

# Understanding and Improving In-Context Learning on Vision-language Models

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## Abstract

Recently, in-context learning (ICL) on large language models (LLMs) has received great attention, and this technique can also be applied to vision-language models (VLMs) built upon LLMs. These VLMs can respond to queries by conditioning responses on a series of multimodal demonstrations, which comprise images, queries, and answers. Though ICL has been extensively studied on LLMs, its research on VLMs remains limited. The inclusion of additional visual information in the demonstrations motivates the following research questions: which of the two modalities in the demonstration is more significant? How can we select effective multimodal demonstrations to enhance ICL performance? This study investigates the significance of both visual and language information. Our findings indicate that ICL in VLMs is predominantly driven by the textual information in the demonstrations whereas the visual information in the demonstrations barely affects the ICL performance. Subsequently, we provide an understanding of the findings by analyzing the model information flow and comparing model inner states given different ICL settings. Motivated by our analysis, we propose a simple yet effective approach, termed Mixed Modality In-Context Example Selection (MMICES), which considers both visual and language modalities when selecting demonstrations and shows better ICL performance. Extensive experiments are conducted to support our findings, understanding, and improvement of the ICL performance of VLMs.

## 1. Introduction

The in-context learning (ICL) ability of large language models (LLMs) has received great attention and demonstrated impressive performance on various downstream tasks [7, 10, 14, 20, 33]. The principal benefit of ICL is its ability to learn and adapt from the context by providing a set of question-and-answer pairs, referred to as demonstrations, without requiring any model parameter updates [6, 7, 12]. Recent vision-language models (VLMs),

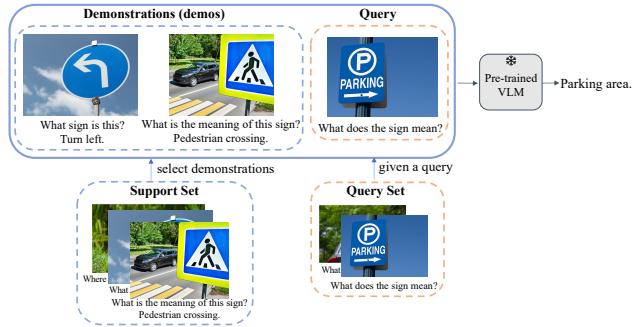


Figure 1. In-context learning (2-shot) on visual question answering. Pre-trained VLMs can perform In-context Learning for a given query based on a few context demonstrations (*i.e.*, a list of images, questions, and answers) selected from a support set.

which are built upon LLMs, have also displayed such ICL ability [1, 4, 16, 28, 34, 40]. These pre-trained models can rapidly adapt to vision-language tasks using few-shot demonstrations, comprised of images, queries, and answers. For example, as shown in Fig. 1, two images and the corresponding questions and answers are selected as demonstrations from an available support set. Then a pre-trained VLM generates answers for the query based on the demonstrations. While the ICL ability of LLMs has been intensively explored [2, 22, 23, 25, 36, 39], the understanding of such capability within VLMs remains largely underexplored. Unlike language models, the in-context demonstrations in VLMs integrate extra visual information. The question of whether visual or textual data in demonstrations contributes more significantly to ICL performance remains open. Furthermore, effective strategies for selecting ICL demonstrations in VLMs have yet to be established.

This study initially investigates the significance of both visual and language information within demonstrations via experiments across a diverse range of VLMs and vision-language tasks. Our experimental results indicate that textual information is crucial for successful ICL in VLMs. Surprisingly, omitting visual information barely affects the ICL performance. Specifically, when the images in the demonstrations are removed or replaced with blank images, ICL performance hardly drops. In comparison, altering text in

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the demonstrations degrades performance significantly.

To understand the observation, we first analyze the masked cross-attention mechanism [1], a widely-adopted approach for incorporating visual data into pre-trained LLMs [1, 4, 16]. Our analysis reveals that the images present in the demonstrations do not hold as much importance as the demonstration texts. The primary reason is the per-image masking in the cross-attention layer [1]. The per-image masking approach limits the model to only process visual tokens from the most recent image for each text token, rather than all preceding images in the interleaved input sequence. For example, when generating an answer token, the model only directly engages with the visual tokens from the query image. Its dependence on all prior demonstration image tokens is indirectly enabled through the subsequent self-attention mechanism with the demonstration text embeddings. We argue that this mechanism makes it challenging to guarantee the influence of visual data in the demonstrations on the model’s output. Additional experiments on the model’s inner states confirm that the visual data from the demonstrations hardly impacts the model’s output. In contrast, text in the demonstrations has a substantial and direct influence on the model’s output.

Based on our analysis, we propose a simple yet effective strategy for choosing demonstrations for ICL on VLMs. This strategy, termed Mixed Modality In-Context Example Selection (MMICES), considers both visual and language modalities when selecting demonstrations. Firstly, the visual modality is used to filter potential demonstration candidates. Then MMICES ranks and selects demonstrations considering the language modality. By factoring in both visual and language information, demonstrations selected by MMICES are related to both the query image and text. Extensive experiments have verified the effectiveness of MMICES across multiple models and various datasets.

To summarize, our main contributions are as follows:

- **Finding:** Our research examines the ICL ability of VLMs and reveals that textual information plays a more significant role than visual information in the demonstrations. Surprisingly, removing images from the demonstrations results in a negligible decline in the ICL performance whereas corruption of texts leads to a significant decrease.
- **Understanding:** We analyze the key component in VLMs responsible for the integration of visual information into the model. It is revealed that images used in the demonstration have less influence on the model output when compared to the demonstration texts.
- **Improvement:** Motivated by our analysis, we propose a simple yet effective method, dubbed MMICES, to enhance the in-context learning performance of pre-trained vision-language models. Extensive experiments show that MMICES outperforms existing demonstration selection methods in various settings.

## 2. Related Work

**In-Context Learning on Vision-Language Models.** Frozen [34] is the first attempt for ICL in multimodality by leveraging a frozen GPT-like LM. Flamingo [1] demonstrated stronger ICL performance and can handle flexible interleaved text and visual sequences. It utilizes a masked cross-attention mechanism that integrates visual information into pre-trained LLMs and allows any number of visual inputs. This capability makes the ICL possible and many VLMs are therefore not suitable for ICL such as BLIP [18], MiniGPT [41], etc. OpenFlamingo [4] and IDEFICS [16] are popular open-source reproductions of Flamingo with competitive ICL performance. Otter [17] adopts instruction tuning to support more flexible tasks but its model architecture is the same as Flamingo’s and still uses masked cross-attention to incorporate visual information. Besides, Yang et al. has explored better in-context configurations but this work has not studied the importance of visual and textual information and only conducted experiments on image captioning. Some other works aim to alleviate the dependency on large-scale pre-training, such as SINC [9] and MetaVL [26]. However, their performances are not competitive compared to pre-trained VLMs such as Flamingo. In contrast to these studies, we focus on the understanding of the in-context learning ability of vision-language models and seek more effective demonstration selection strategies for diverse vision-language tasks.

**Understanding In-Context Learning.** LLMs have demonstrated impressive ICL ability [7, 10, 14, 33], i.e., adapting to a new task conditioned on a few in-context demonstrations without any gradient update. A line of research focuses on understanding the importance of different aspects of the ICL demonstrations on LLMs [2, 22, 23, 25, 39]. Min et al. found that the correct input-label mapping is not as important as expected whereas label space exposure and demonstration distribution have much more influence on the ICL performance. Yoo et al. further found that correct demonstration labels can impact the ICL performance in certain specific scenarios. Moreover, Lu et al. demonstrated the influence of order sensitivity on the ICL performance. Liu et al. revealed that semantically similar examples to a test query can lead to better ICL performance. Besides, An et al. focused on how the diversity, similarity, and complexity of demonstrations affect ICL ability. Moreover, some works studied ICL on LLMs from the perspective of model architectures [5, 27] and revealed that model components are closely related to ICL performance. However, ICL on VLMs differs due to the additional visual information in the demonstrations and different model components. This study focuses on ICL on VLMs and aims to understand which aspect of information in the multimodal demonstrations holds greater significance.

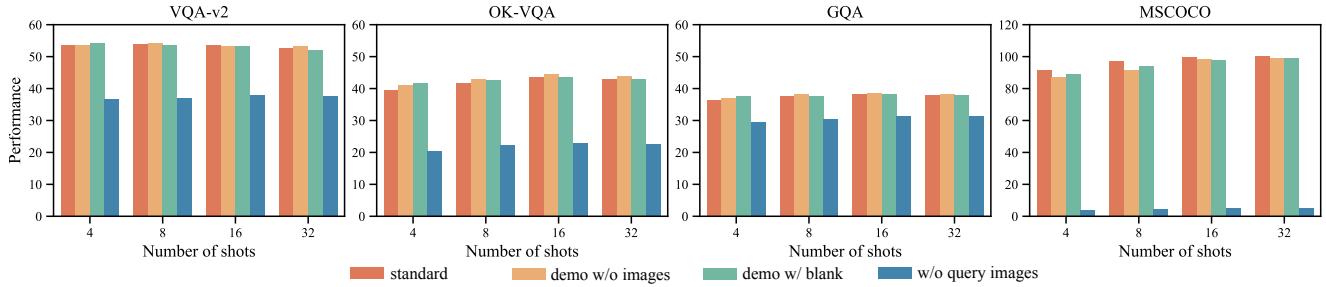


Figure 2. The ICL performance is almost the same when removing the visual information in the demonstration. Compared to the *standard* scenario, exclusion and replacement of images in the demonstration hardly impact the In-Context Learning performance (as shown in the first three bars of each sub-figure). Conversely, the removal of the query image results in substantial performance degradation (as indicated by the last bar in each sub-figure).

### 3. Investigating the Importance of Visual and Textual Information in ICL

**In-Context Learning Formulation on VLMs.** In vision-language in-context learning, an input query  $q$  from a query set, *i.e.*, an image  $I_q$  and a question/instruction  $T_q$ , coming after a context prompt  $C_q$ , is sent to a pre-trained vision-language model  $f$ . The context prompt  $C_q$  consists of  $N$  task demonstrations from a support set  $S$ . Each demonstration includes image  $I_i$ , instruction  $T_i$ , and response  $R_i$ . Then  $f$  generates a response  $R_q$  to the input query  $q$ , *e.g.*, the answer to  $T_q$ , based on image  $I_q$  and the demo context  $C_q$ . Specifically, the ICL can be written as:

$$R_q = f([C_q, q]), \quad (1)$$

where  $q = \langle I_q, T_q \rangle$ ,  $C_q = \{\langle I_i, T_i, R_i \rangle\}_N$ .

**Experimental Setting for ICL Evaluation.** Four popular vision-language datasets across three VL tasks are applied in this study to evaluate the significance of visual and textual information in ICL on VLMs, namely VQAv2 [13] and OK-VQA [24] for visual question answering (VQA), GQA [15] for visual reasoning, and MSCOCO [8] for image captioning. Flamingo [1] is used as an example in the following. Please refer to Appendix B for more results.

