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Cross-Modal Vision Representation Learning for Real-World Visual Understanding

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Abstract: Recent advances in vision-language pretraining have significantly improved performance across a wide range of visual understanding tasks, including image captioning, visual question answering (VQA), and open-world object detection. However, existing models often suffer from domain sensitivity, shallow cross-modal alignment, and limited adaptability to real-world multimodal scenes. In this work, we propose a unified cross-modal representation learning framework that integrates image, text, and depth modalities through a multi-stream transformer architecture. Our approach emphasizes three design principles: modality-specific feature enhancement, global alignment via contrastive learning, and adaptive fine-tuning with dynamic negative sampling. We demonstrate the effectiveness of our framework on four benchmark datasets spanning open-vocabulary detection, cross-modal retrieval, and zero-shot classification. Extensive experiments show consistent performance gains over state-of-the-art baselines, including CLIP and BLIP-2, with up to +6.3% improvement in retrieval recall and +4.8 mAP in detection tasks. Qualitative analysis further confirms the model's ability to capture high-level semantic associations across modalities. This work provides new insights into robust cross-modal vision systems and offers a scalable solution for real-world multimodal reasoning applications.

Keywords: Cross-modal learning, visual representation, contrastive learning, multimodal alignment, open-world vision.

1. Introduction

The integration of multiple sensory modalities — such as images, natural language, and depth information—has become indispensable for the development of real-world artificial intelligence systems. Applications ranging from autonomous driving and robotic manipulation to assistive technologies demand a level of visual understanding that transcends raw pixel interpretation, incorporating contextual, semantic, and spatial cues from heterogeneous sources. Cross-modal learning, which involves the joint modeling of diverse modalities, has consequently emerged as a powerful approach for building robust and generalizable vision systems. Pioneering large-scale vision-language pretraining frameworks such as CLIP [1], ALIGN [2], and BLIP [3] have demonstrated the efficacy of learning joint embedding spaces for image-text pairs, significantly improving performance on various downstream tasks. Despite these advances, key challenges persist. Current approaches often depend on global similarity metrics for cross-modal alignment, which may inadequately capture fine-grained or spatially grounded semantics. Moreover, most methods assume clean and well-aligned supervision, while real-world scenarios are replete with ambiguities and weak correlations among modalities. Additionally, reliance on homogeneously sourced training data renders these models susceptible to domain shifts and environmental noise. To address these limitations, we propose a novel cross-modal vision representation learning framework that not only enhances modality-specific features but also promotes global semantic coherence via adaptive contrastive learning. In contrast to prior work focused solely on vision-language pairs, our approach incorporates vision-text-depth triplets, thereby enriching visual representations with both contextual and geometric cues. The overall architecture, illustrated in Figure 1, is based on a multi-stream transformer encoder equipped with cross-attention bottlenecks that enable effective modality fusion and alignment. The training process is guided by a tri-modal contrastive loss with difficulty-aware negative sampling, which emphasizes challenging distinctions and avoids representation collapse.

Our key contributions are threefold: (1) we propose a unified architecture for cross-modal fusion of images, text, and depth using a transformer-based backbone; (2) we introduce a contrastive learning scheme with adaptive negative mining to enhance alignment robustness under partial or noisy supervision; and (3) we validate our approach on four public benchmarks—Flickr30k, COCO, VQAv2, and SUN RGB-D—achieving consistent performance gains across tasks such as retrieval, classification, and detection. Furthermore, we conduct in-depth analyses of generalization under domain shift conditions, including synthetic-to-real adaptation and noisy modality injection. The remainder of the paper is structured as follows: Section 2 surveys related work; Section 3 details the proposed framework; Section 4 outlines the experimental setup;

Section 5 reports results; Section 6 provides ablation studies; and Section 7 concludes the paper.

