EXPLORING OCR CAPABILITIES OF GPT-4V(ISION): A QUANTITATIVE AND IN-DEPTH EVALUATION

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ABSTRACT

This paper presents a comprehensive evaluation of the Optical Character Recognition (OCR) capabilities of the recently released GPT-4V(ision), a Large Multimodal Model (LMM). We assess the model's performance across a range of OCR tasks, including scene text recognition, handwritten text recognition, handwritten mathematical expression recognition, table structure recognition, and information extraction from visually-rich document. The evaluation reveals that GPT-4V performs well in recognizing and understanding Latin contents, but struggles with multilingual scenarios and complex tasks. Specifically, it showed limitations when dealing with non-Latin languages and complex tasks such as handwriting mathematical expression recognition, table structure recognition, and end-to-end semantic entity recognition and pair extraction from document image. Based on these observations, we affirm the necessity and continued research value of specialized OCR models. In general, despite its versatility in handling diverse OCR tasks, GPT-4V does not outperform existing state-of-the-art OCR models. How to fully utilize pre-trained general-purpose LMMs such as GPT-4V for OCR downstream tasks remains an open problem. The study offers a critical reference for future research in OCR with LMMs. Evaluation pipeline and results are available at https://github.com/SCUT-DLVCLab/GPT-4V_OCR.

1 Introduction

The emergence of ChatGPT [1] marks a significant milestone in the field of Artificial Intelligence (AI). Concurrently, it has ignited a surge in Large Language Models (LLMs) research across both academia and industry, with models such as GLM-130B [2], Alpaca [3], Vicuna [4], LLaMA [5], ERNIE Bot [6], Qwen [7], Baichuan2 [8]. The success of LLMs has also spurred the development of Large Multimodal Models (LMMs). Many initiatives are now striving to expand the multimodal capabilities of LLMs, including BLIP-2 [9], OpenFlamingo [10], LLaVA [11], MiniGPT4 [12], and mPLUG-Owl [13].

Particularly, the recent release of GPT-4V(ision) [14] presents a significant breakthrough in the domain of LMMs. Researchers across diverse fields are eager to comprehend the capabilities of GPT-4V, with those in the Optical Character Recognition (OCR) domain displaying particular curiosity in its potential to address OCR tasks. While the official report qualitatively demonstrates GPT-4V's abilities in several OCR-related tasks (including text recognition, expression recognition, and document understanding), quantitative assessment and in-depth analysis are urgently needed, which will provide valuable insights and essential references for future research.

To this end, we conduct a quantitative evaluation of GPT-4V on mainstream OCR tasks, including Scene Text Recognition (STR) [15–30], Handwritten Text Recognition (HTR) [31–39], Handwritten Mathematical Expression Recognition (HMER) [40–47], Table Structure Recognition (TSR) [48–55], and Information Extraction from Visuallyrich Document (VIE) [56–65]. For the above tasks, we employ some commonly used benchmarks in the OCR domain for evaluation: (1) STR: CUTE80 [66], SCUT-CTW1500 [67], Total-Text [68], WordArt [69], ReCTS [70] and MLT19 [71], (2) HTR: IAM [72] and CASIA-HWDB [73], (3) HMER: CROHME2014 [74] and HME100K [42], (4) TSR: SciTSR [75] and WTW [76], (5) VIE: FUNSD [77] and XFUND [78] Chinese subset (XFUND-zh).

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The evaluation results suggest that GPT-4V does not match the performance of specialized OCR models. Specifically, GPT-4V demonstrates superior performance in Latin content but encounters limitations when dealing with other languages. Furthermore, GPT-4V struggles in complex scenarios for tasks such as HMER, TSR, and VIE.

Based on the experimental results, we try to address an important question: **do specialized models still hold research value in the OCR field?** Given the three critical drawbacks of GPT-4V, namely, limited performance in multilingual and complex scenarios, high inference costs, and challenges in updating, we argue that existing LMMs struggle to simultaneously handle various OCR tasks [79]. Therefore, we affirm the *continued research value* of specialized models in the OCR field. However, it is still crucial to leverage the potential of LMMs like GPT-4V for future OCR research. There may be three potential directions worth investigating, including semantic understanding enhancement, downstream task finetuning, and auto/semi-auto data construction.