**Importance of Visual Information.** Unlike ICL on LLMs, ICL in vision-language models incorporates visual information into the demonstration. This visual information can take the form of images used for tasks such as VQA. To evaluate the significance of images in the demonstrations, we have devised the following settings:

- **standard** setting refers to the scenario where both demonstrations and queries incorporate their respective original image-question pairs.
- **demo w/o images** describes the case where the visual information from the demo context  $C$  is removed by deleting all the images in  $C$ . This results in the context  $C$  with  $N$  text-only instructions such as the questions in VQA or the captions in the task of image captioning.

- **demo w/ blank images** refers to the scenario where the images and image position tokens in the demonstrations are kept but the original images are replaced with blank images, *i.e.*, all the pixel values are set to 255. Although there are still images in the demonstrations, they do not provide any valuable information.
- **demo w/o query images** refers to the setting in which the image  $I_q$  presented in the query input  $Q$  is removed whereas the images in the demonstrations are retained.

Two common approaches to selecting demonstrations are investigated here, *i.e.*, random selection and Retrieval-based In-Context Examples Selection (RICES) [1, 4, 38]. The first approach randomly selects demonstrations from the support set, disregarding different queries. On the other hand, RICES retrieves demonstrations with similar images by comparing them to the query images.

Fig. 2 presents the ICL performance in different visual demonstration settings, given randomly selected demonstrations. Compared with the *standard* setting, both the *demo w/o images* and *demo w/ blank* settings retain most of the ICL performance and some performances remain relatively unchanged. Conversely, the *demo w/o query images* setting results in a substantial decline in the ICL performance, with up to a 50% performance drop on VQA and nearly a 100% performance decrease on image captioning. Fig. 2 suggests that the visual information in the demonstrations has a minimal impact on the ICL performance.

Compared to random selection, RICES has been proven useful to boost the ICL performance on various tasks [1, 4]. If visual information has a minimal impact on ICL performance, why does RICES yield better results? To answer this question, we applied the *demo w/o images* setting to RICES, referred to as *RICES demo w/o images*. It means that the images in the context demonstrations selected by RICES are removed and all the other textual information remains unchanged. The results are presented in Fig. 3. Surprisingly, nearly all of the ICL performances in the *RICES demo w/o images* setting remain relatively unchanged. This suggests that the images in the selected demonstrations do not

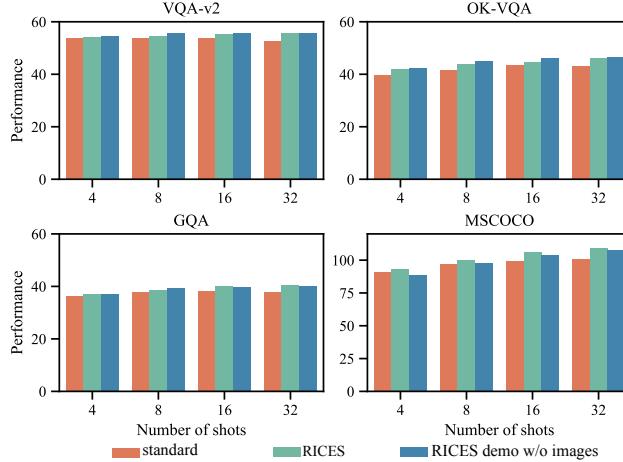


Figure 3. The performance of RICES barely changes when removing the images in the demonstrations. RICES leads to better performance (middle bar in each sub-figure) compared to the standard random selection (the first bar). However, disregarding the images in the demonstrations chosen by RICES has a minimal impact on the performance (the last bar) compared to the original RICES.

significantly contribute to the performance gain. Instead, the remaining textual information plays a more crucial role. The demonstration texts retrieved by RICES contain query-related background information, which is a crucial factor in achieving such performance gain. For instance, given a query image depicting a dinner table laden with food, RICES selects demonstrations that are also related to food and dinner. This relevant background knowledge aids the model in better comprehending the context and recalling the necessary information for generating an appropriate response to the query [11, 22, 27, 38].

**Importance of Textual information.** Besides exploring the impact of visual information, we also assess the significance of textual information given randomly selected demonstrations using the following settings:

- **standard** refers to the case where demonstrations incorporate their respective original image-question pairs.
- **different answer for same question** corresponds to the case where the original answer is replaced with another one from the same question. Despite the question remains the same, the replacement answer can vary due to the differences in the image content.
- **random question** describes the case where the original question  $T_i$  is replaced with another  $T_j$  that has different content but the answer remains unchanged.
- **random words as labels** refers to the case where the original response  $R_i$  in the demonstration, such as answers in VQA and captions in image captioning, is replaced with random English words.

ICL performance across these settings is displayed in Fig. 4. Compared to *standard* setting, *different answer for same question* only marginally impacts performance, re-

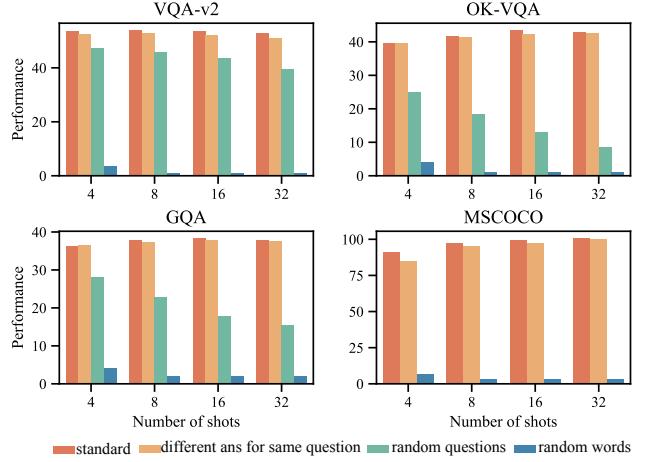


Figure 4. The ICL performance varies under different language demonstration settings. Performance in *different answer for same question* can still be maintained (the light orange bar in each sub-figure). However, performance significantly decreases in *random question* and *random words as labels*, as depicted by the green and blue bars respectively.

gardless of incorrect labels related to the provided query image. This finding is consistent with the conclusion from previous experiments, indicating that images have minimal influence on the outcomes. However, *random question* leads to a significant drop in performance, and altering labels to random words drastically reduces the performance to nearly zero, as seen in the last bar of each sub-figure. When compared to results in Fig. 3, changes in texts can severely affect ICL performance. Hence, we conclude that in VLMs, in-context learning is primarily driven by textual information, which shows a more substantial influence than images.

In summary, this section demonstrates that language information plays a more significant role than visual information in the demonstrations. Excluding images from the demonstrations results in a negligible decline in the ICL performance whereas corruption of texts and removing query images lead to a significant performance decrease.

## 4. Understanding Multimodal Information Flow inside Model

The empirical examination outlined in Sec. 3 highlights the dominant role of textual information in ICL for VLMs, yet leaves several questions unanswered: 1) Why do the images in context demonstrations barely affect the ICL performance? 2) Why is the query image still useful? 3) Why does the textual information dominate the ICL ability? To fully investigate the underlying reasons, this section delves into the model details to analyze the influence of both visual and language information in the context demonstrations.

VLMs with ICL ability can handle interleaved text and visual sequences, making in-context few-shot learning pos-

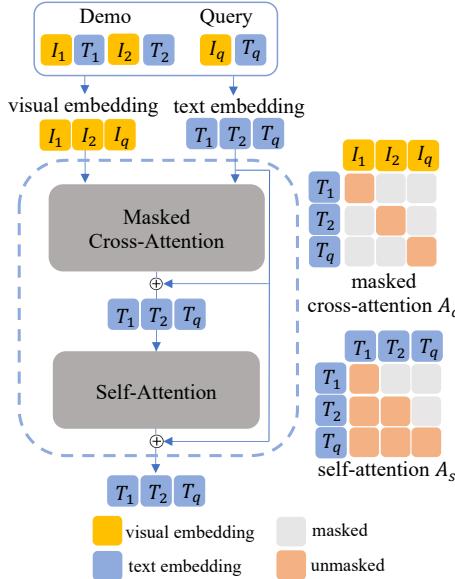


Figure 5. Model block supporting interleaved image-text inputs. Visual and language information, *i.e.*,  $I$  and  $T$ , are first fused using a masked cross-attention layer, where each text token is only conditioned on the last preceding image. Visual embeddings  $I_1$  and  $I_2$  from demonstration images cannot directly influence query text embedding  $T_q$ , and  $T_q$  only sees  $I_q$  in the masked cross-attention, as shown in the last row of  $A_c$ .

sible [1]. An illustration is presented in Fig. 5, with two demonstrations and a query, each of which contains an image and corresponding text such as  $I_1$  and  $T_1$  in the first demonstration. The masked cross-attention layer enables the language models to incorporate visual information for the next-token prediction. This layer also limits which visual tokens the model sees at each text token. Specifically, at a given text token, the model only attends to the visual tokens of the last preceding image, rather than to all previous images in the interleaved sequence. For example, text embedding  $T_q$  can only attend to the query image representation  $I_q$  in the masked cross-attention layer, as shown in the last row of  $A_c$  in Fig. 5. Therefore, demonstration images  $I_1$  and  $I_2$  cannot directly pass their visual information to the query text embedding  $T_q$ , as  $T_q$  is limited to interacting with the query image representation  $I_q$  in the masked cross-attention layer. Only in the subsequent self-attention layer can  $T_q$  indirectly access the information from  $I_1$  and  $I_2$  through the demonstration text embeddings  $T_1$  and  $T_2$ . Because they have already processed the visual information from  $I_1$  and  $I_2$  in the masked cross-attention layer. We argue that the masked cross-attention mechanism with such per-image attention masking [1] complicates the realization of text tokens' dependency on all previous images. In other words, relying solely on the self-attention layer for transferring visual information to text tokens is difficult. Thus, in the ICL settings, it is observed that the generated output

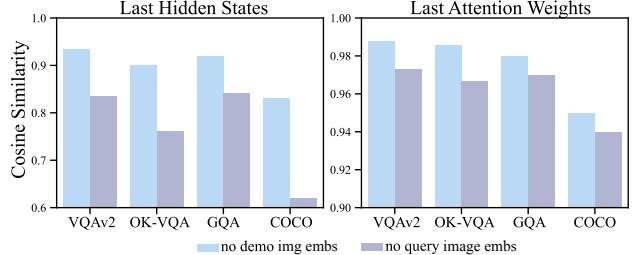


Figure 6. The left figure shows the cosine similarity between hidden states in the standard setting and removing images in the demonstrations (blue bars). Grey bars are cosine similarity between standard setting and removing query images. The right figure shows the similarity of the corresponding attention weights in the last decoder layer. Omitting demonstration visual embeddings leads to similar hidden states, but excluding query images increases their dissimilarity.

tokens primarily focus on the latest image, *i.e.*, the query image. However, it largely disregards the visual information of the previous demonstration images.