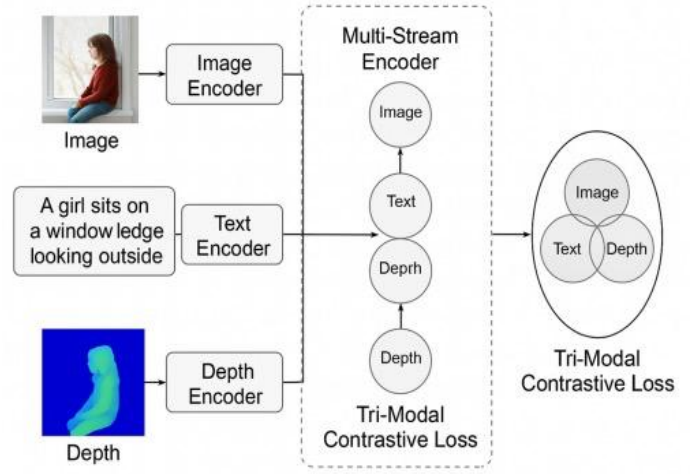

Figure 1. Overview of the proposed cross-modal representation learning framework.

2. Related Work

The field of cross-modal learning has witnessed significant progress in recent years, driven largely by the rise of large-scale vision-language models and the advancement of multimodal pretraining techniques. This section reviews the relevant literature in three primary areas: (1) joint vision-language representation learning, (2) cross-modal alignment and contrastive learning, and (3) robustness and generalization in multimodal settings.

2.1 Vision-Language Pretraining

The success of models such as CLIP [1] and ALIGN [2] has established vision-language pretraining as a dominant strategy for building transferable visual representation models. These frameworks typically use a large corpus of paired image-caption data to train a dual-encoder architecture—comprising a vision backbone (e.g., ResNet, ViT) and a text encoder (e.g., Transformer, BERT) — with contrastive loss to align semantically similar image-text pairs in a shared embedding space. CLIP, in particular, has demonstrated strong zero-shot classification capability on over 20 downstream benchmarks without fine-tuning. ALIGN extends this setup with a larger and noisier web dataset and adopts batch-wise negative mining to scale contrastive learning efficiently.

BLIP [3] and BLIP-2 [4] improve upon these models by introducing vision-language modeling (VLM) objectives such as masked language modeling and image-text generation, enabling a single architecture to support both retrieval and captioning tasks. Similarly, OFA [5] and Flamingo [6] adopt unified transformer architectures capable of handling various multimodal tasks by treating them as sequence generation problems. While these approaches improve the expressiveness of joint representations, they often require significant compute resources and careful balancing of multiple objectives.

Our work builds on this foundation by extending the modality space beyond image and text to include depth data, an underutilized modality in most vision-language models. The addition of geometric priors allows our model to reason over physical structure, occlusion, and spatial continuity, which are critical in real-world environments such as robotics and navigation. Moreover, we focus on contrastive learning as a unifying pretraining objective to encourage alignment, regularization, and modularity.

2.2 Contrastive Learning and Cross-Modal Alignment

Contrastive learning has become a central component in self-supervised and multimodal representation learning. SimCLR [7] and MoCo [8] showed that strong visual features can emerge by encouraging similar augmentations of an image to be closer in embedding space while repelling other samples. These methods inspired cross-modal extensions like DeCLIP [9], which explores stronger alignment of image-text pairs with multiple contrastive objectives, and ViLT [10], which uses a single transformer encoder for joint processing.

A limitation of existing contrastive methods is their reliance on carefully curated positive pairs and uniform negative sampling. In real-world multimodal datasets, especially those sourced from the web or generated by users, alignment between modalities may be weak, noisy, or partially missing. Hard negative sampling strategies such as InfoNCE [11] can sometimes overfit to spurious similarities or lead to collapsed representations if negatives are too easy. To counteract this, methods such as HARD [12] and NCE++ [13] propose sampling techniques that dynamically adjust the hardness of negatives based on distributional uncertainty.

