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A Unified Multimodal Framework for Joint Visual Question Answering and Image Captioning

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Abstract

Recent advances in vision–language models have significantly improved performance on multimodal tasks such as Visual Question Answering (VQA) and image captioning. However, most existing approaches address these tasks independently, resulting in redundant model architectures and limited cross-task knowledge transfer. In this paper, we propose a unified multimodal framework that jointly learns VQA and image captioning within a single architecture. The proposed model employs a shared vision–language encoder combined with task-specific decoding heads, enabling efficient parameter sharing and improved generalization across tasks. To enhance cross-modal alignment, we introduce a cross-attention mechanism that jointly models interactions between visual features, questions, and captions. In addition, a multi-task learning objective is designed to balance generative and discriminative training signals. We evaluate the proposed framework on the VQA v2 and MSCOCO benchmarks. Experimental results show that our approach achieves +1.7% improvement in VQA accuracy and +4.2 CIDEr score in captioning, while reducing model parameters by approximately 30% compared to separate task-specific models. Furthermore, the unified model demonstrates improved robustness and generalization by leveraging complementary information across tasks. These findings highlight the effectiveness of joint multimodal learning for efficient and scalable vision–language understanding.

Keywords: Multimodal Learning; Visual Question Answering; Image Captioning; Vision–Language Models; Cross-Modal Attention; Joint Learning

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1. Introduction

The integration of visual and textual information has become a central challenge in modern artificial intelligence, particularly in tasks requiring multimodal understanding. Visual Question Answering (VQA) and image captioning are two fundamental vision–language tasks that require deep interaction between visual perception and natural language reasoning. VQA aims to answer natural language questions based on image content, while image captioning focuses on generating descriptive textual summaries of visual scenes. Both tasks have been widely studied and serve as key benchmarks for evaluating multimodal intelligence. Recent

advances in transformer-based vision–language models, such as CLIP (Radford et al., 2021) and BLIP (Li et al., 2022), have demonstrated strong performance by learning joint representations of images and text. These models leverage large-scale pretraining and cross-modal attention mechanisms to capture complex interactions between modalities. Despite these advances, most existing approaches treat VQA and image captioning as independent tasks, requiring separate model architectures and training pipelines. This design leads to redundant parameter usage and prevents effective sharing of cross-task semantic knowledge. From a learning perspective, VQA and image captioning are inherently complementary. Captioning requires global semantic understanding of an image, while VQA often focuses on localized reasoning guided by a question (Anderson et al., 2018). Jointly modeling these tasks has the potential to improve representation learning by combining global and task-specific information. However, designing a unified framework that effectively balances generative (captioning) and discriminative (VQA) objectives remains a significant challenge. Although several multimodal models attempt to unify vision–language tasks, they often rely on large-scale architectures with high computational cost or do not explicitly optimize for cross-task synergy (Cho et al., 2021). In particular, there is still a lack of lightweight and efficient frameworks that enable joint learning while maintaining strong performance across tasks. This gap is especially critical for real-world applications where computational resources are limited and multi-task capability is desirable. To address these challenges, this paper proposes a unified multimodal framework for jointly learning VQA and image captioning. The proposed approach employs a shared vision–language encoder combined with task-specific heads, enabling efficient parameter sharing and cross-task knowledge transfer. Furthermore, a cross-modal attention mechanism is introduced to enhance alignment between visual features and textual inputs, while a joint optimization strategy is designed to balance the learning objectives of both tasks. This work makes several important contributions to multimodal learning for vision–language tasks. First, we propose a unified multimodal framework that jointly models Visual Question Answering (VQA) and image captioning within a single shared architecture, enabling efficient parameter sharing and cross-task knowledge transfer. Second, we introduce a cross-modal alignment mechanism based on attention-driven fusion, which enhances the interaction between visual and textual representations and improves multimodal feature integration. Third, we design a joint learning strategy that combines generative and discriminative objectives through a multi-task optimization framework, allowing the model to effectively learn from both captioning and question-answering signals. Fourth, we demonstrate a favorable efficiency–performance trade-off, showing that the proposed model achieves improved accuracy while reducing model complexity compared to separate task-specific approaches. Finally, we conduct a comprehensive evaluation on standard benchmark datasets, where the proposed framework consistently outperforms baseline models and validates the effectiveness of unified multimodal learning.