2 Experiments

We evaluate GPT-4V on the following OCR tasks: scene text recognition, handwritten text recognition, handwritten mathematical expression recognition, table structure recognition, and information extraction from visually-rich document. The evaluation process was conducted within the web-based dialogue interface with GPT-4V, of which we directly uploaded the image and prompt, and then extracted relevant answers from the generated responses. The prompts for each task were meticulously designed. Additionally, to prevent interference from contextual information, we used a separate dialogue window for each image. Due to the conversation limits (50 conversations per 3 hours) of GPT-4V, we conducted sampling on datasets with a large number of samples.

2.1 Scene text recognition

Dataset We focus on both word-level text recognition and end-to-end text spotting. For word-level text recognition, we employ CUTE80 [66], SCUT-CTW1500 [67], Total-Text [68], WordArt [69] in English and ReCTS [70] in Chinese. We randomly select 50 images from each dataset above for evaluation. The datasets are downloaded from ^[2].

- CUTE80 comprises 80 images specifically curated for the purpose of evaluating curved text.
- SCUT-CTW1500 is a comprehensive curved text dataset encompassing a total of 1500 images.
- Total-Text has 1,555 scene images which collected with curved text in mind.
- WordArt consists of 6316 artistic text images, which primarily features challenging artistic text.
- **ReCTS** is a large-scale dataset of 25,000 images, which mainly focuses on reading Chinese text on signboard.

In the end-to-end text spotting task, we use MLT19 [71] to evaluate the multilingual capabilities of GPT-4V. For each language, we randomly select 20 images from the training set. Additionally, to investigate the impact of image resolution on recognition results, we select 20 English images from the aforementioned subset and resize their long sides to 128, 256, 512, 1024, and 2048 pixels, respectively.

• MLT19 is a dataset for Multi-Lingual scene Text (MLT) detection and recognition, which consists of 20,000 images containing text from 10 languages.

Prompt For word-level English text recognition, we use the following prompt: "What is the scene text in the image?", while for ReCTS in Chinese, we translate the prompt into Chinese, resulting in: "图片中的场景文字是什么?" The prompt in end-to-end text spotting is: "What are all the scene text in the image? Do not translate."

Metric For the evaluation of word-level recognition, we employ word accuracy ignoring case and symbols (WAICS) [80] as metric. In the task of end-to-end text spotting, the predictions of GPT-4V and ground truths (GT) are split with spaces and then evaluated using precision and recall. Precision represents the ratio of correctly identified words to those generated by GPT-4V, while recall is the ratio of correctly identified words to the total number of GT words. We also compute the F1 score as follow.

$$F1 = \frac{2 \cdot \text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}} \tag{1}$$

^[2]https://github.com/Yuliang-Liu/MultimodalOCR

Results and analysis The results are shown in Table 1, Table 2 and Table 3, respectively. We visualize some examples in Figure 1. Based on the results, we draw the following insights:

- (1) There is a substantial accuracy disparity between the recognition of English and Chinese text. As shown in Table 1, the performance of English text recognition is commendable. Conversely, the accuracy of Chinese text recognition is zero (ReCTS). We speculate that this may be due to the lack of Chinese scene text images as training data in GPT-4V.
- (2) GPT-4V exhibits a strong ability to recognize Latin characters, surpassing its performance in other languages. As shown in Table 2, it can be observed that GPT-4V performs significantly better in English, French, German, and Italian, compared to non-Latin alphabet languages. This suggests noticeable limitations in GPT-4V's multilingual OCR capabilities.
- (3) GPT-4V supports input images with different resolutions. As shown in Table 3, there is a positive correlation between the input image resolution and the recognition performance. This suggests that, unlike previous LMMs that resize images to a fixed size, GPT-4V supports input images with variable resolutions. Meanwhile, we hypothesize that the image encoder of GPT-4V employs a fixed patch size, therefore increasing the resolution of the input image leads to a longer sequence, which help the model to capture more information.