To verify our assumptions, we design experiments to compare the self-attention weights and self-attention outputs of the language decoder block in the standard setting with two scenarios, *i.e.*, with and without providing visual information in demonstrations. If the combination of masked cross-attention across modalities and the self-attention on text tokens maintains the dependency on previous images, excluding visual information from previous demonstration images will lead to different attention behaviors, *e.g.*, different attention weights and hidden states. Otherwise, if the weights and hidden states remain almost the same after removing visual information in the demonstration examples, it indicates that the model does not much attend to previous demonstration images. Specifically, we compute the cosine similarity on the last row of hidden states and attention weights in the last decoder layer for each generation forward and then average the results over the whole dataset. To remove the visual information in the demonstration, we mask the visual embeddings of the demonstration images, such as  $I_1$  and  $I_2$ , in demonstrations by setting the corresponding weights to 0 and keeping the query image embedding  $I_q$ . Fig. 6 presents the results. The removal of demonstration visual embeddings leads to around 90% similar hidden states whereas excluding query images makes the hidden states much more dissimilar. These differences in similarity confirm our assumption and analysis above. They further highlight the insignificance of demonstration images when applying in-context learning to existing vision-language models.

In summary, this section explores the information flow in the masked cross-attention layers in VLMs and assesses the impact of the visual information in the demonstrations. The analysis reveals that: 1) Image embeddings from demon-

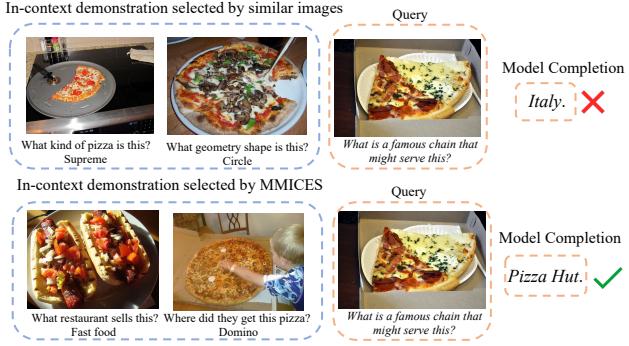


Figure 7. Demonstrations selected by similar images (the first row) and selected by MMICES (the second row) given the same query. Demonstrations containing similar images do not necessarily include related textual information to the given query. MMICES considers both visual and language modalities during retrieval and can provide more informative demonstrations for ICL.

strations do not directly contribute to the attention computation for the answer generation, thus, they have a minimal effect on the ICL performance. 2) However, query image embeddings directly connect with the answer token embeddings, making these images valuable. 3) Textual information from demonstrations can directly influence the generated answer embeddings during the self-attention process, exhibiting a significant influence on model generation.

## 5. Improving ICL Performance on Vision-language models

Previous analysis has revealed the dominant role of textual information in the demonstrations. Therefore, the demonstration selection should also consider this textual information. Random selection from the support set neglects the necessary context for different queries. In contrast, demonstrations retrieved based on visual similarity outperform random selection, and this performance gain can be mostly attributed to the informative text within the selected examples, as discussed in Sec. 3. However, context demonstrations chosen solely on visual similarity may not always be informative for a specific query. This limitation arises because questions related to visually similar images are not necessarily interconnected. In other words, questions in the demonstrations can differ from those in the query despite the images' similarity. As demonstrated in the first row of Fig. 7, the query question addresses the store selling the pizza, while the retrieved demonstrations ask about the type and shape of the pizza. To identify more informative and relevant demonstrations for queries, the retrieval process should not exclusively depend on visual information. It should also integrate the available textual information from both demonstrations and queries to further enhance the pro-

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### Algorithm 1: Mixed Modality In-Context Example Selection (MMICES)

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Input: query dataset  $Q$ , support dataset  $S$ , vision encoder  $E_v$ , text encoder  $E_t$ ,  $K, N$ 
Output: context demonstrations  $C$  chosen from  $S$  for  $Q$ 
1 Initialization:  $C \leftarrow []$ ;
2 for  $query q \in Q$  do
3    $v_q \leftarrow E_v(q)$  ;
4    $t_q \leftarrow E_t(q)$  ;
5   visual similar samples  $\leftarrow$  choose  $K$  most similar samples from  $S$  based on  $v_q$  ;
6   demos  $\leftarrow$  choose  $N$  most similar demos from visual similar samples based on  $t_q$  ;
7    $C +=$  demos ;
8 end

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cess of finding more informative demonstrations. Despite the importance of textual information, retrieval based exclusively on text presents its own challenges. For instance, general queries such as "What is in this picture?" often fail to provide sufficient information.

Addressing the above challenges, we propose to explicitly utilize textual information when selecting demonstrations and design a simple yet effective method, named Mixed Modality In-Context Example Selection (MMICES). It initially selects candidates based on image similarity, followed by a reranking based on text similarity, as shown in Alg. 1. The objective is to select  $N$  context demonstrations for each query  $q$  in the query dataset  $Q$  (e.g., the test dataset of VQAv2) from the support dataset  $S$  (e.g., the training dataset of VQAv2). First,  $K$  pre-filtered samples from  $S$  are selected based on visual feature similarity. The visual features are extracted from the vision encoder of the vision-language model, and  $K$  is a hyperparameter. Then MMICES takes textual information into consideration and selects  $N$  most similar ones from the pre-filtered  $K$  samples based on textual similarity calculated by a text encoder.

**Why is the visual modality in MMICES helpful given its marginal impact in context?** While the impact of demonstration images has been found to be minimal, they are useful in preliminary demonstration retrieval. This is mainly because similar images are more likely to bring texts containing related information. Therefore, MMICES employs a mixed-modality approach to ensure the provision of high-quality context demonstrations. As illustrated in the second row of Fig. 7, the demonstrations selected by MMICES are more closely related to the query and consequently assist the model in generating the correct response.

Dataset	Method	4-shot	8-shot	16-shot	32-shot
VQAv2	Random	53.52 $\pm$ 0.11	53.74 $\pm$ 0.19	53.33 $\pm$ 0.26	52.38 $\pm$ 0.10
	RICES	<b>54.03</b> $\pm$ 0.13	<b>54.67</b> $\pm$ 0.06	<b>55.39</b> $\pm$ 0.12	<b>55.77</b> $\pm$ 0.08
	MMICES	53.11 $\pm$ 0.03	53.56 $\pm$ 0.05	54.04 $\pm$ 0.04	55.14 $\pm$ 0.02
OK-VQA	Random	39.62 $\pm$ 0.29	41.56 $\pm$ 0.20	43.40 $\pm$ 0.39	42.97 $\pm$ 0.11
	RICES	42.13 $\pm$ 0.13	43.87 $\pm$ 0.15	44.90 $\pm$ 0.10	46.15 $\pm$ 0.06
	MMICES	<b>44.18</b> $\pm$ 0.11	<b>45.61</b> $\pm$ 0.08	<b>46.93</b> $\pm$ 0.08	<b>46.79</b> $\pm$ 0.10
GQA	Random	36.32 $\pm$ 0.29	37.74 $\pm$ 0.32	38.28 $\pm$ 0.10	37.85 $\pm$ 0.11
	RICES	36.92 $\pm$ 0.33	38.54 $\pm$ 0.14	40.16 $\pm$ 0.14	40.21 $\pm$ 0.32
	MMICES	<b>40.73</b> $\pm$ 0.09	<b>41.85</b> $\pm$ 0.10	<b>42.21</b> $\pm$ 0.12	<b>42.07</b> $\pm$ 0.08
MSCOCO	Random	89.82 $\pm$ 0.23	96.81 $\pm$ 0.10	99.44 $\pm$ 0.19	100.53 $\pm$ 0.26
	RICES	93.45 $\pm$ 0.07	99.74 $\pm$ 0.27	105.76 $\pm$ 0.03	109.12 $\pm$ 0.20
	MMICES	<b>100.24</b> $\pm$ 0.20	<b>104.90</b> $\pm$ 0.30	<b>108.66</b> $\pm$ 0.17	<b>109.64</b> $\pm$ 0.24

Table 1. The performances of random selection, RICES, and MMICES on OF-9B. The highest performance in each shot scenario is highlighted in bold. The results are averaged over 5 evaluation seeds and are reported along with their standard deviations. The performance metric for the MSCOCO dataset is CIDEr, while for the remaining datasets, accuracy is reported in percentages.

## 6. Experiments

### 6.1. Experimental Setup

**Vision-language Models.** We investigate 7 different models from OpenFlamingo [4] (OF) and IDEFICS [16]. The architecture of these models consists of a frozen large language model with decoder-only structure (*e.g.*, MPT [31] in OpenFlamingo and LLaMA [33] in IDEFICS), a frozen visual encoder (*e.g.*, CLIP-ViT [29]) followed by a trainable perceiver resampler. Trainable cross-attention layers interleaved between pre-trained LM layers bridge the gap between visual and language information. Models used in this study vary in their model size (from 3B to 9B), pre-trained datasets, and whether fine-tuned by instruction tuning. OpenFlamingo is trained on LAION-2B [30] and Multimodal C4 [42], and IDEFICS is trained on OBELICS [16]. Both models achieve competitive performance compared to Flamingo [1]. The instruction-tuned versions are also used in this work. For instance, IDEFICS-9B-I starts from the base IDEFICS models and is fine-tuned on various datasets, such as M3IT [19] and LLaVA-Instruct [21]. More detailed information is in Appendix A.

**Evaluation Datasets and Metrics.** Three representative VL tasks (visual question answering, visual reasoning, and image captioning) and 4 well-known VL datasets are applied in this work. For visual question answering, VQAv2 [13] and OK-VQA [24] are adopted. Additionally, we incorporate GQA [15] for visual reasoning and MSCOCO [8] for image captioning. Accuracy on the Karpathy-test split is evaluated for VQAv2. For OK-VQA, accuracy on the validation split is evaluated, and accuracy on the test-dev split is used for GQA. CIDEr [35] on the Karpathy-test split is used in MSCOCO.

Dataset	Method	4-shot	8-shot	16-shot	32-shot
VQAv2	Random	54.90 $\pm$ 0.05	56.16 $\pm$ 0.02	56.93 $\pm$ 0.18	57.21 $\pm$ 0.17
	RICES	54.79 $\pm$ 0.09	56.45 $\pm$ 0.05	57.49 $\pm$ 0.06	58.52 $\pm$ 0.02
	MMICES	<b>56.15</b> $\pm$ 0.01	<b>58.17</b> $\pm$ 0.03	<b>59.23</b> $\pm$ 0.01	<b>59.69</b> $\pm$ 0.02
OK-VQA	Random	49.24 $\pm$ 0.22	49.54 $\pm$ 0.12	50.89 $\pm$ 0.12	51.86 $\pm$ 0.12
	RICES	48.82 $\pm$ 0.02	50.55 $\pm$ 0.05	52.42 $\pm$ 0.03	53.22 $\pm$ 0.04
	MMICES	<b>49.63</b> $\pm$ 0.02	<b>52.16</b> $\pm$ 0.03	<b>53.65</b> $\pm$ 0.07	<b>54.16</b> $\pm$ 0.05
GQA	Random	39.35 $\pm$ 0.26	40.54 $\pm$ 0.17	41.38 $\pm$ 0.18	41.86 $\pm$ 0.13
	RICES	39.86 $\pm$ 0.13	41.27 $\pm$ 0.29	42.65 $\pm$ 0.21	43.67 $\pm$ 0.19
	MMICES	<b>42.66</b> $\pm$ 0.05	<b>44.22</b> $\pm$ 0.08	<b>45.19</b> $\pm$ 0.05	<b>45.36</b> $\pm$ 0.09
MSCOCO	Random	96.45 $\pm$ 0.36	100.85 $\pm$ 0.36	103.96 $\pm$ 0.38	105.02 $\pm$ 0.43
	RICES	91.20 $\pm$ 0.10	102.58 $\pm$ 0.15	108.93 $\pm$ 0.10	111.02 $\pm$ 0.08
	MMICES	<b>101.13</b> $\pm$ 0.12	<b>109.31</b> $\pm$ 0.09	<b>112.72</b> $\pm$ 0.05	<b>113.37</b> $\pm$ 0.09

Table 2. The performances of random selection, RICES, and MMICES on IDEFICS-9B. MMICES achieves the best ICL performance in all settings.