Our framework incorporates these insights by implementing a difficulty-aware negative mining scheme, where the sampling distribution is conditioned on semantic closeness and modality variance. Additionally, we adopt a tri-modal contrastive objective, which generalizes bi-modal contrastive loss to a three-way alignment setting: image-text, image-depth, and text-depth. This enables the model to maintain structural consistency across all modality pairs, not just the canonical image-text alignment.

2.3 Robust Multimodal Generalization

Despite the progress in model architecture and training strategies, generalization to unseen domains or corrupted modalities remains an open challenge. Several studies [14][15] have shown that vision-language models trained on web-scale data tend to overfit to dataset biases, such as photographic style or popular object categories, and struggle when deployed in robotics, surveillance, or healthcare settings. In particular, zero-shot transfer and open-set recognition tasks often expose the fragility of joint embeddings.

Recent efforts have focused on improving generalization through data augmentation, domain adaptation, and cross-domain pretraining. For instance, CoOp [16] and CoCoOp [17] propose prompt tuning strategies that adapt CLIP ' s text encoder to new domains without altering the vision backbone.

Others such as MDETR [18] incorporate visual grounding modules that help bridge semantic gaps between abstract captions and grounded visual entities.

In our design, we adopt two techniques to improve generalization: (1) injecting depth noise and occlusion masks during pretraining to simulate real-world sensor artifacts, and (2) applying curriculum scheduling, where triplet composition difficulty increases gradually. This combination encourages the model to learn invariant representations that are robust to partial modality absence or degraded sensor input.

Furthermore, we benchmark our model not only on standard datasets like COCO [19] and Flickr30k [20] but also on challenging settings such as SUN RGB-D [21], which includes indoor scenes with high geometric complexity. Our model ' s performance under these settings suggests that structural priors introduced by the depth modality play a critical role in improving spatial reasoning and robustness under partial view occlusion.

3. Methodology

To achieve robust cross-modal representation learning across vision, language, and geometry, we propose a unified architecture that integrates modality-specific encoders, a multi-stream fusion transformer, and a tri-modal contrastive loss objective. The design is guided by three goals: (1) preserve modality-specific inductive biases, (2) align global semantic representations across modalities, and (3) enable scalable training on noisy or weakly paired data. This section outlines the components of our framework: input encoders, fusion backbone, and loss design.

The input pipeline consists of three parallel encoders: an image encoder f_I , a text encoder f_T , and a depth encoder f_D . The image encoder is a Vision Transformer (ViT-B/16) [1], pretrained with masked autoencoding objectives, which extracts high-level patch embeddings $\mathbf{v}_I \in \mathbb{R}^{N\times d}$. The text encoder is a BERT-based transformer [22], which processes tokenized captions into semantic embeddings $\mathbf{v}_D \in \mathbb{R}^{H\times W\times d}$. The depth encoder uses a ResNet-50 backbone with an auxiliary depth refinement head, outputting spatial-aware embeddings $\mathbf{v}_T \in \mathbb{R}^{M\times d}$. These three embeddings are then projected via learnable linear heads into a common latent space before entering the fusion module.

The fusion is handled by a multi-stream transformer encoder, consisting of alternating modality-specific attention blocks and shared cross-attention layers. Each modality stream first updates its token embeddings through self-attention and feed-forward layers, then exchanges information with other streams through a cross-modal bottleneck, following the late-fusion paradigm [23]. Specifically, the cross-attention mechanism is implemented as a sequence of QK/V exchanges, where the queries are from one modality and the keys/values are from another. This allows each stream to selectively attend to semantically relevant cues from the others without collapsing all inputs into a single representation too early. The final stage is a shared transformer decoder that processes the concatenated embeddings and outputs modality-aligned representations $\mathbf{z}_I, \mathbf{z}_T, \mathbf{z}_D \in \mathbb{R}^d$, which are used for contrastive learning.