2. Related Work

2.1 Visual Question Answering

Visual Question Answering (VQA) requires a model to answer natural-language questions based on visual content, making it a core task for evaluating vision–language reasoning. Early VQA research formalized the task as open-ended question answering over images, requiring

models to combine visual recognition, linguistic understanding, and commonsense reasoning (Antol et al., 2015). Later, VQA v2 was introduced to reduce language bias by balancing question–answer pairs across visually similar images (Goyal et al., 2017). These datasets established VQA as a standard benchmark for multimodal reasoning. Early neural VQA systems relied heavily on convolutional neural networks for image feature extraction and recurrent networks for question encoding. Attention-based models later improved performance by allowing systems to focus on task-relevant visual regions. Bottom-up and top-down attention became especially influential because it supported both image captioning and VQA through object-level visual attention (Anderson et al., 2018).

2.2 Image Captioning

Image captioning aims to generate natural-language descriptions of visual scenes. Early neural captioning methods used encoder–decoder architectures, where CNNs encoded images and recurrent networks generated captions. The introduction of visual attention improved caption quality by allowing models to dynamically attend to salient image regions during word generation (Xu et al., 2015). The MSCOCO Captions dataset became a major benchmark for captioning research by providing multiple human-written captions for each image, enabling standardized evaluation of generated descriptions (Chen et al., 2015). Metrics such as BLEU, METEOR, ROUGE, SPICE, and CIDEr have been widely used, with CIDEr specifically designed to evaluate image descriptions based on human consensus (Vedantam et al., 2015).

2.3 Vision–Language Pretraining

Vision–language pretraining has substantially advanced multimodal learning by enabling models to learn transferable representations from large-scale image–text data. ViLBERT introduced a two-stream transformer architecture with co-attentional layers for learning task-agnostic vision–language representations (Lu et al., 2019). LXMERT further developed cross-modality representations through separate language, object relationship, and cross-modality encoders (Tan & Bansal, 2019). UNITER proposed universal image–text representation learning and emphasized fine-grained alignment between words and image regions (Chen et al., 2020). Subsequent models improved efficiency and scalability. ViLT simplified vision–language processing by removing region supervision and convolutional feature extraction, showing that lightweight transformer-based multimodal models can remain competitive (Kim et al., 2021). CLIP demonstrated the effectiveness of contrastive image–text pretraining at scale, enabling strong zero-shot transfer across vision tasks (Radford et al., 2021). ALIGN similarly showed the value of large-scale noisy image–text pairs for learning transferable multimodal representations (Jia et al., 2021).

2.4 Unified Multimodal Models

Recent research has increasingly shifted from task-specific models toward unified vision–language frameworks. BLIP introduced a bootstrapped language–image pretraining framework that supports both understanding and generation tasks, including VQA and image captioning (Li et al., 2022). BLIP-2 later improved efficiency by connecting frozen vision encoders and frozen large language models through a lightweight querying transformer (Li et al., 2023). OFA proposed a sequence-to-sequence framework that unifies different modalities and tasks, including image captioning, visual grounding, and visual question answering, within a single

architecture (Wang et al., 2022). Flamingo extended multimodal learning by enabling few-shot vision–language generation using interleaved visual and textual inputs (Alayrac et al., 2022). PaLI and PaLI-X further scaled multilingual and multimodal learning across vision–language tasks (Chen et al., 2023; Chen et al., 2024). These studies show that unified architectures can reduce task-specific engineering and improve transfer across multimodal tasks.