Model	Method	4-shot	8-shot	16-shot	32-shot
OF-3B	Random	44.79 $\pm$ 0.12	45.05 $\pm$ 0.05	45.30 $\pm$ 0.17	45.64 $\pm$ 0.20
	RICES	44.64 $\pm$ 0.09	45.71 $\pm$ 0.12	46.30 $\pm$ 0.03	47.48 $\pm$ 0.05
	MMICES	<b>47.00</b> $\pm$ 0.06	<b>48.46</b> $\pm$ 0.07	<b>49.50</b> $\pm$ 0.06	<b>49.68</b> $\pm$ 0.03
OF-4B	Random	47.74 $\pm$ 0.24	47.10 $\pm$ 0.04	44.32 $\pm$ 0.12	41.88 $\pm$ 0.25
	RICES	47.70 $\pm$ 0.04	46.68 $\pm$ 0.18	44.91 $\pm$ 0.07	42.86 $\pm$ 0.08
	MMICES	<b>48.89</b> $\pm$ 0.04	<b>48.61</b> $\pm$ 0.09	<b>46.45</b> $\pm$ 0.07	<b>43.73</b> $\pm$ 0.06
OF-9B	Random	53.52 $\pm$ 0.11	53.74 $\pm$ 0.19	53.33 $\pm$ 0.26	52.38 $\pm$ 0.10
	RICES	<b>54.03</b> $\pm$ 0.13	<b>54.67</b> $\pm$ 0.06	<b>55.39</b> $\pm$ 0.12	<b>55.77</b> $\pm$ 0.08
	MMICES	53.11 $\pm$ 0.03	53.56 $\pm$ 0.05	54.04 $\pm$ 0.04	55.14 $\pm$ 0.02
IDEFICS-9B	Random	54.90 $\pm$ 0.05	56.16 $\pm$ 0.02	56.93 $\pm$ 0.18	57.21 $\pm$ 0.17
	RICES	54.79 $\pm$ 0.09	56.45 $\pm$ 0.05	57.49 $\pm$ 0.06	58.52 $\pm$ 0.02
	MMICES	<b>56.15</b> $\pm$ 0.01	<b>58.17</b> $\pm$ 0.03	<b>59.23</b> $\pm$ 0.01	<b>59.69</b> $\pm$ 0.02

Table 3. The performances of random selection, RICES, and MMICES on VQAv2 across OpenFlamingo and IDEFICS. MMICES achieves the best performance in most cases

### 6.2. Results

MMICES outperforms random selection and RICE across almost all datasets on both OpenFlamingo and IDEFICS, as shown in Tab. 1 and Tab. 2. MMICES consistently boosts the ICL performance on OpenFlamingo across various vision-language tasks. On GQA, MMICES with only 4 shots (40.73%) is better than the 32-shot random selection (37.85%) and 32-shot RICES (40.35%). MMICES is also consistently better on OK-VQA where given only 8 context examples, the performance (*i.e.*, 45.5%) is better than random 32 shots (42.97%) and RICES’s 16 shots (44.70%).

The performance gain is also evident on IDEFICS-9B across all datasets. For instance, MMICES increases the accuracy on GQA by around 10% given 8 context examples (from 40.54% to 44.22%) compared to random selection and by around 7% compared to RICES (from 41.27% to 44.22%). Besides, MMICES achieves comparable accuracy on GQA given only 4 demonstrations compared to RICES with 16 demonstrations. All the 16-shot performances from MMICES are higher compared to 32-shot random selection and 32-shot RICES, which indicates that with only half of the context examples, MMICES achieves even better re-

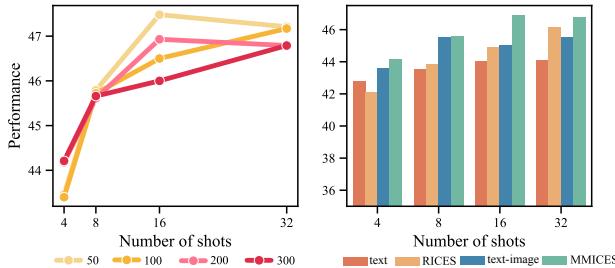


Figure 8. Comparison of performance on OK-VQA given different  $K$  (left) and different mixture of modality (right).

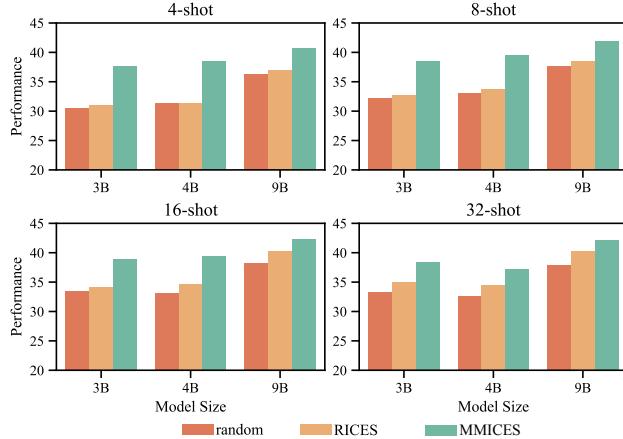


Figure 9. MMICES consistently enhances the ICL performance across models of varying sizes. MMICES on smaller models can even outperform RICES on larger models. Results here are from GQA and more results are in Appendix D.

sults. On VQAv2, although the performances on OF-9B do not outperform the RICES, MMICES on all other models still achieves better results (Tab. 3). Overall, MMICES achieves better performance compared to random selection in all scenarios and RICES in most cases. More results and analysis are in Appendix D.

### 6.3. Ablation Study

The number of pre-filtered samples, *i.e.*,  $K$  defined in Alg. 1, selected by visual similarity is a hyperparameter in MMICES. Besides different  $K$ , as MMICES considers both visual and language modalities, we also investigate the ICL performance when the examples are retrieved only by text similarity (termed as *text*), and when retrieved by first comparing language and then selecting based on image similarity (termed as *text-image*). Fig. 8 shows the performance comparison on OK-VQA. A larger  $K$  leads to more candidate demonstrations filtered by visual similarity and is more useful when the number of shots is small. Regarding the mixture of modalities, the results are consistent with our analysis in Sec. 5. Retrieval based on a single modality, such as RICES on visual and *text*, underperforms mixed modality retrieval. Besides, MMICES consistently achieves

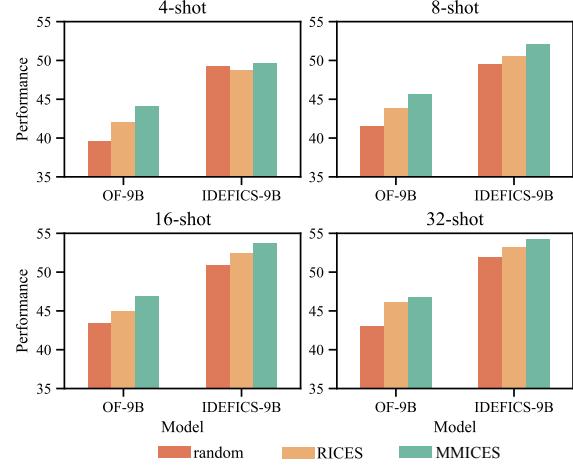


Figure 10. The performance of ICL (on OK-VQA) is consistently enhanced by MMICES across different models.

better results compared to *text-image* (more analysis in Appendix E).

### 6.4. Impact of Underlying Vision-language Models

This study has also conducted extensive experiments on different vision-language models with varying sizes. Fig. 9 presents a performance comparison on the GQA dataset across models from OF-3B to OF-9B. MMICES consistently outperforms random selection and RICES by a notable margin. It is worth mentioning that MMICES on smaller-size models can achieve better performance, compared to larger-size models using RICES and random selection, especially in 4 and 8-shot settings. Moreover, the performance gained from MMICES is consistent across different models as shown in Fig. 10. Please refer to Appendix E for more details.

## 7. Conclusion

This study explores the in-context learning capabilities of vision-language models. We find that the visual information in the demonstrations has a minimal impact on the ICL performance, while the text is more important. To understand the underlying reasons, we investigate how VLMs incorporate multimodal information, *i.e.*, masked cross-attention over multimodal tokens and self-attention over text tokens. The masked cross-attention process diminishes the VLMs' dependency on the visual information in the demonstrations, causing the models to prioritize language input over visual input when generating the response. Based on our analysis, we propose selecting demonstrations based on both visual and text modalities and have designed the Mixed Modality In-Context Example Selection (MMICES) algorithm, which outperforms existing in-context example selection methods. We believe this study can help the community better understand the ICL ability of VLMs.

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## A. Experimental Setup

**Vision-language Models.** We investigate different models from OpenFlamingo [4] and IDEFICS [16] with various model sizes as shown in Tab. 4. OpenFlamingo [4] and IDEFICS [16] are popular open-source reproductions of Flamingo with competitive ICL performance. The architecture of these models consists of a frozen large language model with decoder-only structure (*e.g.*, MPT [31] in OpenFlamingo and LLaMA [33] in IDEFICS), a frozen visual encoder (*e.g.*, CLIP-ViT [29]) followed by a trainable perceiver resampler. There are also trainable gated cross-attention layers interleaved between pre-trained LM layers to bridge the gap between visual and language information. Per-image attention masking is adopted in these cross-attention layers. This ensures that at any particular text token, the model focuses solely on the visual tokens from the immediately preceding image in the interleaved sequence, rather than on all preceding images. The 7 models used in this study vary in their model size (from 3B to 9B), pre-trained datasets, and whether fine-tuned by instruction tuning. OpenFlamingo is trained on 2B image-text pairs in LAION-2B [30] and 43M interleaved image-text sequences in Multimodal C4 [42]. IDEFICS is trained on OBELICS [16] which contains 141M multimodal English web documents with 353M images and 115B tokens. Both models achieve competitive performance compared to Flamingo [1]. The instruction-finetuned versions are also used in this work. For instance, IDEFICS-9B-I starts from the base IDEFICS models and is fine-tuned by unfreezing all the parameters on various datasets, such as M3IT [19] and LLaVA-Instruct [21].

**Evaluation Datasets and Metrics.** Three popular VL tasks (*i.e.*, visual question answering, visual reasoning, and image captioning) and 4 well-known VL datasets are applied in this work. For visual question answering, VQAv2 [13] and OK-VQA [24] are adopted. Additionally, we incorporate GQA [15] for visual reasoning and MSCOCO [8] for image captioning. The statistics are in Tab. 5. Accuracy on the Karpathy-test split is evaluated for VQAv2. For OK-VQA, accuracy on the validation split is evaluated, and accuracy on the test-dev split is used for GQA. CIDEr [35] on the Karpathy-test split is used in MSCOCO.

