander Spiridonov, Ryan Sepassi, David Dohan, Shivani Agrawal, Mark Omernick, Andrew M. Dai, Thanumalayan Sankaranarayanan Pillai, Marie Pellat, Aitor Lewkowycz, Erica Moreira, Rewon Child, Oleksandr Polozov, Katherine Lee, Zongwei Zhou, Xuezhi Wang, Brennan Saeta, Mark Diaz, Orhan Firat, Michele Catasta, Jason Wei, Kathy Meier-Hellstern, Douglas Eck, Jeff Dean, Slav Petrov, and Noah Fiedel. Palm: Scaling language modeling with pathways, 2022.
- Paul F Christiano, Jan Leike, Tom Brown, Miljan Martic, Shane Legg, and Dario Amodei. Deep reinforcement learning from human preferences. *Advances in neural information processing systems*, 30, 2017.

- Kevin Clark, Minh-Thang Luong, Quoc V. Le, and Christopher D. Manning. ELECTRA: Pre-training Text Encoders as Discriminators Rather Than Generators. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 6101–6111, 2020.
- Aaron Daniel Cohen, Adam Roberts, Alejandra Molina, Alena Butryna, Alicia Jin, Apoorv Kulshreshtha, Ben Hutchinson, Ben Zevenbergen, Blaise Hilary Aguera-Arcas, Chung ching Chang, Claire Cui, Cosmo Du, Daniel De Freitas Adiwardana, Dehao Chen, Dmitry (Dima) Lepikhin, Ed H. Chi, Erin Hoffman-John, Heng-Tze Cheng, Hongrae Lee, Igor Krivokon, James Qin, Jamie Hall, Joe Fenton, Johnny Soraker, Kathy Meier-Hellstern, Kristen Olson, Lora Mois Aroyo, Maarten Paul Bosma, Marc Joseph Pickett, Marcelo Amorim Menegali, Marian Croak, Mark Díaz, Matthew Lamm, Maxim Krikun, Meredith Ringel Morris, Noam Shazeer, Quoc V. Le, Rachel Bernstein, Ravi Rajakumar, Ray Kurzweil, Romal Thoppilan, Steven Zheng, Taylor Bos, Toju Duke, Tulsee Doshi, Vincent Y. Zhao, Vinodkumar Prabhakaran, Will Rusch, YaGuang Li, Yanping Huang, Yanqi Zhou, Yuanzhong Xu, and Zhifeng Chen. Lamda: Language models for dialog applications. In *arXiv*. 2022.
- Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. BERT: Pre-training of deep bidirectional transformers for language understanding. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pages 4171–4186, Minneapolis, Minnesota, June 2019. Association for Computational Linguistics. doi: 10.18653/v1/N19-1423. URL <https://aclanthology.org/N19-1423>.
- Alexey Dosovitskiy, Lucas Beyer, Alexander Kolesnikov, Dirk Weissenborn, Xiaohua Zhai, Thomas Unterthiner, Mostafa Dehghani, Matthias Minderer, Georg Heigold, Sylvain Gelly, et al. An image is worth 16x16 words: Transformers for image recognition at scale. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 10687–10696, 2020.
- Nan Du, Yanping Huang, Andrew M. Dai, Simon Tong, Dmitry Lepikhin, Yuanzhong Xu, Maxim Krikun, Yanqi Zhou, Adams Wei Yu, Orhan Firat, Barret Zoph, Liam Fedus, Maarten Bosma, Zongwei Zhou, Tao Wang, Yu Emma Wang, Kellie Webster, Marie Pellat, Kevin Robinson, Kathleen Meier-Hellstern, Toju Duke, Lucas Dixon, Kun Zhang, Quoc V Le, Yonghui Wu, Zhifeng Chen, and Claire Cui. Glam: Efficient scaling of language models with mixture-of-experts, 2022.
- Junxian He, Chunting Zhou, Xuezhe Ma, Taylor Berg-Kirkpatrick, and Graham Neubig. Towards a unified view of parameter-efficient transfer learning. *arXiv preprint arXiv:2110.04366*, 2021.
- Dan Hendrycks and Kevin Gimpel. Gaussian error linear units (gelus). *arXiv preprint arXiv:1606.08415*, 2016.
- Neil Houlsby, Andrei Giurgiu, Stanislaw Jastrzebski, Bruna Morrone, Quentin De Laroussilhe, Andrea Gesmundo, Mona Attariyan, and Sylvain Gelly. Parameter-efficient transfer learning for nlp. In *International Conference on Machine Learning*, pages 2790–2799. PMLR, 2019.
- Edward J Hu, yelong shen, Phillip Wallis, Zeyuan Allen-Zhu, Yanzhi Li, Shean Wang, Lu Wang, and Weizhu Chen. LoRA: Low-rank adaptation of large language models. In *International Conference on Learning Representations*, 2022. URL <https://openreview.net/forum?id=nZeVKeeFYf9>.
- Menglin Jia, Luming Tang, Bor-Chun Chen, Claire Cardie, Serge Belongie, Bharath Hariharan, and Ser-Nam Lim. Visual prompt tuning. In *Computer Vision—ECCV 2022: 17th European Conference, Tel Aviv, Israel, October 23–27, 2022, Proceedings, Part XXXIII*, pages 709–727. Springer, 2022.
- Wonjae Kim, Bokyung Son, and Ildoo Kim. Vilt: Vision-and-language transformer without convolution or region supervision. In *International Conference on Machine Learning*, pages 5583–5594. PMLR, 2021.
- Junnan Li, Dongxu Li, Silvio Savarese, and Steven Hoi. Blip-2: Bootstrapping language-image pre-training with frozen image encoders and large language models. *arXiv preprint arXiv:2301.12597*, 2023.