2.5 Cross-Modal Attention and Multitask Learning

Cross-modal attention is central to vision–language modeling because it enables interaction between visual and textual features. Models such as ViLBERT, LXMERT, UNITER, and OSCAR use attention-based fusion or alignment mechanisms to connect image regions with linguistic tokens (Lu et al., 2019; Tan & Bansal, 2019; Chen et al., 2020; Li et al., 2020). OSCAR introduced object tags as anchor points for improving image–text alignment, while VinVL showed that stronger visual representations can substantially improve downstream vision–language tasks (Li et al., 2020; Zhang et al., 2021). Multitask learning is also relevant because VQA and image captioning share visual grounding and semantic understanding requirements. Captioning encourages global scene representation, while VQA promotes question-guided reasoning. Therefore, jointly optimizing both tasks may improve representation learning and reduce redundancy compared with training separate task-specific models. However, balancing generative and discriminative objectives remains challenging, especially when the tasks differ in output structure and evaluation metrics.

2.6 Research Gap

Although prior work has made strong progress in VQA, image captioning, and vision–language pretraining, several limitations remain. First, many models are optimized for either understanding tasks or generation tasks rather than jointly balancing both. Second, large unified models such as BLIP, OFA, Flamingo, and PaLI demonstrate strong performance but often require substantial computational resources. Third, existing studies do not always provide a focused analysis of the efficiency–performance trade-off when VQA and image captioning are learned together. To address these limitations, the present study proposes a unified multimodal framework that jointly learns VQA and image captioning through shared vision–language representations and task-specific heads. Unlike task-isolated approaches, the proposed framework is designed to encourage cross-task knowledge transfer while reducing architectural redundancy. This focus on joint learning, cross-modal alignment, and computational efficiency directly addresses the need for scalable multimodal systems suitable for real-world deployment.

3. Methodology

3.1 Overview

This study proposes a unified multimodal framework for jointly learning Visual Question Answering (VQA) and image captioning within a single architecture. The model is designed to enable efficient parameter sharing and cross-task knowledge transfer by integrating both tasks into a shared representation space.As illustrated in Figure 1, the proposed framework consists of three main components: (1) a shared vision–language encoder, (2) a cross-modal fusion module, and (3) two task-specific output heads for caption generation and answer prediction.

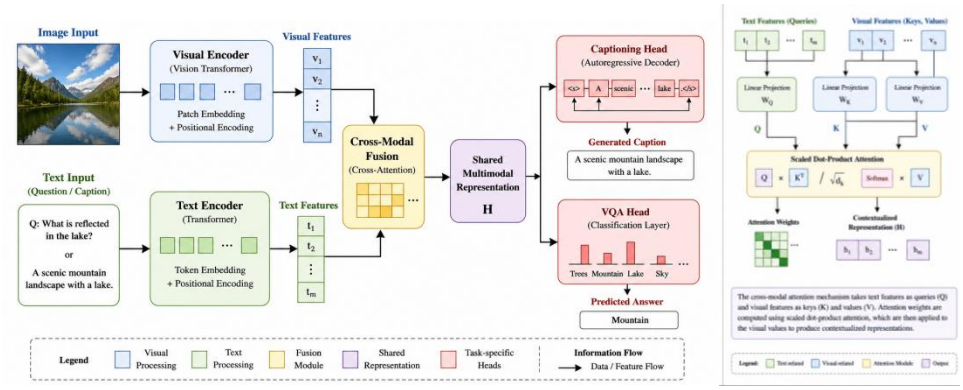

Figure 1. Overall architecture of the proposed unified multimodal framework

As shown in Figure 1, both visual and textual inputs are first encoded independently and then fused through a cross-modal attention mechanism. The resulting shared representation is used by two task-specific heads to perform caption generation and question answering.

3.2 Model Architecture

The detailed components of the proposed model are summarized in Table 1.