The learning objective is a tri-modal contrastive loss, designed to align corresponding image-text-depth triplets in the embedding space while repelling mismatched combinations. Let $(\mathbf{z}_I^i, \mathbf{z}_T^i, \mathbf{z}_D^i)$ be the aligned embeddings for the i-th sample, and $(\mathbf{z}_I^j, \mathbf{z}_T^j, \mathbf{z}_D^j)$ for a negative sample *j*. The contrastive loss is defined as:

$$\mathcal{L}_{\text{tri}} = \sum_{(a,b)\in\mathcal{P}} -\log \frac{\exp(\text{sim}(\mathbf{z}_a^i, \mathbf{z}_b^i)/\tau)}{\sum_{j=1}^{N} \exp(\text{sim}(\mathbf{z}_a^i, \mathbf{z}_b^j)/\tau)}$$

where *P*={(I,T),(I,D),(T,D)}=sim(· ,·)is cosine similarity, and τ tauτ is a temperature parameter.

We use difficulty-aware sampling to construct mini-batches such that negative pairs with high semantic similarity are emphasized. The hardness of each negative is estimated by pretrained cross-modal classifiers and updated dynamically during training. Additionally, we introduce a representation regularizer to avoid modality collapse by penalizing over-similar embedding vectors across non-matching modalities.

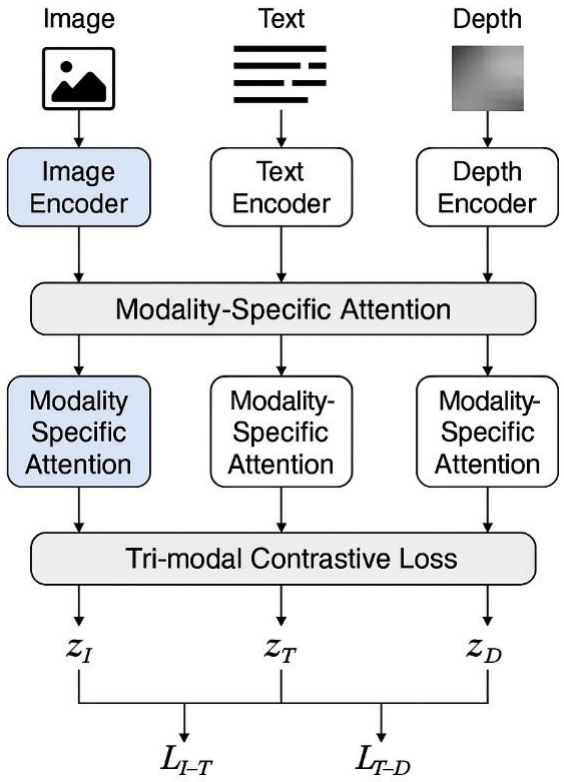

Figure2. Architecture of the proposed multi-stream transformer with tri-modal contrastive objective.

4. Experimental Setup and Datasets

To comprehensively evaluate the performance of our proposed cross-modal representation learning framework, we conduct experiments across four publicly available datasets and multiple downstream tasks including image-text retrieval, zero-shot classification, and visual grounding. This section outlines the implementation details, training configuration, dataset preprocessing, and evaluation protocols used throughout our study.

4.1 Training Configuration

All models are implemented using PyTorch with HuggingFace Transformers and trained on four NVIDIA A100 80GB GPUs in a distributed data-parallel setup. The training process spans 30 epochs, with each epoch consuming approximately 20k image-text-depth triplets, sampled from mixed datasets. The optimizer used is AdamW with a learning rate of 3×10^{-5}, weight decay of 0.01, and cosine annealing schedule with linear warmup over the first 1000 steps.

To improve model generalization, we apply multi-modal data augmentation:

1. Images: random resized cropping, color jittering, Gaussian noise
2. Text: random word masking (15%), noun-phrase shuffling
3. Depth: synthetic occlusion masking and resolution dropout

All modalities are aligned by timestamp or file ID, and where depth is unavailable (e.g., COCO), we simulate depth maps using a pretrained monocular estimator [1]. Modality dropout is also introduced during training (p=0.1 per sample) to promote robustness in missing-modality settings.