- Xiang Lisa Li and Percy Liang. Prefix-tuning: Optimizing continuous prompts for generation. In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, pages 4582–4597, 2021.
- Junyang Lin, Rui Men, An Yang, Chang Zhou, Ming Ding, Yichang Zhang, Peng Wang, Ang Wang, Le Jiang, Xianyan Jia, Jie Zhang, Jianwei Zhang, Xu Zou, Zhikang Li, Xiaodong Deng, Jie Liu, Jinbao Xue, Huiling Zhou, Jianxin Ma, Jin Yu, Yong Li, Wei Lin, Jingren Zhou, Jie Tang, and Hongxia Yang. M6: A chinese multimodal pretrainer, 2021.
- Tsung-Yi Lin, Michael Maire, Serge Belongie, James Hays, Pietro Perona, Deva Ramanan, Piotr Dollár, and C Lawrence Zitnick. Microsoft coco: Common objects in context. In *Computer Vision—ECCV 2014: 13th European Conference, Zurich, Switzerland, September 6-12, 2014, Proceedings, Part V 13*, pages 740–755. Springer, 2014.
- Haotian Liu, Chunyuan Li, Qingyang Wu, and Yong Jae Lee. Visual instruction tuning, 2023.
- Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. RoBERTa: A Robustly Optimized BERT Pretraining Approach. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, pages 3285–3295, 2019.
- OpenAI. Introducing chatgpt. <https://openai.com/blog/chatgpt>, 2022. Accessed: May 3, 2023.
- OpenAI. Gpt-4 technical report, 2023.
- Long Ouyang, Jeffrey Wu, Xu Jiang, Diogo Almeida, Carroll Wainwright, Pamela Mishkin, Chong Zhang, Sandhini Agarwal, Katarina Slama, Alex Ray, et al. Training language models to follow instructions with human feedback. In *Proceedings of the 35th Conference on Neural Information Processing Systems (NeurIPS)*, pages 27730–27744, 2021.
- Zhiwu Qing, Shiwei Zhang, Ziyuan Huang, Xiang Wang, Yuehuan Wang, Yiliang Lv, Changxin Gao, and Nong Sang. Mar: Masked autoencoders for efficient action recognition. *IEEE Transactions on Multimedia*, 2023.
- Alec Radford, Karthik Narasimhan, Tim Salimans, and Ilya Sutskever. Improving language understanding by generative pre-training. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, pages 1–10, 2018.
- Alec Radford, Jeffrey Wu, Rewon Child, David Luan, Dario Amodei, and Ilya Sutskever. Language Models are Unsupervised Multitask Learners. In *Proceedings of the 2019 Neural Information Processing Systems (NeurIPS)*, pages 3657–3667, 2019.
- Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J. Liu. Exploring the Limits of Transfer Learning with a Unified Text-to-Text Transformer. In *Advances in Neural Information Processing Systems*, pages 11791–11802, 2019.
- Christoph Schuhmann, Romain Beaumont, Richard Vencu, Cade Gordon, Ross Wightman, Mehdi Cherti, Theo Coombes, Aarush Katta, Clayton Mullis, Mitchell Wortsman, et al. Laion-5b: An open large-scale dataset for training next generation image-text models. *arXiv preprint arXiv:2210.08402*, 2022.
- Rohan Taori, Ishaan Gulrajani, Tianyi Zhang, Yann Dubois, Xuechen Li, Carlos Guestrin, Percy Liang, and Tatsunori B. Hashimoto. Stanford alpaca: An instruction-following llama model. https://github.com/tatsu-lab/stanford_alpaca, 2023.
- Maria Tsimpoukelli, Jacob L Menick, Serkan Cabi, SM Eslami, Oriol Vinyals, and Felix Hill. Multimodal few-shot learning with frozen language models. *Advances in Neural Information Processing Systems*, 34:200–212, 2021.