## B. Additional Results of Importance Investigation on Visual and Textual Information

### B.1. Importance of Visual Information

To evaluate the importance of visual information, we have designed various demonstration settings as shown in Tab. 6.

- **standard** setting refers to the scenario where both demonstrations and queries incorporate their respective original image-question pairs.

Model	Vision Encoder	Language Model
OF-3B	CLIP Vit-L/14	MPT-1B [31]
OF-3B-I	CLIP Vit-L/14	MPT-1B-I [31]
OF-4B	CLIP Vit-L/14	RedPajama-3B [32]
OF-4B-I	CLIP Vit-L/14	RedPajama-3B-I [32]
OF-9B	CLIP Vit-L/14	MPT-7B [31]
IDEFICS-9B	OpenCLIP Vit-H/14	LLaMA-7B [33]
IDEFICS-9B-I	OpenCLIP Vit-H/14	LLaMA-7B [33]

Table 4. Vision-language models studied in this work. OF stands for OpenFlamingo [4] and I means instructed version.

Task	Dataset	# Images	# Image-text pairs
Visual Question Answering	VQAv2 [3]	123.2K	658.1K
	OK-VQA [24]	14K	14K
Visual Reasoning	GQA [15]	82.3K	1087.7K
Image Captioning	MSCOCO [8]	123.2K	576.8K

Table 5. Dataset Statistics. Four well-known datasets from three popular vision-language tasks are used in this study.

- **demo w/o images** describes the case where the visual information from the demo context is removed by deleting all the images in the context demonstration. The context then only includes  $N$  text-only instructions such as the questions in VQA or the captions in the task of image captioning.
- **demo w/ blank images** refers to the scenario where the images and image position tokens in the demonstrations are kept but the original images are replaced with blank images, *i.e.*, all the pixel values are set to 255. Although there are still images in the demonstrations, they do not provide any valuable information.
- **demo w/o query images** refers to the setting in which the image presented in the query input is removed whereas the images in the demonstrations are retained.

Performance of OF-9B and IDEFICS-9B across 4 datasets given random selected demonstrations are presented in Tab. 8 and Tab. 9. When compared to the *standard* setting, the *demo w/o images* and *demo w/ blank* settings largely maintain the ICL performance, with some aspects showing little change. In contrast, the *demo w/o query images* setting leads to a significant reduction in ICL performance, including up to a 50% decrease in VQA performance and nearly a 100% decrease in image captioning performance. We also conducted experiments using RICES, *i.e.*, Retrieval-based In-Context Examples Selection, in the *demo w/o images* setting and the results are in Tab. 10 and Tab. 11. The results also suggest that the images in the selected demonstrations do not significantly contribute to the performance gain. Instead, the remaining textual information plays a more crucial role.

Setting	demo image	demo question	demo response	query image	query question
<b>standard</b>		What sign is this?	Turn left		What does the sign mean?
<b>demo w/o images</b>		What sign is this?	Turn left		What does the sign mean?
<b>demo w/ blank images</b>		What sign is this?	Turn left		What does the sign mean?
<b>demo w/o query images</b>		What sign is this?	Turn left		What does the sign mean?

Table 6. Examples for different visual demonstration settings with one demonstration and one query. *Demo w/o images* removes the images in the demonstration. *demo w/ blank images* replaces the images in the demonstration with blank ones. *demo w/o query images* removes the images in the query.

Setting	demo image	demo question	demo response	query image	query question
<b>standard</b>		What sign is this?	Turn left		What does the sign mean?
<b>different answer for same question</b>		What sign is this?	No entry		What does the sign mean?
<b>random question</b>		What kind of food is this?	Turn left		What does the sign mean?
<b>random words as labels</b>		What sign is this?	Hello		What does the sign mean?

Table 7. Examples for different textual demonstration settings with one demonstration and one query. The differences compared to the standard setting are highlighted in blue.

## B.2. Importance of Textual Information

To evaluate the importance of visual information, we have designed various demonstration settings as shown in Tab. 7.

- **standard** refers to the case where demonstrations incorporate their respective original image-question pairs.
- **different answer for same question** corresponds to the case where the original answer is replaced with another one from the same question. Despite the question remains the same, the replacement answer can vary due to the differences in the image content.
- **random question** describes the case where the original question is replaced with another one that has different content but the answer remains unchanged.
- **random words as labels** refers to the case where the original response in the demonstration, such as answers in VQA and captions in image captioning, is replaced with random English words.

Performance of OF-9B and IDEFICS-9B across 4 datasets given randomly selected demonstrations are presented in Tab. 12 and Tab. 13.

## C. More Details of Understanding Multimodal Information Flow

Masked cross-attention enables the processing of interleaved text and visual sequences, allowing for in-context few-shot learning to be possible [1]. As depicted in Fig. 11, the visual information from demonstration images  $I_1$  and  $I_2$  cannot directly influence the query text embedding  $T_q$ . This is because  $T_q$  only interacts with the query image representation  $I_q$  in the masked cross-attention layer. To assess the impact of visual information from the demonstration on the generated content, we have devised three settings.

- **standard** refers to the original ICL setting where visual embeddings in demonstrations and queries are retained.

Dataset	Setting	4-shot	8-shot	16-shot	32-shot
VQAv2	standard	53.60	53.85	53.60	52.74
	demo w/o img	53.61	54.15	53.36	53.15
	demo w/ blank img	54.13	53.71	53.12	52.10
	demo w/o query img	36.72	37.11	37.95	37.67
OK-VQA	standard	39.62	41.56	43.40	42.97
	demo w/o img	40.98	42.86	44.61	43.91
	demo w/ blank img	41.77	42.57	43.64	42.82
	demo w/o query img	20.42	22.38	22.95	22.67
GQA	standard	36.32	37.74	38.28	37.85
	demo w/o img	36.86	38.13	38.40	38.23
	demo w/ blank img	37.63	37.73	38.36	38.03
	demo w/o query img	29.39	30.24	31.23	31.41
MSCOCO	standard	91.22	96.88	99.44	100.53
	demo w/o img	87.26	91.49	98.35	98.85
	demo w/ blank img	89.25	93.88	97.91	96.91
	demo w/o query img	3.57	4.30	4.90	4.85

Table 8. The performances of OF-9B on different visual demonstration settings given random selected demonstrations.

Dataset	Setting	4-shot	8-shot	16-shot	32-shot
VQAv2	standard	54.90	56.16	56.93	57.21
	demo w/o img	53.66	54.57	55.41	55.34
	demo w/ blank img	53.69	54.38	54.98	55.04
	demo w/o query img	38.64	39.27	39.71	39.99
OK-VQA	standard	49.24	49.54	51.47	51.86
	demo w/o img	47.63	48.28	48.74	48.99
	demo w/ blank img	47.66	48.55	49.83	50.24
	demo w/o query img	26.91	27.70	28.32	28.67
GQA	standard	39.35	40.54	41.38	41.87
	demo w/o img	38.64	39.45	40.27	40.85
	demo w/ blank img	38.36	39.94	40.71	41.36
	demo w/o query img	31.82	32.47	33.12	33.50
MSCOCO	standard	97.45	101.85	102.96	105.62
	demo w/o img	67.77	81.01	85.81	90.72
	demo w/ blank img	88.75	92.27	95.49	96.83
	demo w/o query img	2.86	3.14	3.05	3.02

Table 9. The performances of IDEFICS-9B on different visual demonstration settings given random selected demonstrations.

- **hide demo visual embedding** describes the case where the visual embeddings from demonstration images are masked and the model can only see the images from the query, as shown in the left side of Fig. 12.
- **hide query visual embedding** refers the case where the visual embeddings from query images are masked, as shown in the right side of Fig. 12.

To examine the varying effects of visual embeddings in demonstrations and queries, we can compare the hidden states and attention weights in the last layer. In particular, we extract the last row of the hidden states (referred to as  $\mathbf{T}_q^L$  in Fig. 13) and the attention weights in the last layer. We then compute the cosine similarity between these extracted values and their counterparts in the *standard* setting.

Dataset	Method	4-shot	8-shot	16-shot	32-shot
VQAv2	Random	53.60	53.85	53.60	52.74
	RICES	54.17	54.67	55.39	55.77
	RICES demo w/o img	54.38	55.46	55.56	55.71
OK-VQA	Random	39.62	41.56	43.40	42.97
	RICES	42.00	43.87	44.70	46.15
	RICES demo w/o img	42.23	44.94	46.20	46.65
GQA	Random	36.32	37.74	38.28	37.85
	RICES	36.92	38.54	40.17	40.35
	RICES demo w/o img	37.21	39.37	397.84	40.05
MSCOCO	Random	91.22	96.88	99.44	100.53
	RICES	93.45	99.74	105.76	109.12
	RICES demo w/o img	88.49	97.82	103.67	107.69

Table 10. The performances of OF-9B on different visual demonstration settings given demonstrations selected by RICES.

Dataset	Method	4-shot	8-shot	16-shot	32-shot
VQAv2	Random	54.90	56.16	56.93	57.21
	RICES	54.79	56.45	57.49	58.60
	RICES demo w/o img	54.94	56.20	57.19	57.67
OK-VQA	Random	49.24	49.54	51.47	51.86
	RICES	48.82	50.55	52.42	53.22
	RICES demo w/o img	48.02	50.24	51.60	51.76
GQA	Random	39.35	40.54	41.38	41.87
	RICES	39.86	41.27	43.01	43.67
	RICES demo w/o img	39.33	41.15	42.44	43.41
MSCOCO	Random	97.45	101.85	102.96	105.62
	RICES	91.20	102.58	108.93	111.03
	RICES demo w/o img	64.15	73.62	79.45	84.92

Table 11. The performances of IDEFICS-9B on different visual demonstration settings given demonstrations selected by RICES.

Dataset	Setting	4-shot	8-shot	16-shot	32-shot
VQAv2	standard	53.60	53.85	53.46	52.74
	diff ans for same question	52.49	52.70	52.06	50.92
	random question	41.48	33.94	27.93	20.03
	random words as labels	3.59	0.03	0.00	0.00
OK-VQA	standard	39.62	41.56	43.40	42.97
	diff ans for same question	39.63	41.23	42.41	42.44
	random question	25.03	18.23	13.00	8.59
	random words as labels	3.95	0.10	0.01	0.00
GQA	standard	36.23	35.92	37.29	34.38
	diff ans for same question	36.38	37.25	37.75	37.58
	random question	28.01	22.83	17.71	15.44
	random words as labels	2.06	0.05	0.00	0.00
MSCOCO	standard	91.23	96.88	99.44	100.53
	diff ans for same question	84.96	94.95	97.44	99.71
	random words as labels	1.60	0.62	0.17	0.00

Table 12. The performances of OF-9B on different textual demonstration settings given random selected demonstrations.