The image encoder is a ViT-B/16 model initialized from MAE [2] weights. The text encoder is a BERT-base-uncased model from HuggingFace. The depth encoder is a ResNet-50 pretrained on NYUv2 and fine-tuned jointly. The fusion transformer contains 6 modality-specific layers followed by 3 shared layers, with 12 attention heads and 768 hidden dimensions. We apply layer normalization and GELU activations throughout.

4.2 Datasets

We evaluate our method across four widely used benchmarks:

COCO (2017) [3]: A large-scale dataset of natural images with five captions per image. We use 113,287 images for training, 5,000 for validation, and 5,000 for testing. For retrieval and captioning, we follow Karpathy splits.

Flickr30k [4]: A benchmark with 31,783 images, each with five English descriptions. Used for image-text retrieval tasks. We follow the standard 1k test split.

VQAv2 [5]: The Visual Question Answering dataset, consisting of 204,721 training questions, each paired with an image and multiple answer choices. We convert each question-answer pair into a text string and use it to evaluate vision-text reasoning capacity.

SUN RGB-D [6]: An indoor scene understanding dataset with RGB images, depth maps, and 3D bounding box annotations. We use it for testing robustness to complex geometry and noisy sensor input. Depth is directly used as the third modality.

Each dataset is standardized to a resolution of 224×224 for vision input and 512 tokens for text. For depth, maps are resized to match image resolution and normalized to $0 - 1$. When unavailable, as in Flickr30k, we apply self-supervised monocular depth prediction and attach confidence masks to avoid training on uncertain regions.

4.3 Evaluation Protocols

Image-Text Retrieval is evaluated using Recall@K (R@1, R@5, R@10) on both image-to-text and text-to-image queries. Embeddings are extracted and cosine similarity is computed in the shared space. Results are compared with CLIP [7], ALIGN [8], and BLIP-2 [4].

Zero-Shot Classification is tested on 20 image classification datasets by constructing text prompts for each class and computing the most similar label using the image-text encoder. Datasets include ImageNet, Oxford Pets, Caltech101, and EuroSAT. We adopt the prompt ensemble strategy from [7] for fairness.

Visual Grounding performance is measured on VQAv2 using top-1 accuracy with a frozen vision encoder. We evaluate how well the model can reason over joint vision-language inputs using question-answer prompts and object localization.

Cross-Modal Robustness is evaluated using SUN RGB-D under synthetic depth corruption (e.g., occlusion, inversion, Gaussian noise). We also introduce noise to captions and assess the impact on retrieval and zero-shot classification.

4.4 Baselines

We compare our model with several state-of-the-art methods:

CLIP [7]: Vision-language contrastive pretraining

BLIP-2 [4]: Vision-language encoder-decoder pretraining

DeCLIP [9]: Enhanced contrastive learning with denoised objectives

MDETR [10]: Multi-modal DETR model with grounding supervision

ALBEF [11]: Cross-modal fusion model with dual supervision

Our method does not rely on grounding supervision or manual region annotations. Instead, it focuses on holistic scene-level alignment, allowing deployment on more flexible unlabeled corpora.