- Jianfeng Wang, Zhengyuan Yang, Xiaowei Hu, Linjie Li, Kevin Lin, Zhe Gan, Zicheng Liu, Ce Liu, and Lijuan Wang. Git: A generative image-to-text transformer for vision and language. Technical report, Microsoft, May 2022a. URL <https://www.microsoft.com/en-us/research/publication/git-a-generative-image-to-text-transformer-for-vision-and-language/>.
- Yizhong Wang, Yeganeh Kordi, Swaroop Mishra, Alisa Liu, Noah A. Smith, Daniel Khashabi, and Hannaneh Hajishirzi. Self-instruct: Aligning language model with self generated instructions, 2022b.
- Taojiannan Yang, Yi Zhu, Yusheng Xie, Aston Zhang, Chen Chen, and Mu Li. AIM: Adapting image models for efficient video action recognition. In *The Eleventh International Conference on Learning Representations*, 2023. URL https://openreview.net/forum?id=CIoSZ_HKHS7.
- Zhilin Yang, Zihang Dai, Yiming Yang, Jaime Carbonell, Ruslan Salakhutdinov, and Quoc V Le. Xlnet: Generalized autoregressive pretraining for language understanding. In *Advances in neural information processing systems*, pages 5754–5764, 2019.
- Peter Young, Alice Lai, Micah Hodosh, and Julia Hockenmaier. From image descriptions to visual denotations: New similarity metrics for semantic inference over event descriptions. In *Transactions of the Association for Computational Linguistics*, volume 2, pages 67–78, 2014.
- Elad Ben Zaken, Yoav Goldberg, and Shauli Ravfogel. Bitfit: Simple parameter-efficient fine-tuning for transformer-based masked language-models. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers)*, pages 1–9, 2022.
- Qiming Zhang, Jing Zhang, Yufei Xu, and Dacheng Tao. Vision transformer with quadrangle attention. *arXiv preprint arXiv:2303.15105*, 2023.
- Deyao Zhu, Jun Chen, Xiaoqian Shen, Xiang Li, and Mohamed Elhoseiny. Minigt-4: Enhancing vision-language understanding with advanced large language models. *arXiv preprint arXiv:2304.10592*, 2023.

Appendix

The following four examples demonstrate that ArtGPT-4 possesses comparable or even superior image comprehension abilities compared to GPT-4. This achievement is a remarkable breakthrough, given that ArtGPT-4 has only 13 billion parameters, significantly fewer than GPT-4’s 175+ billion parameters.