Dataset	Setting	4-shot	8-shot	16-shot	32-shot
VQAv2	standard	54.90	56.16	56.93	57.21
	diff ans for same question	54.10	55.21	56.15	57.01
	random question	47.25	45.94	43.53	39.48
OK-VQA	random words as labels	5.91	0.34	0.03	0.00
	standard	49.24	49.54	51.47	51.86
	diff ans for same question	49.25	50.18	51.11	50.95
GQA	random question	38.41	34.04	30.08	29.53
	random words as labels	7.38	1.33	0.30	0.11
	standard	39.35	40.54	41.38	41.87
MSCOCO	diff ans for same question	38.80	40.07	41.49	41.92
	random question	33.65	33.61	32.13	30.04
	random words as labels	3.14	0.27	0.02	0.03
MSCOCO	standard	97.45	101.85	102.96	105.62
	diff ans for same question	84.12	64.83	52.70	53.38
	random words as labels	0.00	0.00	0.00	0.00

Table 13. The performances of IDEFICS-9B on different textual demonstration settings given random selected demonstrations.

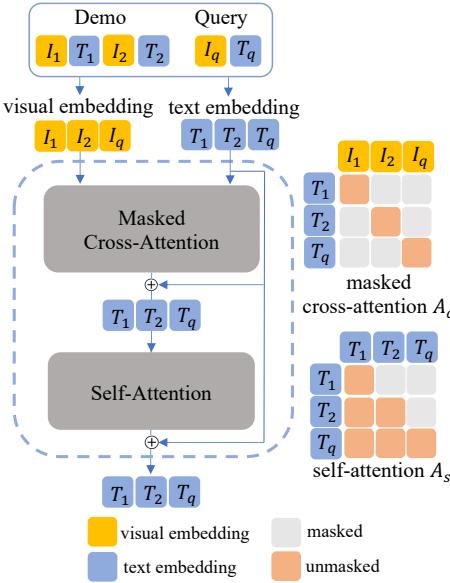


Figure 11. Model block supporting interleaved image-text inputs. Visual and language information, i.e.,  $I$  and  $T$ , are first fused using a masked cross-attention layer, where each text token is only conditioned on the last preceding image. Visual embeddings  $I_1$  and  $I_2$  from demonstration images cannot directly influence query text embedding  $T_q$ , and  $T_q$  only sees  $I_q$  in the masked cross-attention, as shown in the last row of  $\mathbf{A}_c$ .

## D. More Results on the ICL Performance Improvement

### D.1. More Results

We have conducted experiments using various models and VL datasets, which are listed in Table 4 and Table 5. The results, based on all models, are obtained from demonstrations selected using random selection, RICES, and MMICES, and are presented in Table 14 to Table 20.

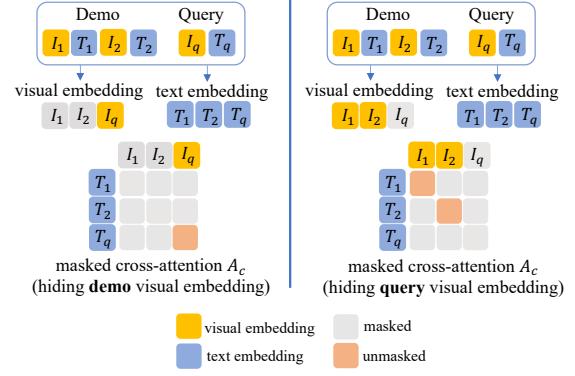


Figure 12. Compared with the standard setting, we hide demo visual embedding and query visual embedding respectively to explore the influence of different visual embeddings.

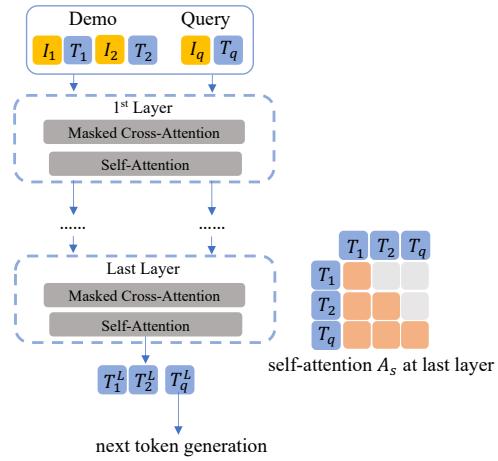


Figure 13. We compute the cosine similarity on the last row of hidden states, i.e.,  $\mathbf{T}_q^L$  in this figure, and attention weights, i.e.,  $\mathbf{A}_s$  in this figure, in the last decoder layer for each generation forward and then average the results over the whole dataset.

Overall, MMICES outperforms the other two methods and achieves the best results in most cases. Tab. 24 presents examples selected by MMICES and RICES.

### D.2. Ablation Study

**The choices of  $K$ .** The number of pre-filtered samples, denoted as  $K$ , selected by visual similarity is a hyperparameter in MMICES. A larger value of  $K$  allows for a broader selection space for the second filtering stage, while a smaller value of  $K$  is more efficient. The performance comparison for different values of  $K$  ( $k \in \{50, 100, 200, 300\}$ ) is presented in Table 21. A larger  $K$  results in a greater number of candidate demonstrations filtered by visual similarity, which is particularly useful when the number of shots is small. However, a larger  $K$  may also include visually unrelated demonstrations despite having similar text, poten-

Dataset	Method	0-shot	4-shot	8-shot	16-shot	32-shot
VQAv2	Random	43.45 (0.16)	44.79 (0.12)	45.05 (0.05)	45.30 (0.17)	45.64 (0.20)
	RICES	43.45 (0.16)	44.64 (0.09)	45.71 (0.12)	46.30 (0.03)	47.48 (0.05)
	MMICES	43.45 (0.16)	<b>47.00 (0.06)</b>	<b>48.46 (0.07)</b>	<b>49.50 (0.06)</b>	<b>49.68 (0.03)</b>
OK-VQA	Random	28.18 (0.25)	30.46 (0.29)	30.29 (0.50)	31.40 (0.25)	31.40 (0.44)
	RICES	28.18 (0.25)	30.89 (0.09)	32.47 (0.04)	33.97 (0.12)	34.85 (0.04)
	MMICES	28.18 (0.25)	<b>35.34 (0.19)</b>	<b>37.41 (0.01)</b>	<b>38.00 (0.13)</b>	<b>38.23 (0.09)</b>
GQA	Random	28.70 (0.22)	30.57 (0.09)	32.31 (0.19)	33.49 (0.30)	33.33 (0.10)
	RICES	28.70 (0.22)	30.96 (0.06)	32.69 (0.20)	34.08 (0.11)	35.02 (0.04)
	MMICES	28.70 (0.22)	<b>37.70 (0.06)</b>	<b>38.49 (0.10)</b>	<b>38.85 (0.17)</b>	<b>38.37 (0.16)</b>
MSCOCO	Random	75.14 (0.69)	76.48 (0.50)	82.01 (0.35)	86.52 (1.00)	90.53 (0.42)
	RICES	75.14 (0.69)	90.30 (0.09)	97.38 (0.36)	102.91 (0.26)	105.62 (0.10)
	MMICES	75.14 (0.69)	<b>99.21 (0.23)</b>	<b>103.42 (0.35)</b>	<b>106.94 (0.21)</b>	<b>109.19 (0.31)</b>

Table 14. The performances of random selection, RICES, and MMICES on OF-3B. The highest performance in each shot scenario is highlighted in bold. The results are averaged over 5 evaluation seeds and are reported along with their standard deviations. The performance metric for the MSCOCO dataset is CIDEr, while for the remaining datasets, accuracy is reported in percentages. MMICES achieves the best performance in all settings on all datasets.

Dataset	Method	0-shot	4-shot	8-shot	16-shot	32-shot
VQAv2	Random	43.55 (0.18)	45.54 (0.12)	45.77 (0.19)	45.71 (0.15)	45.05 (0.19)
	RICES	43.55 (0.18)	45.06 (0.09)	45.41 (0.07)	45.65 (0.04)	46.11 (0.12)
	MMICES	43.55 (0.18)	<b>48.41 (0.01)</b>	<b>48.38 (0.05)</b>	<b>48.96 (0.05)</b>	<b>48.86 (0.04)</b>
OK-VQA	Random	29.07 (0.17)	31.26 (0.44)	31.85 (0.10)	32.08 (0.20)	31.37 (0.12)
	RICES	29.07 (0.17)	32.30 (0.11)	33.76 (0.14)	34.52 (0.07)	35.51 (0.03)
	MMICES	29.07 (0.17)	<b>37.10 (0.13)</b>	<b>38.65 (0.09)</b>	<b>39.04 (0.10)</b>	<b>38.24 (0.03)</b>
GQA	Random	29.68 (0.17)	32.07 (0.06)	33.43 (0.30)	33.75 (0.24)	33.18 (0.28)
	RICES	29.68 (0.17)	30.96 (0.06)	33.27 (0.26)	34.17 (0.15)	34.36 (0.08)
	MMICES	29.68 (0.17)	<b>37.72 (0.11)</b>	<b>38.64 (0.06)</b>	<b>38.58 (0.03)</b>	<b>38.25 (0.15)</b>
MSCOCO	Random	75.10 (0.24)	82.11 (0.68)	86.14 (0.39)	90.17 (0.46)	92.86 (0.44)
	RICES	75.10 (0.24)	92.43 (0.23)	99.36 (0.23)	104.48 (0.33)	106.88 (0.21)
	MMICES	75.10 (0.24)	<b>100.43 (0.14)</b>	<b>104.82 (0.13)</b>	<b>107.61 (0.18)</b>	<b>109.44 (0.25)</b>

Table 15. The performances of random selection, RICES, and MMICES on OF-3BI. MMICES achieves the best performance in all settings on all datasets.

Dataset	Method	0-shot	4-shot	8-shot	16-shot	32-shot
VQAv2	Random	44.05 (0.20)	47.74 (0.24)	47.10 (0.04)	44.32 (0.12)	41.88 (0.25)
	RICES	44.05 (0.20)	47.70 (0.04)	46.68 (0.18)	44.91 (0.07)	42.86 (0.08)
	MMICES	44.05 (0.20)	<b>48.89 (0.04)</b>	<b>48.61 (0.09)</b>	<b>46.45 (0.07)</b>	<b>43.73 (0.06)</b>
OK-VQA	Random	31.31 (0.32)	35.01 (0.25)	33.87 (0.20)	29.04 (0.16)	27.09 (0.29)
	RICES	31.31 (0.32)	34.97 (0.16)	33.41 (0.07)	29.47 (0.09)	28.79 (0.08)
	MMICES	31.31 (0.32)	<b>37.46 (0.09)</b>	<b>37.20 (0.10)</b>	<b>33.99 (0.12)</b>	<b>30.23 (0.05)</b>
GQA	Random	27.16 (0.01)	31.45 (0.35)	33.07 (0.25)	33.17 (0.33)	32.64 (0.13)
	RICES	27.16 (0.01)	31.38 (0.24)	33.68 (0.18)	34.58 (0.25)	34.42 (0.19)
	MMICES	27.16 (0.01)	<b>38.54 (0.16)</b>	<b>39.53 (0.13)</b>	<b>39.31 (0.12)</b>	<b>37.22 (0.11)</b>
MSCOCO	Random	76.45 (0.65)	81.41 (0.19)	90.48 (0.35)	92.83 (0.66)	93.72 (0.61)
	RICES	76.45 (0.65)	89.25 (0.17)	96.60 (0.24)	102.70 (0.20)	105.14 (0.05)
	MMICES	76.45 (0.65)	<b>98.61 (0.17)</b>	<b>102.56 (0.13)</b>	<b>105.66 (0.04)</b>	<b>105.89 (0.21)</b>

Table 16. The performances of random selection, RICES, and MMICES on OF-4B. MMICES achieves the best performance in all settings on all datasets.

tially leading to a negative impact on performance.