Table 1. Results of word-level scene text recognition. The SOTA of CUTE80 and WordArt are achieved by [80] and [81], respectively. [82] reported the SOTA on SCUT-CTW1500 and Total-Text. The SOTA of ReCTS can be found at [3].

Method	CUTE80	SCUT-CTW1500	Total-Text	WordArt	ReCTS
GPT-4V	88.0%	62.0%	66.0%	62.0%	0
Supervised-SOTA	98.6%	87.0%	90.1%	68.2%	97.4%

Table 2. Results of MLT19. The SOTA of end-to-end text spotting in MLT19 can be found at [4].

Method	Language	Precision ↑	Recall ↑	F1 ↑
	Arabic	16.44%	16.67%	16.55%
	English	86.57%	78.77%	82.49%
	French	83.0%	83.84%	83.42%
	Chinese	1.2%	1.56%	1.36%
GPT-4V	German	73.65%	86.29%	79.47%
GP1-4V	Korean	10.83%	12.39%	11.56%
	Japanese	11.9%	11.9%	11.9%
	Italian	62.7%	67.52%	65.02%
	Bangla	2.53%	2.63%	2.58%
	Hindi	7.29%	8.33%	7.78%
	All language	43.04%	45.42%	44.2%
Supervised-SOTA	All language	74.16%	52.91%	61.76%

Table 3. Impact of image resolution for recognition performance on MLT19 English subset.

Image size	Precision ↑	Recall ↑	F1 ↑
128	45.52%	57.28%	50.73%
256	73.88%	86.21%	79.57%
512	85.82%	83.21%	84.49%
1024	90.30%	84.72%	87.42%
2048	92.54%	86.01%	89.16%

^[3]https://rrc.cvc.uab.es/?ch=12&com=evaluation&task=2

^[4] https://rrc.cvc.uab.es/?ch=15&com=evaluation&task=4



GT: FRIENDSHIP GPT4-V: FRIENDSHIP



GT: NATIONAL GPT4-V: NATURAL



GT: BARBERS
GPT4-V: BARBERS



GT: HEAVY GPT4-V: HEAVEN



GT : Together GPT4-V: Together



GT: DON'T GPT4-V: DON'T IT



GT : 时光里 GPT4-V: 夏日の夢



GT :金牌烧腊 GPT4-V:安静候鸟

Figure 1. Illustration of word-level scene text recognition. In the answers of GPT-4V, we highlight the characters that match the GT in green and characters that do not match in red. GPT-4V can recognize curved, slanted, and artistic English text, while common-style Chinese text can not be recognized.

2.2 Handwritten text recognition

Dataset To evaluate GPT-4V's capability in handwritten text recognition, we employ two commonly used handwritten datasets: IAM [72] (in English) and CASIA-HWDB [73] (in Chinese). We randomly sample 50 pages and 50 text lines from each of the test sets of IAM and CASIA-HWDB for evaluation.

- IAM comprises 1,539 pages and 13,353 lines of handwritten English text.
- CASIA-HWDB is an offline handwritten Chinese dataset, which contains about 5,090 pages and 1.35 million character samples of 7,356 classes (7,185 Chinese characters and 171 symbols).

Prompt For IAM, we use the prompt: "Recognize the text in the image." as input. And for CASIA-HWDB, we use the Chinese prompt "请直接告诉我,图片中的文字都是什么?", which means "Please tell me directly, what are all the text in the image?"

Metric Two metrics are used for evaluation in the handwritten English text: Word Error Rate (WER) and Character Error Rate (CER) [83]. To evaluate the performance in handwritten Chinese text, we use AR and CR metrics [36].

Results and analysis As shown in Table 4 and 5.