A Image Depiction Capability

As shown in Table 4, ArtGPT-4’s description of the image is highly effective in conveying a sense of action and excitement. The desert landscape and the figure in the space suit are rendered in vibrant detail, with expert use of texture, lighting and colour. It is successful in creating a tangible sense of atmosphere and energy. The description’s emphasis on the image’s artistic merits, such as its vibrant colours and realistic textures, provides a vivid impression of the image as a digital artwork.

B Understanding Human Emotional Capabilities

As shown in Table 5 and Table 6, the ArtGPT-4 performs remarkably well in understanding human emotions. It even surpasses GPT-4 in certain aspects, such as its ability to accurately capture the squirrel’s expression. It provides a rich vocabulary and expressive language when describing the image, such as the use of "cute" and "playful", which effectively convey the image’s sense of humor and charm. Moreover, it is able to describe facial expressions and actions depicted in the image, which is an important aspect of understanding human emotions.

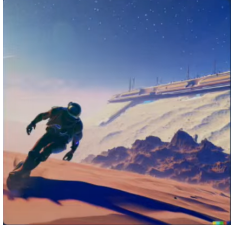
ArtGPT-4 and image example compare	
Ures	Here is an audience submitted image 
GPT-4	This image depicts an astronaut exploring a snowy, mountainous landscape on an alien planet. In the background, we see a large spacecraft resting on the snow-covered ground, with its antennas and various equipment. The sky above is filled with stars, and a celestial body can be seen in the distance. The astronaut appears to be wearing a green spacesuit and is captured in motion, perhaps making his way towards the spacecraft.
ArtGPT-4	This is a screen shot of a video game or virtual environment. The image shows a desert landscape with mountains in the background, and a person wearing a spacesuit standing on the ground with their arms outstretched. It looks like they are running or jumping, but it is not clear from this image alone. The image has a clear and detailed representation of the environment, with realistic textures and lighting. The colors are vibrant and contrasting, making the image look very appealing. The overall quality of the image is high, with excellent details and contrast.

Table 4: In the example video (<https://www.youtube.com/watch?v=outcGtbnMuQ>) the image description capability of GPT-4 compared with the ArtGPT-4


ArtGPT-4 and image example compare	
Ures	What's funny about this image? 
GPT-4	The image is funny because it shows a squirrel holding a camera and taking a photo of a nut as if it were a professional photographer. let's humorous situation because squirrels typically eat nuts, and we don't expect them to use a camera or act like humans,
ArtGPT-4	This image is funny because it depicts a cartoon squirrel holding a camera with a nut in its hand. The squirrel is wearing a camera strap and looking at the camera with a smile on its face. It is a cute and playful image that can make people laugh. The squirrel's facial expression is funny because it is playful and expressive. The fact that the squirrel is holding a camera while eating nuts is also amusing because it shows that the animal is multitasking and is not afraid to try new things. Overall, this image is funny because it is a cute and playful representation of a squirrel doing something unexpected, which is taking a photo with a camera while eating nuts.

Table 5: In the example video (<https://www.youtube.com/watch?v=outcGtbnMuQ>) the human emotion capability of GPT-4 compared with the ArtGPT-4


ArtGPT-4 and image example compare	
Ures	<p>What's funny about this image?</p> <p>Sometimes I just look at pictures of the earth from space and I marvel at how beautiful it all is.</p> 
GPT-4	<p>This meme is a joke that combines two unrelated things: pictures of the earth from space and chicken nuggets. The text of the meme suggests that the image below is a beautiful picture of the earth from space. However, the image is actually of chicken nuggets arranged to vaguely resemble a map of the world. The humor in this meme comes from the unexpected juxtaposition of the text and the image. The text sets up an expectation of a majestic image of the earth, but the image is actually something mundane and silly.</p>
ArtGPT-4	<p>The humor in this image comes from the idea of using food to represent a map of the world and the absurdity of using such a small and seemingly insignificant object to represent something as large and complex as the Earth. The fact that the image is presented as a meme on social media further adds to the humor by making it seem like a silly and unexpected thing to do.</p>