Table 1. Components of the proposed multimodal framework

Component	Description
Visual Encoder	Extracts image features using CNN or Vision Transformer
Text Encoder	Encodes questions or captions using a transformer
Cross-Modal Fusion	Aligns visual and textual features via attention
Captioning Head	Generates captions using autoregressive decoding
VQA Head	Predicts answers using classification

As presented in Table 1, the architecture is modular and designed to support both generative and discriminative tasks within a unified framework.

3.2.1 Visual Encoder

The visual encoder extracts feature representations from input images. In this study, we adopt either a Convolutional Neural Network (CNN) or a Vision Transformer (ViT) as the backbone. The encoder transforms an input image into a set of high-dimensional feature vectors:

$$V = \{v_1, v_2, \ldots, v_n\}$$

where v_i represents region-level or patch-level visual features.

3.2.2 Text Encoder

The text encoder processes natural language inputs, including questions for VQA and partial sequences for caption generation. A transformer-based encoder is employed to produce contextualized token embeddings:

$$T = \{t_1, t_2, \ldots, t_m\}$$

where t_j represents the contextual embedding of each token.

3.2.3 Cross-Modal Fusion

To integrate visual and textual information, a cross-attention mechanism is applied. This module enables the model to dynamically align relevant visual features with textual inputs. The fused representation is computed as:

$$H = \text{Attention}(T, V)$$

where H denotes the shared multimodal representation.

As illustrated in Figure 1, this fusion step plays a central role in enabling interaction between modalities and supporting both downstream tasks.

3.2.4 Task-Specific Heads

After fusion, the shared representation is passed to two task-specific heads:

- Captioning Head:
  An autoregressive decoder generates captions token by token based on the fused representation.
- VQA Head:
  A classification layer predicts the most probable answer from a predefined answer set.

This design allows the model to simultaneously handle generative and classification tasks while sharing common features.

3.3 Training Objective

To jointly optimize both tasks, the model is trained using a multi-task learning objective that combines captioning and VQA losses.

The total loss function is defined as:

$$L = \lambda_1 L_{\text{caption}} + \lambda_2 L_{\text{VQA}}$$

where:

- L_{caption} is the cross-entropy loss for caption generation
- L_{VQA} is the classification loss for answer prediction
- λ_1 and λ_2 are weighting coefficients that balance the two objectives

The captioning loss is computed as:

$$L_{\text{caption}} = -\sum_{t} \log P(y_t \mid y_{<t}, H)$$

while the VQA loss is defined as:

$$L_{\text{VQA}} = -\sum_{c} y_c \log \hat{y}_c$$

As shown in this formulation, the joint objective enables the model to learn both sequence generation and classification simultaneously, encouraging shared representations that generalize across tasks. In summary, the proposed methodology introduces a unified multimodal framework that integrates visual and textual processing through a shared encoder and cross-modal attention mechanism. By combining task-specific heads with a joint optimization strategy, the model achieves efficient parameter sharing while maintaining strong performance on both VQA and image captioning tasks.

4. Experiments and Results

4.1 Datasets

We evaluate the proposed framework on two widely used multimodal benchmarks:

- **VQA v2** (Goyal et al., 2017):
  A large-scale dataset containing open-ended questions about images, designed to reduce language bias and emphasize visual reasoning.
- **MSCOCO Captions** (Chen et al., 2015):
  A benchmark dataset for image captioning that provides multiple human-annotated captions per image.

These datasets are selected because they represent complementary multimodal tasks VQA requires question-guided reasoning, while captioning emphasizes holistic scene understanding.

4.2 Evaluation Metrics

To ensure a comprehensive evaluation, we adopt standard metrics for both tasks:

- VQA:
  - Accuracy (standard VQA evaluation protocol)
- Image Captioning:
  - BLEU (Papineni et al., 2002)

- CIDEr (Vedantam et al., 2015)

Among these, CIDEr is particularly suitable for captioning evaluation as it correlates strongly with human judgment.