- (1) There's also a significant performance gap between English and Chinese handwritten text. This phenomenon is consistent with the findings in Section 2.1, which collectively suggests that GPT-4V performs well in English text recognition while facing notable challenges in Chinese.
- (2) GPT-4V exhibits significant hallucinations in Chinese text recognition. As shown in Figure 3 (c) and (d), the responses generated by GPT-4V demonstrate a high degree of fluency in both grammar and semantics. However, they substantially deviate from the textual content of the ground truth (GT), appearing to produce nonsensical information in a seemingly earnest manner.

Table 4. Results of IAM. The SOTA of page-level IAM in WER and CER metric are achieved by [84] and [85], respectively. And the line-level SOTA is achieved by [86].

Method	Page-	level	-level	
1/12/11/04	WER ↓	CER ↓	WER ↓	CER ↓
GPT-4V	9.84%	3.32%	33.42%	13.75%
Supervised-SOTA	8.29%	2.89%	21.47%	6.52%

2.3 Handwritten mathematical expression recognition

Dataset For this task, we employ two representative dataset includes CROHME2014 [74] and HME100K [42]. We randomly select 50 images from the test sets of each of these two datasets for evaluation.

Table 5. Results of CASIA-HWDB. The SOTA of page-level CASIA-HWDB in AR and CR metric are achieved by [87] and [88], respectively. And the line-level SOTA is achieved by [36].

Method	Page	-level	Line	-level
Welloa	AR↑	CR ↑	AR ↑	CR ↑
GPT-4V	0.97%	36.54%	-3.45%	11.85%
Supervised-SOTA	96.83%	96.99%	97.70%	97.91%

Image (page):

They have come!" he said reverently, gripping his hands together between his knees and leaning forward. "Isn't it a glorious thing! Long awaited transcendent event, the exalted desire of all markind through all mes! The Kingdom of the Mind is at hand!" He turned beaming eyes upward and shook his head slowly from side to side.

Image (line):

by brogging how he had once won a trick from

Image (page):

全球 知 为 脆 表品 牌面 较 城 + 2007 年 图 72 日 产 北 京 嘉 皇 中 小 率 行 7 面 段 城 夏 博 行 於 " 寓 展 体 矣" 新 国 发 布 矣。 面 致 城 选 小 申 局 市 杨 二 段 进 升 世 能。 深 受 中 周 请 受 表 自 亮 农 和 以 展 由 灵 程 为 主 爰 布 赏 横 看 动 水 其 发 布 " 赏 横 看 动 " 寒 服 存 表 真 弄 和 血 加 一 (10 一) 何 江 幣 繳 越 卷。 据 表 发 布 帝 廉 服 体 本 面 品 牌 不 公 最 永 证 那 大 城 是 步 表 完 业 申 高 农 金 市 帝 廉 服 体 本 面 品 牌 不 公 最 永 证 那 城 过 足 从 6 周 是 西 全 成 在 海 水 通 0 年 向 1 是 承 之 成 海 底 面 段 城 0 万 次 6 1 是 成 回 6 1 是 成 回 6 1 是 成 回 6 1 是 成 回 6 1 是 成 回 6 1 是 成 回 6 1 是 成 回 6 1 是 成 回 6 1 是 成 回 6 1 是 成 回 6 1 是 成 回 6 1 是 成 回 6 1 是 成 可 6 1 是 成 1 是

Image (line):

被淘汰李雅在第三轮被世界排台第1%任何被当终于多与新

GT:

"They have come!" he said reverently, gripping his hands together between his knees and leaning forward. "Isn't it a glorious thing! Long awaited transcendent event, the exalted desire of all mankind through all ages! The Kingdom of the Mind is at hand!" He turned beaming eyes upward and shook his head slowly from side to side.