Table 6: In the example artical [OpenAI, 2023] the human emotion capability of GPT-4 compared with the ArtGPT-4


ArtGPT-4 and image example compare	
Ures	<p>What is unusual about this image?</p> 
GPT-4	<p>The unusual thing about this image is that a man is ironing clothes on an ironing board attached to the roof of a moving taxi.</p>
ArtGPT-4	<p>It is unusual because it shows a man standing on the back of a taxi holding an iron in his hand and ironing clothes. This is not a common sight in most cities.</p>

Table 7: In the example artical [OpenAI, 2023] the abnormal image capability of GPT-4 compared with the ArtGPT-4

C Abnormal Image Understanding Skills

As shown in Table 7, ArtGPT-4 can depict the abnormalities of the image as well as GPT-4.

D Data Analysis Capability

ArtGPT-4, exhibits an exceptional ability to comprehend mathematical problems and solve them methodically, similar to human cognition. Moreover, its performance is on par with the renowned GPT-4. As shown in Table 8, the model accurately identifies and extracts relevant information from a graph to derive the sum of average daily meat consumption for Georgia and Western Asia in 1997. Its proficiency in solving such problems showcases the model’s potential to contribute to various fields, including data analysis and decision-making.

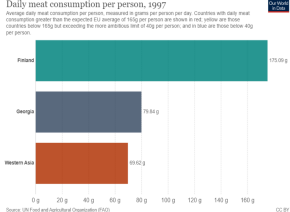
ArtGPT-4 and image example compare									
Ures	<p>What is unusual about this image?</p>  <p>Daily meat consumption per person, 1997</p> <p>Meat consumption per person (kg per person per day). Countries with daily meat consumption greater than the reported U.S. average of 100 kg per person are shown in red. Others are shown in blue. Values are rounded to the nearest 0.1 kg per person.</p> <table border="1"> <thead> <tr> <th>Region</th> <th>Daily meat consumption (kg per person per day)</th> </tr> </thead> <tbody> <tr> <td>Romania</td> <td>175.84</td> </tr> <tr> <td>Georgia</td> <td>79.84</td> </tr> <tr> <td>Western Asia</td> <td>69.62</td> </tr> </tbody> </table> <p>Source: FAO Food and Agriculture Organization (FAO)</p>	Region	Daily meat consumption (kg per person per day)	Romania	175.84	Georgia	79.84	Western Asia	69.62
Region	Daily meat consumption (kg per person per day)								
Romania	175.84								
Georgia	79.84								
Western Asia	69.62								
GPT-4	<p>To find the sum of average daily meat consumption for Georgia and Western Asia, we will follow these steps:</p> <ol style="list-style-type: none"> 1. Identify the average daily meat consumption for Georgia. 2. Identify the average daily meat consumption for Western Asia. 3. Add the values from steps 1 and 2. <p>Step 1: From the provided chart, we see that the average daily meat consumption for Georgia is 79.84 grams per person per day.</p> <p>Step 2: From the chart, we see that the average daily meat consumption for Western Asia is 69.62 grams per person per day.</p> <p>Step 3: Add the values from steps 1 and 2. $79.84 \text{ g (Georgia)} + 69.62 \text{ g (Western Asia)} = 149.46 \text{ g}$</p> <p>So, the sum of average daily meat consumption for Georgia and Western Asia is 149.46 grams per person per day.</p>								
ArtGPT-4	<p>To find the sum of average daily meat consumption for Georgia and Western Asia, we need to look at the data provided in the graph.</p> <p>Georgia’s average daily meat consumption per person in 1997 was 79.84 grams.</p> <p>Western Asia’s average daily meat consumption per person in 1997 was 69.62 grams.</p> <p>The sum of the average daily meat consumption per person for Georgia and Western Asia in 1997 is $79.84 + 69.62 = 149.46$ grams.</p> <p>Therefore, the sum of average daily meat consumption per person for Georgia and Western Asia in 1997 is 149.46 grams.</p>								

Table 8: In the example article [OpenAI, 2023] the analysis data capability of GPT-4 compared with the ArtGPT-4