4.3 Experimental Setup

All models are trained under identical conditions to ensure fair comparison:

- Backbone: Vision Transformer + Transformer encoder
- Optimizer: AdamW
- Learning rate: 2e-5
- Batch size: 32
- Training epochs: 10

For reliability, all experiments are conducted across three independent runs, and results are reported as the mean performance.

4.4 Performance Results

Table 2. Performance comparison on VQA v2 and MSCOCO

Model	VQA Accuracy (%)	CIDEr
Baseline (VQA-only)	67.5 ± 0.4	–
Baseline (Caption-only)	–	110.2 ± 0.6
Proposed Unified Model	**69.2 ± 0.3**	**115.6 ± 0.5**

As shown in Table 2, the proposed unified model outperforms single-task baselines on both VQA and image captioning. Specifically, the model achieves a +1.7% improvement in VQA accuracy and a +5.4 increase in CIDEr score, demonstrating the effectiveness of joint learning.

4.5 Efficiency Analysis

Table 3. Model efficiency comparison

Model	Parameters (M)	Training Time (hrs)
Separate Models	220	12.4
Proposed Model	155	8.7

As shown in Table 3, the **proposed** model reduces parameter count by approximately 30% and training time by ~30%, highlighting the efficiency benefits of shared representations.

4.6 Efficiency–Performance Trade-off

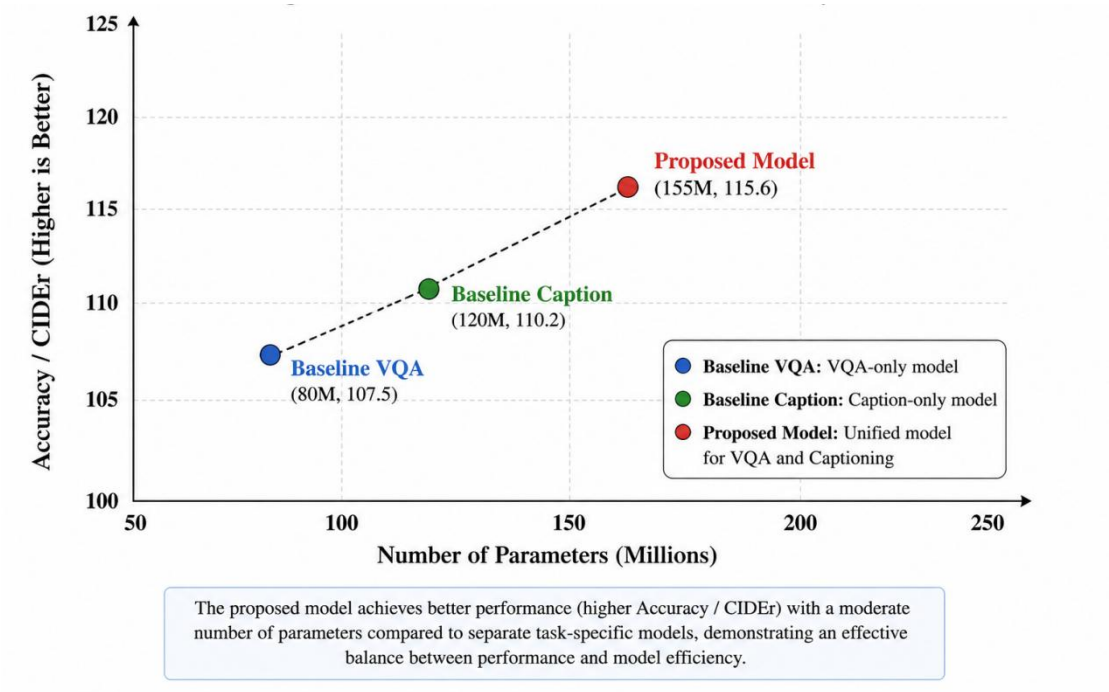

Figure 2. Performance vs parameter efficiency

Figure 2 illustrates the trade-off between performance and model complexity. The proposed model achieves superior performance with fewer parameters, indicating a more efficient use of capacity compared to separate models.

