A. Fine-tuning Datasets

During our fine-tuning stage, VLMs are optimized using a variety of datasets with different tasks. These datasets, introduced in Table 2, include InfographicVQA [25], Kleister Charity [31], WikiTableQuestions [28], VizWiz-VQA [10], and ST-VQA [4], and are briefly described as follows:

Infographic VQA (InfoVQA) [25]: This dataset is a collection of over five thousand infographic images, along with a large number of question-answer pairs. These infographics are sourced from various web domains and feature diverse layouts and designs. The Infographic VQA challenges vision language models to interpret and reason over complex visual documents, often necessitating understanding of graphical elements, data visualization, reasoning, and arithmetic skills.

Kleister Charity (KLC) [31]: This dataset consists of annual financial reports from UK charity organizations. The task involves key information extraction (KIE) such as charity names, addresses, charity numbers, and reporting dates. Primarily comprising scanned documents, this dataset poses challenges due to its length, diverse layout, and the necessity to interpret both text and structural features.

WikiTableQuestions (WTQ) [28]: This dataset includes question and answer pairs collected from thousands of HTML tables extracted from Wikipedia. The questions are designed to be complex, requiring multi-step reasoning and various data operations such as comparison, aggregation, and arithmetic computation.

VizWiz-VQA (**VizWiz**) [10]: Comprising a large number of question-answer pairs, this dataset features images captured by blind individuals using mobile phones and spoken questions about those images. Unique in terms of its image quality, which is often blurred, and the nature of its questions, a significant portion of the images are unanswerable due to poor image quality.

ST-VQA [4]: Designed specifically for understanding textual information within natural images, this dataset requires models to read and interpret scene text to accurately answer questions. It includes a large collection of images sourced from various public datasets such as COCO-text, Visual Genome, and ImageNet, challenging models to comprehend images across a wide range of scenarios and textual appearances within images.

B. More Qualitative Results

Figure 5 presents additional quantitative results derived from various evaluation datasets comparing QA-ViT method [9] and our QID method, implemented with Qwen-VL-Chat [3]. These results highlight the effectiveness of our method in enhancing the vision model's ability to identify relevant visual cues and improve comprehension in both text-rich and natural scene environments.

Furthermore, we outline the limitations of our approach in Figure 6. Although our method aids in enhancing understanding of text-rich images, it does not significantly improve the model's reasoning and arithmetic capabilities. Consequently, our future research will focus on refining the model's ability to perform complex reasoning tasks more effectively in dense-text settings.

C. Broader Impact

The enhanced capabilities of vision-language models (VLMs) offer substantial promise for improving document comprehension in environments with extensive textual content. However, the interaction between question embeddings and vision representations remains relatively unexplored. Our approach encourages this interaction with limited fine-tuning samples while preserving the structural integrity of pre-trained VLMs. It also minimizes the necessity for extensive retraining, thereby reducing the computational resources required for deploying sophisticated AI solutions. Additionally, our method's efficiency with limited data can decrease both the time and costs involved in annotating large datasets, enhancing the accessibility and affordability of advanced document understanding technologies. We encourage the research community to further explore and adopt our QID for text-intensive tasks, anticipating significant benefits in various applications.

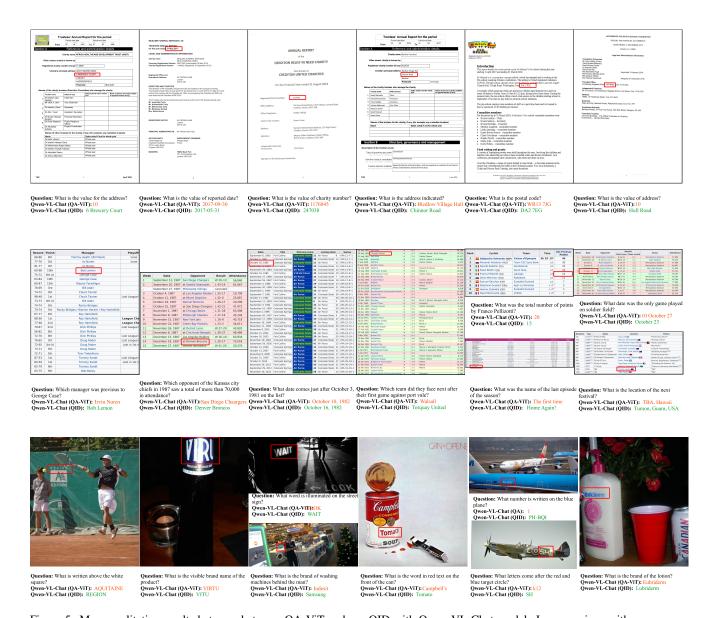
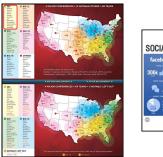
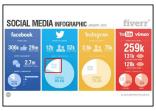


Figure 5. More qualitative results between DA-ViT and our QID with Qwen-VL-Chat model. Image regions with answers are highlighted.









Question: How many teams did SEC conference have before re-alignment? Qwen-VL-Chat (QID): 14 Ground Truth: 12 $\begin{array}{ll} \textbf{Question:} \ What is the percentage market share others have in comparison to Fiverr in Twitter? \\ \textbf{Qwen-V1-Chat (QID):} & 80.4\% \\ \textbf{Ground Truth:} & 19.6\% \\ \end{array}$

Question: How many states have 97.1% equity? Qwen-VL-Chat (QID): 3 Ground Truth: 2 Question: What is the average length of the festival as of 2012? Qwen-VL-Chat (QID): 10 years Ground Truth: 14 days

Figure 6. Failure cases of QID on documents and questions require arithmetic and reasoning skills. Image regions with answers are highlighted.