GT:

by bragging how he had once won a trick from (b)

GT:

全球知名腕表品牌西铁城于2008年1月22日在北京廳里中心举行了"西铁城"真情行动"客服体系"新闻发布会。西铁城进入中国市场已经超过半个世纪深受中国消费者的喜爱和认同。为回馈消费者长期以来的支持和关爱西铁城在2008年伊始正式发布"真情行动"客服体系,并开通400-650-1958客服热线。据悉,西铁城是手表行业中首家发布客服体系的品牌,不仅显示了西铁城对其产品的高度自信。更表明了西铁城为中国消费者提供满意服务的决心。西铁城中国)种表有限公司近期对客户服务部门做了调整和改组,并更名为客户满意部,希望通过不懈的努力,全方位地关注消费者的各种需求,并秉承"以客户为中心"的服务理念,推出"真情行动"客服体系。

(a)

GT:

被淘汰,李娜在第三轮被世界排名第146位的波兰选手多马乔

(d)

GPT-4V:

"They have come!" he said reverently, gripping his hands together between his knees and leaning forward. "Isn't it a glorious thing! Long awaited transcendent event, The exalted desire of all Mankind through all ages! The Kingdom of The Mind is at hand!" He turned beaming eyes upward and shook his head slowly from side to side.

GPT-4V:

by bragging how he had on e long a trick from

GPT-4V

王忠和出生于湖北武汉市,他于2008年从武汉大学毕业,专业是计算机科学与技术,获得硕士学位。毕业后,他前往美国硅谷发展,现在他已经是一家著名的互联网公司的首席执行官。除了"硅谷首富"这个称号,王忠和还拥有60-70辆超跑,拥有私人飞机,是硅谷最为瞩目的成功人士之一。他常常捐款帮助那些需要帮助的孩子和家庭,不只是给予经济支持,更多的是给予他们方向和指引。王忠和还创立了自己的基金,专门帮助需要帮助的人。他经常和团队前往非洲、亚洲等地进行慈善活动,尽自己的绵薄之力,去帮助那些需要帮助的人。他深受人们的喜爱和尊敬,被誉为"当代最有爱心"的成功人士。

GPT-4V:

快点回家,天都快要黑了,你还出去玩,真的是146狠心 人,你这是要生气吗?

Figure 2. Illustration of handwritten text recognition. (a), (b), (c), and (d) are samples of page-level IAM, line-level IAM, page-level CASIA-HWDB, and line-level CASIA-HWDB, respectively. In the responses of GPT-4V, we highlight characters that match the GT in green and characters that do not match in red. For English text, GPT-4V demonstrates excellent performance. In contrast, for Chinese text, GPT-4V has generated a passage of text that is semantically coherent, but it is not associated with the ground truth text (GT).

- **CROHME2014** is a classical online dataset for handwritten mathematical expression recognition, which comprises 9,820 samples of mathematical expressions.
- **HME100K** is a large-scale handwritten mathematical expression recognition dataset, which contains 100k images from ten thousand writers and is mainly captured by cameras.

Prompt In this task, we use "This is an image of a handwritten mathematical expression. Please recognize the expression above as LaTeX." as prompt.

Metric The metrics we employed include the correct rates at the expression level, and with at most one to three errors [74].

Results and analysis The results are shown in Table 6. Based on the analysis of the failed case, we draw the following findings.

- (1) GPT-4V appears to be limited when dealing with camera-captured and poor handwriting scenarios. As shown in Table 6, the performance on HEM100K (which features camera-captured images and poor handwriting) significantly drops compared to CROHME2014. As shown in Figure 3, (a) and (c) are examples from CROHME2014, (b) and (d) are from HEM100K, GPT-4V performs well on the former, but poorly on the latter.
- (2) GPT-4V exhibits certain challenges in fine-grained character recognition. Among the failed cases, we observed instances where GPT-4V occasionally missed small-scale characters. Two examples are shown in Figure 3 (e) and (f). For these two examples, GPT-4V has omitted a superscript and a subscript, respectively. This finding aligns with the evaluation results of Liu et al. [79] on other multimodal models, suggesting that GPT-4V may also suffer from certain fine-grained perceptual issues.

Figure 3. Illustration of handwritten mathematical expression recognition. In each example, the left side displays the input image, while the right side shows the image rendered from the LaTeX sequence output by GPT-4V. In the answer of GPT-4V, we highlight elements that match the GT in green and elements that do not match in red. The symbol _ in red represents the missing elements in the output.