**Textual information on image captioning.** MMICES considers both visual and textual information when selecting demonstrations. It chooses demonstrations that have both similar images and similar texts. However, in the task of image captioning, the textual information in the queries cannot be directly used as the desired response. To obtain the desired textual information, MMICES first uses the gener-

Dataset	Method	0-shot	4-shot	8-shot	16-shot	32-shot
VQAv2	Random	45.55 (0.29)	47.74 (0.11)	46.20 (0.15)	44.01 (0.23)	46.33 (0.14)
	RICES	45.55 (0.29)	48.24 (0.08)	46.27 (0.12)	44.32 (0.13)	47.55 (0.12)
	MMICES	45.55 (0.29)	<b>49.03 (0.04)</b>	<b>48.22 (0.07)</b>	<b>47.42 (0.03)</b>	<b>48.85 (0.05)</b>
OK-VQA	Random	32.15 (0.21)	34.56 (0.31)	33.73 (0.27)	31.61 (0.15)	34.29 (0.62)
	RICES	32.15 (0.21)	34.86 (0.05)	34.40 (0.09)	32.52 (0.13)	36.73 (0.06)
	MMICES	32.15 (0.21)	<b>38.14 (0.07)</b>	<b>38.23 (0.16)</b>	<b>36.08 (0.09)</b>	<b>37.32 (0.14)</b>
GQA	Random	28.42 (0.07)	32.10 (0.23)	33.53 (0.32)	34.32 (0.25)	35.53 (0.29)
	RICES	28.42 (0.07)	32.59 (0.08)	34.51 (0.25)	35.19 (0.15)	37.07 (0.10)
	MMICES	28.42 (0.07)	<b>38.61 (0.09)</b>	<b>39.48 (0.16)</b>	<b>39.73 (0.13)</b>	<b>39.56 (0.06)</b>
MSCOCO	Random	80.30 (0.15)	85.97 (0.46)	91.71 (0.12)	96.70 (0.19)	98.06 (0.31)
	RICES	80.30 (0.15)	92.67 (0.08)	101.38 (0.15)	105.75 (0.13)	<b>108.22 (0.05)</b>
	MMICES	80.30 (0.15)	<b>100.59 (0.07)</b>	<b>105.16 (0.22)</b>	<b>108.68 (0.10)</b>	107.96 (0.20)

Table 17. The performances of random selection, RICES, and MMICES on OF-4BI. MMICES achieves the best performance in most cases.

Dataset	Method	0-shot	4-shot	8-shot	16-shot	32-shot
VQAv2	Random	51.38 (0.17)	53.52 (0.11)	53.74 (0.19)	53.33 (0.26)	52.38 (0.10)
	RICES	51.38 (0.17)	<b>54.03 (0.13)</b>	<b>54.67 (0.06)</b>	<b>55.39 (0.12)</b>	<b>55.77 (0.08)</b>
	MMICES	51.38 (0.17)	53.11 (0.03)	53.56 (0.05)	54.04 (0.04)	55.14 (0.02)
OK-VQA	Random	37.62 (0.39)	39.62 (0.29)	41.56 (0.20)	43.40 (0.39)	42.97 (0.11)
	RICES	37.62 (0.39)	42.13 (0.13)	43.87 (0.15)	44.90 (0.10)	46.15 (0.06)
	MMICES	37.62 (0.39)	<b>44.18 (0.11)</b>	<b>45.61 (0.08)</b>	<b>46.93 (0.08)</b>	<b>46.79 (0.10)</b>
GQA	Random	34.04 (0.19)	36.32 (0.29)	37.74 (0.32)	38.28 (0.10)	37.85 (0.11)
	RICES	34.04 (0.19)	36.92 (0.33)	38.54 (0.14)	40.16 (0.14)	40.21 (0.32)
	MMICES	34.04 (0.19)	<b>40.73 (0.09)</b>	<b>41.85 (0.10)</b>	<b>42.21 (0.12)</b>	<b>42.07 (0.08)</b>
MSCOCO	Random	79.52 (0.31)	89.82 (0.23)	96.81 (0.10)	99.44 (0.19)	100.53 (0.26)
	RICES	79.52 (0.31)	93.45 (0.07)	99.74 (0.27)	105.76 (0.03)	109.12 (0.20)
	MMICES	79.52 (0.31)	<b>100.24 (0.20)</b>	<b>104.90 (0.3)</b>	<b>108.66 (0.17)</b>	<b>109.64 (0.24)</b>

Table 18. The performances of random selection, RICES, and MMICES on OF-9B. MMICES achieves the best performance in most cases.

Dataset	Method	0-shot	4-shot	8-shot	16-shot	32-shot
VQAv2	Random	52.59 (0.30)	54.90 (0.05)	56.16 (0.02)	56.93 (0.18)	57.21 (0.17)
	RICES	52.59 (0.30)	54.79 (0.09)	56.45 (0.05)	57.49 (0.06)	58.52 (0.02)
	MMICES	52.59 (0.30)	<b>56.15 (0.01)</b>	<b>58.17 (0.03)</b>	<b>59.23 (0.01)</b>	<b>59.69 (0.02)</b>
OK-VQA	Random	44.77 (0.22)	49.24 (0.22)	49.54 (0.12)	50.89 (0.12)	51.86 (0.12)
	RICES	44.77 (0.22)	48.82 (0.02)	50.55 (0.05)	52.42 (0.03)	53.22 (0.04)
	MMICES	44.77 (0.22)	<b>49.63 (0.02)</b>	<b>52.16 (0.03)</b>	<b>53.65 (0.07)</b>	<b>54.16 (0.05)</b>
GQA	Random	36.45 (0.22)	39.35 (0.26)	40.54 (0.17)	41.38 (0.18)	41.87 (0.13)
	RICES	36.45 (0.22)	39.86 (0.13)	41.27 (0.29)	42.65 (0.21)	43.67 (0.19)
	MMICES	36.45 (0.22)	<b>42.66 (0.05)</b>	<b>44.22 (0.08)</b>	<b>45.19 (0.05)</b>	<b>45.36 (0.09)</b>
MSCOCO	Random	48.61 (0.52)	96.45 (0.36)	100.85 (0.36)	103.96 (0.38)	105.02 (0.43)
	RICES	48.61 (0.52)	91.20 (0.10)	102.58 (0.15)	108.93 (0.10)	111.02 (0.08)
	MMICES	48.61 (0.52)	<b>101.13 (0.12)</b>	<b>109.31 (0.09)</b>	<b>112.72 (0.05)</b>	<b>113.37 (0.09)</b>

Table 19. The performances of random selection, RICES, and MMICES on IDEFTCS-9B. MMICES achieves the best performance in all cases.

ated captions from the in-context learning setting with randomly selected demonstrations. It then further selects similar demonstrations. The performance comparison for different shot numbers is shown in Tab. 22. MMICES achieves the best performance when using generated captions based on the 4-shot setting.

**Different Choice of Modality Mixture.** Compared to RICES, which only compares image similarity, MMICES considers both visual and language modalities. We also investigate the performance of ICL when examples are retrieved using only text similarity (referred to as *text*), and when retrieved by first comparing language and then selecting based on image similarity (referred to as *text-image*).

Dataset	Method	0-shot	4-shot	8-shot	16-shot	32-shot
VQAv2	Random	62.99 (0.03)	63.94 (0.13)	64.43 (0.14)	64.64 (0.10)	64.87 (0.09)
	RICES	62.99 (0.03)	<b>64.13 (0.08)</b>	<b>64.69 (0.03)</b>	65.11 (0.05)	65.22 (0.03)
	MMICES	62.99 (0.03)	63.51 (0.13)	64.46 (0.04)	<b>65.26 (0.04)</b>	<b>65.50 (0.02)</b>
OK-VQA	Random	46.18 (0.17)	48.78 (0.48)	49.92 (0.16)	51.18 (0.20)	51.41 (0.12)
	RICES	46.18 (0.17)	49.80 (0.03)	51.32 (0.02)	52.42 (0.05)	53.35 (0.03)
	MMICES	46.18 (0.17)	<b>51.65 (0.08)</b>	<b>53.21 (0.03)</b>	<b>53.89 (0.03)</b>	<b>54.14 (0.01)</b>
GQA	Random	41.83 (0.21)	43.99 (0.20)	45.70 (0.16)	46.39 (0.08)	46.89 (0.17)
	RICES	41.83 (0.21)	44.79 (0.18)	45.63 (0.07)	46.57 (0.16)	46.82 (0.06)
	MMICES	41.83 (0.21)	<b>46.33 (0.12)</b>	<b>47.51 (0.09)</b>	<b>47.87 (0.13)</b>	<b>48.47 (0.11)</b>
MSCOCO	Random	124.15 (0.63)	<b>132.80 (0.63)</b>	<b>133.02 (0.39)</b>	<b>132.23 (0.37)</b>	<b>132.93 (0.32)</b>
	RICES	124.15 (0.63)	124.97 (0.11)	126.84 (0.10)	127.85 (0.10)	128.76 (0.08)
	MMICES	124.15 (0.63)	125.42 (0.12)	128.50 (0.09)	129.71 (0.06)	130.55 (0.09)

Table 20. The performances of random selection, RICES, and MMICES on IDEFICS-9BI. MMICES achieves the best performance in most cases.

Dataset	K	4-shot	8-shot	16-shot	32-shot
GQA	50	39.43	40.50	40.99	40.48
	100	40.72	41.15	41.89	41.09
	200	40.73	41.85	42.21	42.07
	300	40.76	41.63	42.28	42.20
OK-VQA	50	43.46	45.79	47.48	47.21
	100	43.40	45.72	46.50	47.17
	200	44.18	45.61	46.93	46.79
	300	44.21	45.66	46.00	46.79

Table 21. Performance of MMICES given different K.

ICL Setting	4-shot	8-shot	16-shot	32-shot
Random	89.82	96.81	99.44	100.53
RICES	93.45	99.74	105.76	109.12
MMICES given Random				
0-shot	95.31	100.53	105.06	107.90
4-shot	97.72	102.81	107.37	110.15
8-shot	99.90	104.95	108.20	110.31
16-shot	100.08	104.82	109.11	110.26
32-shot	100.24	104.90	108.66	109.64

Table 22. MMICES on MSCOCO with generated captions from ICL with randomly selected demonstrations. Based on results with 0-shot, MMICES obtain better results in r-shot and 8-shot settings. Given generated captions with 4-shot, MMICES achieves the best results in all settings.

Full results are presented in Table 23. Factoring in both modalities consistently improves ICL performance compared to selecting based solely on one modality.

## E. Additional Experimental Analysis

This study has conducted extensive experiments on various vision-language models, using different sizes, backbone language models, and pre-training datasets (as shown in Tab. 4). This section further discusses our observations and findings for these different models.