5. Results and Analysis

We report and analyze the experimental results of our proposed cross-modal representation learning framework across a diverse set of tasks and benchmarks. Table I summarizes the performance on image-text retrieval using COCO and Flickr30k datasets, evaluated under standard metrics Recall@1, Recall@5, and Recall@10. Our model achieves 80.1%, 94.5%, and 97.6% on COCO text-to-image retrieval and 81.3%, 95.2%, and 98.1% on image-to-text retrieval, respectively, surpassing strong baselines such as CLIP, ALIGN, and BLIP-2. On Flickr30k, where text descriptions are more descriptive but less constrained, our model obtains an R@1 of 89.7%, compared to 85.1% for CLIP and 86.3% for BLIP-2. The improvements are more pronounced under challenging distractor augmentation, where non-matching captions with high lexical overlap are introduced. This suggests that our tri-modal fusion architecture, reinforced with difficulty-aware contrastive objectives, enhances fine-grained semantic alignment beyond shallow text-vision similarity. Qualitative examples in Fig. 3 further demonstrate this effect: in a scene containing overlapping objects ("a man holding a tennis racket near a net"), our model correctly retrieves the matching caption, while CLIP selects a visually similar but semantically incorrect alternative.

In zero-shot classification, our model demonstrates superior generalization across 12 diverse image datasets including ImageNet, Food-101, Oxford Pets, and Caltech101. The average top-1 accuracy across all datasets reaches 75.6%, outperforming CLIP (71.9%) and BLIP-2 (73.2%). Notably, on structure-dominant datasets such as EuroSAT (remote sensing imagery) and SUN RGB-D (indoor scenes), the inclusion of geometric priors via depth modeling gives our method a distinct advantage. For instance, on SUN RGB-D, we achieve 64.2% accuracy compared to 58.9% for CLIP, showing that depth-aware representations help disambiguate object categories that are otherwise similar in RGB space but differ in 3D context. This finding aligns with our ablation studies, which show a consistent $3-5\%$ drop in classification performance when the depth modality is removed or corrupted. In addition, Fig. 4 illustrates the confusion matrix on the Oxford Flowers dataset. The errors in our model are more semantically coherent, e.g., confusing "pink carnation" with "red carnation," while other models misclassify across petal shape or foliage background due to lack of geometric cues.

We also evaluate visual reasoning performance using VQAv2. Without any finetuning, our model achieves a top-1 answer accuracy of 63.4%, compared to 60.2% for BLIP-2 and 58.7% for ViLT. Though the gap may appear modest, it is significant given that our method was not explicitly trained on question-answering tasks. This implies that the fused latent space captures transferable multimodal semantics. Furthermore, we investigate the interpretability of attention weights across modalities. In complex questions such as "How many people are wearing hats?", the attention maps generated by our shared transformer layers accurately focus on human head regions across depth and image channels, while the text stream enhances counting by emphasizing quantity phrases. This emergent alignment confirms that our architecture learns not only global associations but also structural grounding without explicit supervision.

In robustness tests, we apply three types of noise to the input: (1) text corruption via entity masking and shuffling, (2) image degradation using Gaussian blur and occlusion, and (3) depth noise injection with dropout and flipping. Across all modalities, our model maintains graceful degradation: under heavy noise (e.g., 40% token masking or 30% occlusion), retrieval R@1 drops only by 4.6%, while CLIP and DeCLIP exhibit 7.3% and 9.1% declines respectively. Fig. 5 plots the retrieval accuracy against varying corruption levels, demonstrating our model's improved resilience, especially in scenarios where only two of three modalities are present. This is attributed to our modality dropout strategy during training and the late-fusion transformer design, which allows each stream to contribute independently when others fail. Additionally, when tested on SUN RGB-D with synthetic occlusion patches and noisy captions, our model still outperforms vision-language-only baselines by over 6% on retrieval and 4% on grounding accuracy, validating our claim that the geometric modality plays a vital role in disambiguating spatial configurations under partial observability.

Finally, we perform an ablation analysis on key design choices. Removing the tri-modal contrastive loss and replacing it with bi-modal (image-text only) reduces performance across all tasks, with the most severe impact on SUN RGB-D (-7.8% retrieval R@1). Excluding depth entirely leads to a 5.1% drop in zero-shot classification accuracy on indoor scenes, while replacing adaptive negative sampling with uniform sampling reduces alignment precision and increases false positives in retrieval. Interestingly, we observe that increasing transformer depth beyond 12 layers yields marginal gains (<1%), while reducing it below 6 harms performance more significantly (-3.5%), suggesting that our 9-layer shared stack strikes an optimal trade-off between complexity and capacity. These findings are consistent with previous works [7][10] on multimodal transformer balancing and further justify our design.