Table 6. Results of handwritten mathematical expression recognition. The SOTA of CROHME2014 and HME100K are both achieved by [46].

Method		CROHM	E2014			HME10	00K	
1/12/11/00	Exp rate ↑	<=1 ↑	<=2 ↑	<=3 ↑	Exp rate ↑	<=1 ↑	<=2 ↑	<=3 ↑
GPT-4V	34.0%	44.0%	50.0%	54.0%	16.0%	18.0%	22.0%	28.0%
Supervised-SOTA [42]	65.89%	77.97%	84.16%	-	68.09%	83.22%	89.91%	-

2.4 Table structure recognition

Dataset The datasets we used for this task includes SciTSR [75] and WTW [76]. We randomly select 50 tables from each of the test sets of SciTSR and WTW for evaluation. Following [53], we crop table regions from original images for evaluation.

- **SciTSR** is a dedicated dataset created to address the task of table structure recognition in scientific papers. The dataset consists of 12.000 training samples and 3.000 test samples.
- WTW's images are collected in the wild. The dataset is split into training/testing sets with 10,970 and 3,611 samples respectively.

Prompt For both SciTSR and WTW, we use the prompt "Please read the table in this image and return a html-style reconstructed table in text, do not omit anything." as input.

Metric To evaluate the performance of GPT-4V in table structure recognition, we use TEDS-S metrics [48], which is a variation of Tree-Edit-Distance-Based Similarity (TEDS) [48] that disregards the textual content of the cells and only evaluates the accuracy of the table structure prediction.

Results and analysis The results are shown in Table 7. We gain two important findings based on the results:

- (1) **GPT-4V** struggles with complex tables. GPT-4V demonstrates outstanding performance when handling tables with structured layouts and consistent text distributions, such as Figure 4 (a). However, when dealing with other types of tables, including those with numerous empty cells, uneven text distribution, skewing, rotation, or densely packed arrangements, its performance noticeably declines.
- (2) Content omission issues are observed in GPT-4V when processing lengthy tables. Despite emphasizing the requirement of "do not omit anything" in the prompt, we still observed some instances of content omission in the responses, particularly in the case of a large table. A typical example is shown in Figure 4 (e), the table image Figure 4 (c) contains many rows, but GPT-4V only reconstructs three of them.

Table 7. The TEDS-S of SciTSR and WTW. The SOTA of SciTSR and WTW are both achieved by [52].

Method	SciTSR	WTW
GPT-4V	87.47%	25.60%
Supervised-SOTA	99.19%	91.91%

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balanc	ced, w	/ warn	ning-up	9	3.1		81.	9		92.8		94.3	3		balanced, v	w/ warm	ing-	up	93.1	1		81.9			92.8	9	4.3	
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Figure 4. Illustration of table structure recognition. (a) and (c) are two input images, (b) and (d) are the corresponding visualized images of GPT-4V's html-style output sequence. (e) is the output sequence of (c), where the elements that GPT-4V indicate the omitted content are highlighted in red.

2.5 Information Extraction from Visually-rich Document

Dataset We evaluate GPT-4V on FUNSD [77] and XFUND [78] Chinese subset (XFUND-zh).

- **FUNSD** dataset is a commonly used form understanding benchmark, which contains 199 scanned form-like documents with noisy images.
- **XFUND** dataset is a multilingual extension of FUNSD that covers seven languages (Chinese, Japanese, French, Italian, German, Spanish, and Portuguese).

We evaluate GPT-4V on the Semantic Entity Recognition (SER) and the end-to-end Pair Extraction tasks. The SER task requires the model to identify the category of each text segments, which are predefined as header, question, answer, and other in FUNSD and XFUND. The end-to-end pair extraction task asks the model to extract all the key-value pairs in the given document image. We use the full test set (both FUNSD and XFUND-zh contain 50 samples) for performance evaluation.