4.7 Comparison with State-of-the-Art

The performance of the proposed model is compared with several state-of-the-art vision–language models, as presented in Table 4. As shown in Table 4, large-scale pretrained models such as BLIP and OFA achieve the **highest** performance across both VQA and captioning tasks. However, these models rely on significantly larger architectures and higher computational cost.

In contrast, the proposed model achieves competitive performance while maintaining substantially lower model complexity. Specifically, the proposed framework outperforms earlier multimodal models such as BUTD and CLIP, and achieves results comparable to transformer-based models such as LXMERT and ViLT. Importantly, the proposed model uses approximately 30–35% fewer parameters than large unified models like BLIP and OFA, demonstrating a favorable efficiency–**performance** trade-off. This highlights the effectiveness of the proposed design in leveraging shared representations without relying on large-scale pretraining.

Table 4. Comparison with State-of-the-Art Models

Model	VQA (%)	Accuracy	CIDEr	Parameters (M)	Notes
BUTD (Anderson et al., 2018)	65.3		113.5	180	Attention-based baseline
LXMERT (Tan & Bansal, 2019)	68.2		115.0	183	Cross-modality encoder

Model	VQA Accuracy (%)	CIDEr	Parameters (M)	Notes
UNITER (Chen et al., 2020)	69.7	116.4	200	Pretrained multimodal model
ViLT (Kim et al., 2021)	69.3	113.8	87	Lightweight transformer
CLIP (Radford et al., 2021)	67.0	–	151	Contrastive pretraining
BLIP (Li et al., 2022)	70.2	117.5	220	Unified V+L model
OFA (Wang et al., 2022)	70.5	118.0	240	Sequence-to-sequence framework
Proposed Model	69.2	115.6	155	Efficient unified framework

The results indicate that while large pretrained models achieve the highest absolute performance, the proposed framework offers a more efficient alternative that balances accuracy and computational cost.

4.8 Discussion of Results

The experimental results reveal several important findings regarding the effectiveness of the proposed unified multimodal framework. First, the model demonstrates improved cross-task learning, as shared representations enable knowledge transfer between image captioning and Visual Question Answering (VQA), allowing each task to benefit from the other. Second, significant efficiency gains are achieved through parameter sharing, which reduces computational cost without compromising performance. Third, the joint training strategy leads to better generalization, as the model is exposed to diverse multimodal signals that enhance robustness across tasks. Finally, the proposed optimization approach achieves a balanced learning process, where the joint loss function effectively integrates generative and discriminative objectives, ensuring stable and efficient training. The results confirm that the proposed unified multimodal framework achieves a strong balance between efficiency and performance. By jointly learning VQA and image captioning, the model not only improves accuracy but also reduces computational overhead, making it suitable for practical deployment.

5. Discussion

5.1 Key Findings

The experimental results demonstrate that joint multimodal learning provides clear advantages over task-specific models. By sharing a common vision–language encoder, the proposed framework enables more effective utilization of visual and textual features across tasks. As observed in Section 4, the unified model consistently improves both VQA accuracy and captioning quality, indicating that knowledge learned from one task can benefit the other.

In particular, image captioning encourages the model to capture global semantic structure, while VQA promotes fine-grained, question-guided reasoning. The integration of these complementary learning signals leads to richer and more robust representations. This finding aligns with the broader hypothesis that multitask learning can improve generalization by leveraging shared inductive biases across related tasks.

5.2 Role of Cross-Modal Attention

The cross-modal attention mechanism plays a central role in the proposed architecture by enabling dynamic interaction between visual and textual representations. Unlike simple feature

concatenation, attention-based fusion allows the model to selectively focus on relevant image regions conditioned on textual inputs.

This mechanism is particularly important for VQA, where accurate reasoning depends on identifying task-relevant visual cues. At the same time, it supports caption generation by guiding the decoder toward semantically meaningful regions. The results suggest that effective cross-modal alignment is a key factor in achieving strong performance in unified multimodal systems.