**Experiments across models with different sizes.** The ICL

Data	Method	4-shot	8-shot	16-shot	32-shot
VQAv2	Random	53.52	53.74	53.33	52.38
	RICES	54.03	54.67	55.39	55.77
	text	47.71	47.46	47.49	47.83
	text-image	50.27	50.37	49.84	50.56
OK-VQA	MMICES	53.11	53.56	54.04	55.14
	Random	39.62	41.56	43.40	42.97
	RICES	42.13	43.87	44.90	46.15
	text	42.80	43.54	44.01	44.07
GQA	text-image	43.61	45.53	45.01	45.50
	MMICES	44.18	45.61	46.93	46.79
	Random	36.32	37.74	38.28	37.85
	RICES	36.92	38.54	40.16	40.21
COCO	text	39.18	40.68	41.59	41.58
	text-image	40.93	42.12	42.70	42.63
	MMICES	40.73	41.85	42.21	42.07
	Random	89.82	96.81	99.44	100.53
COCO	RICES	93.45	99.74	105.76	109.12
	text	99.84	102.88	105.57	106.52
	text-image	100.72	104.93	106.97	108.56
	MMICES	100.24	104.90	108.66	109.64

Table 23. Performance with different modality mixture. RICES compares image similarity. *text* only considers text similarity. *text-image* selects demonstrations by first comparing language similarity and then comparing image similarity.

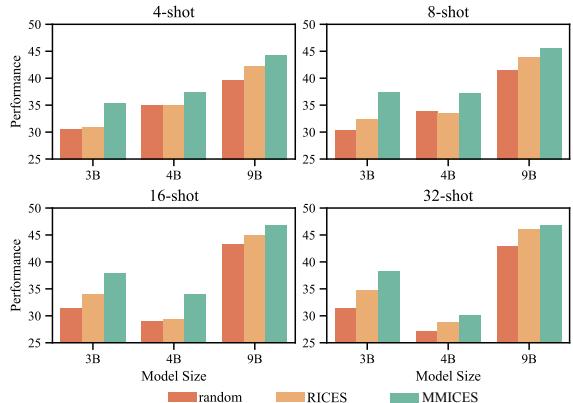


Figure 14. The performance of ICL (on OK-VQA) is consistently enhanced by MMICES on OpenFlamingo with different sizes.

performance of different sizes of OpenFlamingo models is presented in Fig. 14 to Fig. 16. MMICES consistently improves the ICL performance on these datasets across various model sizes. Larger models, such as OF-9B, demonstrate better performance compared to smaller models, particularly in visual question answering (Fig. 14) and visual reasoning (Fig. 15). It is worth noting that MMICES achieves better performance on smaller-size models compared to larger-size models using RICES and random selection, especially in the 4 and 8-shot settings.

**Experiments across different models.** The performance

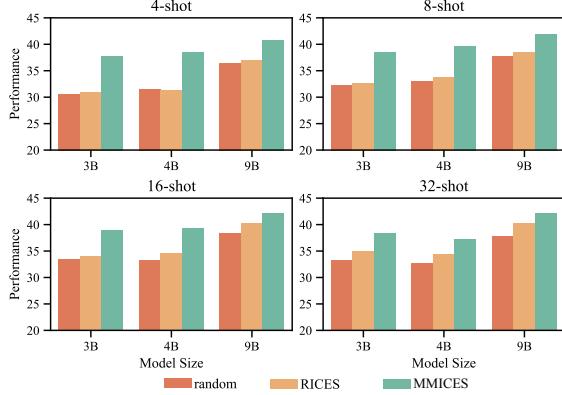


Figure 15. The performance of ICL (on GQA) is consistently enhanced by MMICES on OpenFlamingo with different sizes.

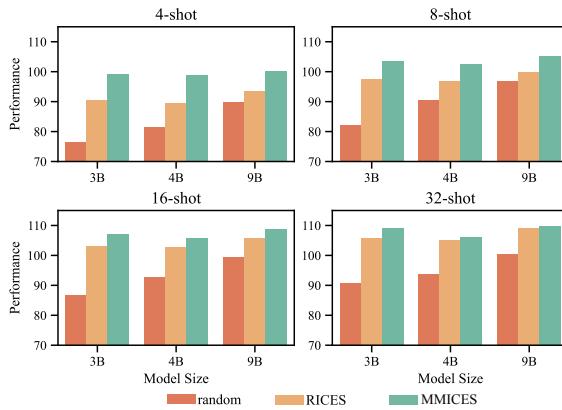


Figure 16. The performance of ICL (on COCO) is consistently enhanced by MMICES on OpenFlamingo with different sizes.

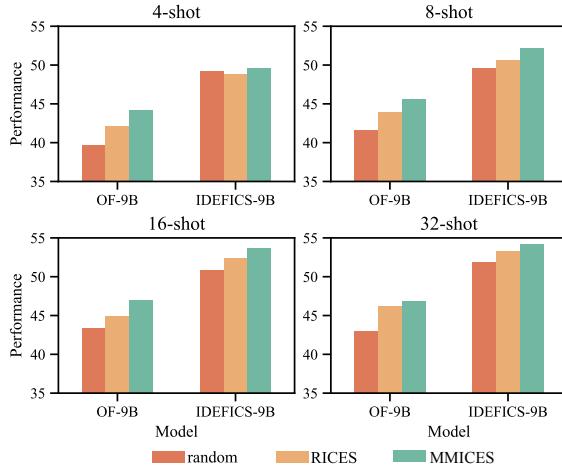


Figure 17. The performance of ICL (on OK-VQA) is consistently enhanced by MMICES across different models.

gained from MMICES is consistent across different models, as shown in Fig. 17 to Fig. 19. IDEFICS achieves better performance compared to OpenFlamingo, and this difference can be attributed to the use of different pre-training datasets and language models in these two models [16].

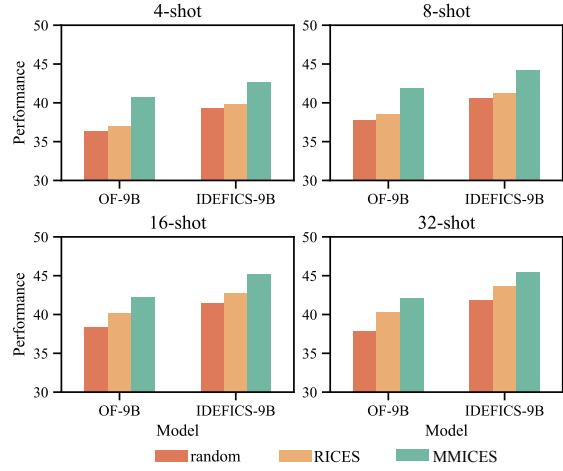


Figure 18. The performance of ICL (on GQA) is consistently enhanced by MMICES across different models.

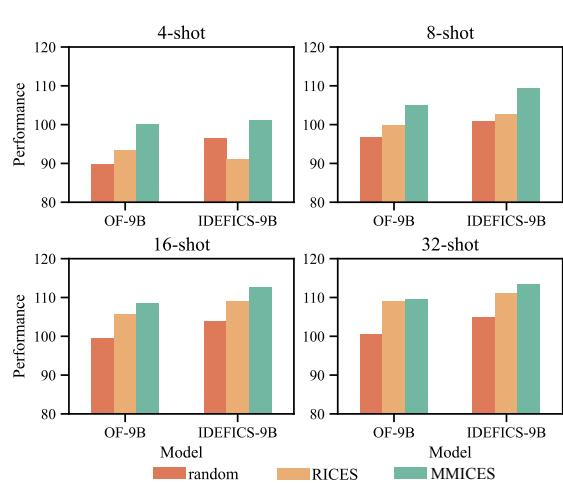


Figure 19. The performance of ICL (on COCO) is consistently enhanced by MMICES across different models.

Query	Method	Demo 1	Demo 2	Demo 3	Model Generation
	MMICES	 Who makes the luggage in this room? <i>samsomte</i>	 Who invented the device pictured? <i>steve job</i>	 Who manufactures this bag? <i>ll bean</i>	fender
Who makes the guitar on the wall?	RICES	 What kind of suitcase is this? <i>carry on</i>	 Where can you buy these luggages? <i>walmart</i>	 What items would you typically find in these bags? <i>cloth</i>	yamaha
	MMICES	 What material are the umbrellas made of? <i>straw</i>	 What is the pattern on the umbrella? <i>striped</i>	 What do you call this type of window covering? <i>blind</i>	plastic
Name the material used to make this umbrella shown in this picture?	RICES	 What causes high and low tides? <i>moon</i>	 What is the orange triangle in the road called? <i>cone</i>	 When is it bad luck to open the black and pink object in the photo? <i>inside</i>	rubber
	MMICES	 What happened here? <i>accident</i>	 What safety precaution did both of these people take? <i>helmet</i>	 What is being done on this road? <i>construction</i>	power line
What were they fixing?	RICES	 What purpose does the white and red striped bar in the picture serve? <i>stop traffic</i>	 Is this person crossing illegally or legally? <i>legally</i>	 What is the job title for the man pictured here? <i>electrician</i>	light pole
	MMICES	 What food is this? <i>carrot cake</i>	 What food is this? <i>cake</i>	 What food is this? <i>candy apple</i>	donut
What food item do you think this ornament resembles?	RICES	 What can this make you become if you eat a lot of it? <i>fat</i>	 What type of computer is shown in this image? <i>desktop</i>	 What are donuts topped with? <i>ice</i>	cookie
	MMICES	 What is the elephant doing? <i>paint</i>	 Why does the elephant go to the water? <i>thirsty</i>	 Why are they riding an elephant? <i>for fun</i>	decoration
What is the purpose of the elephant here?	RICES	 What country was this photograph taken in? <i>thailand</i>	 How tall do these animals typically grow to be? <i>11 feet</i>	 When was this type of vehicle with two equal sized wheels invented? <i>1850</i>	park meter
	MMICES	 What is the name of the body style of the grey vehicle? <i>minivan</i>	 What make and model is the car pictured? <i>toyota avalon</i>	 What liquid makes the vehicle in the picture move? <i>gasoline</i>	yellow
What color is the taxi?	RICES	 What is the use of that pink object over her head? <i>keep dry</i>	 What photo technique is being used? <i>sephia</i>	 Who invented the blue item in this picture? <i>samuel fox</i>	black
	MMICES	 What is the silver tool called? <i>tong</i>	 What type of jewelry uses a term similar to one of these veggies? <i>carrot</i>	 Which of these items depicted grows underground? <i>potato</i>	stainless steel
Name a metal shown?	RICES	 When would i eat this? <i>dinner</i>	 How is the meat in this dish prepared? <i>grilled</i>	 What food group is mostly represented? <i>meat</i>	copper
	MMICES	 What do these animals eat? <i>plant</i>	 What do you feed these animals? <i>hay</i>	 What is a staple of the diet of these animals? <i>fish</i>	grass
What do these animals eat?	RICES	 What type of food does this animal eat? <i>berry</i>	 What is a staple of the diet of these animals? <i>fish</i>	 what do these animals do in the winter? <i>hibernate</i>	berry

Table 24. Examples of demonstrations selected by MMICES and RICES on OK-VQA. Model generations in green are correct and red means wrong prediction.