Prompt For FUNSD, we use the following prompt for SER:

Please read the text in this image and return the information in the following JSON format (note xxx is placeholder, if the information is not available in the image, put "N/A" instead). "header": [xxx, ...], "key": [xxx, ...], "value": [xxx, ...]

It's important to highlight that, we redefined the official entity type of "question" and "answer" as "key" and "value" to maintain consistency with the Pair Extraction task.

For end-to-end Pair Extraction, we use the following prompt:

You are a document understanding AI, who reads the contents in the given document image and tells the information that the user needs. Respond with the original content in the document image, do not reformat. No extra explanation is needed. Extract all the key-value pairs from the document image.

Metric For the SER task, we employ the entity-level F1-score [60] for performance evaluation. Additionally, Normalized Edit Distance (NED) is also calculated as is done in other end-to-end VIE methods [65]. However, due to limitations in GPT-4V's ability to generate precise bounding boxes for entities, we aligned predictions with ground-truth using the principle of minimum edit distance.

Results and analysis The SER and Pair Extraction results are shown in 8 and 9, respectively. We found that:

- (1) **GPT-4V** might have constraints in comprehending the spatial arrangement of documents. As shown in Figure 5, some text content located near the top of the page, which lacks both visual and semantic alignment with the *header* category, is erroneously identified as a *header*. Additional visualizations are presented in 6. It is evident that GPT-4V excels in analyzing documents with straightforward layouts but struggles to comprehend those featuring intricate layouts.
- (2) GPT4V tends to generate new keys for non-kv-pair contents. For instance, as shown in Figure 7, contents "09 / 17 / 97 10:55" at the header part are recognized as "Date: 09/18/97", "Time: 10:55", "Fax Number: 503 841 1898", "Company: LORILLARD PTLD", "Page Number: 001".

Table 8. SER Results of FUNSD and XFUND-zh. The SOTA of FUNSD is provided in [65].

Method		FUN	SD			XFUN	D-zh	
1/10/11/00	Precision ↑	Recall ↑	F1 ↑	1-NED↑	Precision ↑	Recall ↑	F1 ↑	1-NED↑
GPT-4V	41.85%	29.36%	34.51%	0.2697	25.87%	15.15%	19.11%	0.1544
Supervised-SOTA [65]	-	-	-	0.5500	-	-	-	-

Table 9. Pair Extraction Results of FUNSD and XFUND-zh.

Dataset	Precision ↑	Recall ↑	F1 ↑	1-NED↑
FUNSD	20.69%	10.25%	13.71%	0.1979
XFUND-zh	0.07%	0.02%	0.03%	0.0420

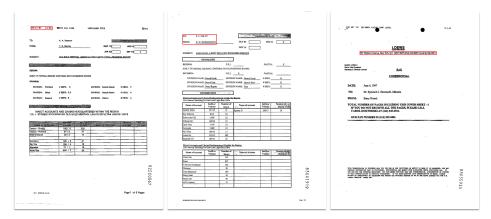


Figure 5. Illustration of error cases of the SER task. The text content enclosed within the red box is incorrectly identified as *header* entities.

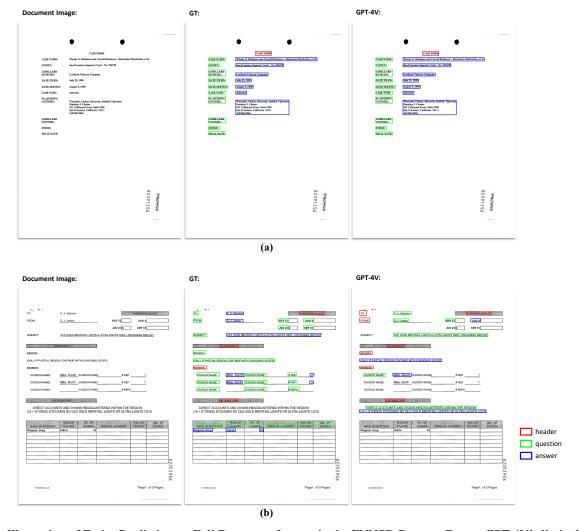


Figure 6. Illustration of Entity Prediction on Full Document Images in the FUNSD Dataset. Due to GPT-4V's limited capability in recognizing Chinese characters, we have excluded examples from the XFUND-zh dataset in this context. Zoom in for the best review.