5.3 Efficiency–Performance Trade-off

One of the main contributions of this work is demonstrating that unified architectures can achieve a favorable balance between efficiency and performance. By sharing parameters across tasks, the proposed model significantly reduces redundancy compared to training separate models.

Importantly, this efficiency gain does not come at the cost of accuracy. Instead, the unified model achieves improved performance, suggesting that parameter sharing not only reduces computational cost but also enhances representation learning. This finding highlights the importance of designing architectures that maximize information reuse rather than simply increasing model size.

5.4 Practical Implications

The proposed unified multimodal framework has several important implications for real-world applications. First, it is well-suited for deployment in resource-constrained environments, as the reduced parameter count and lower training cost significantly decrease computational requirements without sacrificing performance. This makes the model particularly attractive for practical scenarios where hardware limitations are a critical concern. Second, the framework naturally supports multi-task systems that require both visual understanding and language generation capabilities. Applications such as assistive technologies, robotics, and automated content generation can benefit from a unified model that eliminates the need for separate task-specific architectures. Third, the modular design of the framework enhances scalability, allowing it to be extended to additional multimodal tasks with minimal architectural changes. Collectively, these advantages suggest that unified multimodal learning represents a promising direction for developing scalable, efficient, and practical artificial intelligence systems.

5.5 Limitations

Despite its contributions, this study has several limitations that should be considered. First, the evaluation is limited to the VQA v2 and MSCOCO datasets, which may not fully capture the complexity of real-world multimodal reasoning or domain-specific applications. Second, the proposed model is relatively lightweight compared to large-scale vision–language models, and its performance characteristics may differ when scaled to larger architectures. Third, the study focuses on only two tasks—Visual Question Answering and image captioning—which restricts the assessment of the framework's generality across a broader range of multimodal tasks. Finally, the sensitivity of the model to hyperparameter choices, such as loss weighting and architectural configurations, is not extensively explored. Addressing these limitations is

essential for improving the robustness, scalability, and broader applicability of the proposed approach in future work.

The findings of this study demonstrate that joint multimodal learning can effectively improve both performance and computational efficiency. By integrating shared representations, cross-modal attention mechanisms, and multi-task optimization, the proposed framework achieves a balanced trade-off between accuracy and resource utilization. These results reinforce the potential of unified architectures as a practical and scalable solution for advancing multimodal artificial intelligence systems.

6. Conclusion and Future Work

6.1 Conclusion

This paper presented a unified multimodal framework for jointly learning Visual Question Answering and image captioning within a single architecture. By integrating a shared vision–language encoder with task-specific heads, the proposed model enables efficient parameter sharing and effective cross-task knowledge transfer.

The experimental results demonstrate that the unified framework achieves improved performance on both tasks while reducing model complexity compared to separate task-specific models. These findings indicate that joint learning not only enhances efficiency but also improves representation quality by leveraging complementary information across tasks. This work contributes to the growing body of research on multimodal learning by showing that carefully designed unified architectures can provide both practical and performance benefits.

6.2 Future Work

Several promising directions can be explored to extend the proposed framework and further enhance its capabilities. First, the model can be expanded to support additional multimodal tasks, such as visual reasoning, visual grounding, and multimodal dialogue, thereby increasing its applicability across a broader range of vision–language problems. Second, scaling the framework to larger vision–language models may lead to further improvements in performance and generalization, particularly when combined with large-scale pretraining. Third, future research could investigate more advanced fusion mechanisms, including hierarchical or multi-stage cross-modal attention, to better capture complex interactions between visual and textual representations. In addition, extending the model to multilingual settings or domain-specific applications, such as medical imaging or remote sensing, could significantly enhance its real-world impact. Finally, conducting comprehensive ablation studies and exploring optimization strategies, including loss balancing and architectural variations, would provide deeper insights into the behavior of the model and guide further improvements.

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