Figure 7. Illustration of error cases of the Pair Extraction task. The text content enclosed within the red box is incorrectly identified as entity pairs.

3 Discussions

Do specialized models still hold research value in the OCR field? There are three main drawbacks of GPT-4V. (1) Based on the experimental results in Section 2, GPT-4V's ability in OCR is limited to Latin contents and struggles to cope with multilingual and complex scenarios. (2) The inference cost and delay are significantly high, thereby posing usability challenges in some practical scenarios. (3) The long cycle and complex process of updating make it difficult to promptly address minor issues. Considering the aforementioned shortcomings and limited OCR capabilities of some other LMMs [79], we believe that existing LMMs struggle to simultaneously excel in various OCR tasks. Therefore, we contend that specialized models in the field of OCR continue to hold significant value for research.

How can we fully leverage the potential of LMMs like GPT-4V in the OCR domain? These are some possible strategies. (1) Semantic understanding enhancement: A significant characteristic of LMMs lies in their outstanding semantic capabilities after extensive training on large-scale data. Since semantic understanding is a crucial factor in document comprehension and some related tasks, harnessing the semantic potential of LMMs can greatly enhance the performance in these tasks. (2) Downstream task finetuning: Another approach that fully leverages the prior knowledge of LMMs is fine-tuning, especially in scenarios with limited data. Fine-tuning allows the model to adapt to specific tasks or domains, thus improving the performance [89]. (3) Auto/semi-auto data construction: Using LMMs for automatic/semi-automatic data annotation and generation will substantially reduce the cost of manual labeling, which is an effective strategy for tackling the difficulties of data acquisition [90].

4 Limitations

There are three main limitations of our work. First, the test sample of our evaluation is small-scale (mostly 50 samples per dataset) due to the conversation limits (50 conversations per 3 hours) of GPT-4V. This could potentially limit the generalizability of the results. Second, our assessment primarily focuses on mainstream OCR tasks and does not include other OCR-related tasks. Hence, the findings might not cover the full spectrum of OCR capabilities of GPT-4V. Third, only the zero-shot capacity of GPT-4V in OCR was evaluated, without exploring few-shot scenarios. As a result, the potential benefits of further training or fine-tuning the LLM model for specific tasks are not addressed. Few-shot scenarios with technology such as in-context learning [91] are worth of exploring in the future.

5 Conclusion

In this paper, we present a comprehensive evaluation of the OCR capabilities of GPT-4V through a variety of experiments. For the first time, we offer not only qualitative demonstrations but also quantitative performance analysis of GPT-4V across a wide spectrum of tasks. These tasks encompass scene text recognition, handwritten text recognition, handwritten mathematical expression recognition, table structure recognition, and information extraction from visually rich documents.

Our findings, grounded in meticulous experimental results, provide an in-depth analysis of the strengths and limitations of GPT-4V. Although the model shows a strong ability to accurately recognize Latin content and supports input images of variable resolutions, it displays notable struggles with multilingual and complex scenarios. Additionally, the high inference costs and the challenges associated with continuous updating pose significant barriers to the real-world deployment of GPT-4V. Therefore, we contend that specialized models in the field of OCR continue to hold significant value for research. Despite these limitations, GPT-4V and other existing general LMMs could still significantly contribute to the development of the OCR field in several ways. These would include enhancing semantic understanding, fine-tuning for downstream tasks, and facilitating auto/semi-auto data construction.

In summary, this paper presents a first-of-its-kind, in-depth quantitative evaluation of GPT-4V's performance in OCR tasks. We will continuously update the evaluation results in the future, and we hope the findings in this paper will provide valuable insights and strategies for researchers and practitioners working on OCR tasks using large multi-modal models.

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