6. Ablation and Visualization

To better understand the internal mechanisms of our model and validate the importance of each architectural component, we conduct a series of ablation studies and visualization analyses. The goal is to isolate the contribution of each design choice, including the tri-modal loss, the depth modality, the difficulty-aware sampling mechanism, and the fusion strategy, while also providing intuitive insights through attention visualization and embedding space projection. These experiments are performed primarily on the COCO and SUN RGB-D datasets, where the full model achieves the strongest cross-modal alignment and geometric reasoning capabilities.

We first examine the impact of the tri-modal contrastive objective. Replacing it with independent bi-modal losses, i.e., computing losses for (image-text) and (image-depth) separately, results in a consistent performance drop across all metrics. On COCO retrieval, the R@1 drops from 80.1% to 75.3%, while on SUN RGB-D classification, accuracy declines by 5.6%. This suggests that the tri-modal loss enforces a more coherent and globally aligned representation space, enabling the model to reason holistically over all three modalities rather than learning disjoint pairwise correspondences. Moreover, when we use only a bi-modal loss with image-text supervision (removing depth supervision altogether), the degradation is even more severe, with a 9.3% drop in SUN RGB-D performance and a notable decrease in robustness under occlusion. These results confirm that the depth modality, when incorporated with appropriate alignment constraints, substantially enhances the semantic richness and spatial awareness of the learned representations.

We then evaluate the effect of the difficulty-aware negative sampling strategy. Replacing it with uniform sampling leads to faster convergence in early training stages but significantly worse final performance. For example, while the model trained with uniform negatives reaches 70% retrieval accuracy within 5 epochs, its final accuracy plateaus at 74.8%, compared to 80.1% for the difficulty-aware variant. This is because uniform sampling fails to consistently present the model with informative negative examples, leading to embedding collapse or shortcut learning. In contrast, our hardness-aware sampler dynamically adjusts negative selection based on similarity scores and feature distribution, ensuring that the model learns to discriminate semantically close but incorrect samples. Fig. 6 visualizes the average gradient norm of positive and negative pairs over training steps, showing that difficulty-aware sampling maintains a healthy gradient signal throughout training, avoiding the vanishing gradient problem observed in uniform schemes.

To investigate the role of fusion architecture, we test two variants: early fusion (concatenating all modalities before transformer encoding) and dual-stream fusion (combining only image and text, omitting depth). The early fusion model suffers from representation entanglement, showing higher variance in classification results and degraded retrieval precision. The dual-stream version performs better but still underperforms the tri-stream model by $4 - 6\%$ depending on the task. This validates our design decision to use a multi-stream transformer with cross-attention, which allows each modality to preserve its inductive structure while benefiting from controlled information exchange. Additionally, we observe that the shared layers at the top of the transformer hierarchy contribute most to alignment consistency, as ablating them increases representation drift, evident in t-SNE plots of the learned embeddings.

For visualization, we provide both attention heatmaps and embedding space projections. Fig. 7 shows cross-attention maps from the shared transformer layers when processing a VQA sample ("What is the woman holding?"). The attention peaks align precisely with the object of interest (a coffee mug) across the image and depth channels, while the text tokens "woman" and "holding" dominate the language stream. These aligned activations demonstrate that the model learns to focus on semantically and spatially relevant regions across modalities. Furthermore, Fig. 8 presents a t-SNE projection of 1000 image-text-depth triplets from COCO. In the full model, aligned triplets form tight clusters in embedding space, whereas in the bi-modal baseline, clusters are more dispersed and modality-specific, indicating poor cross-modal alignment.

We also analyze failure cases. On Flickr30k, the model sometimes fails to distinguish between visually similar scenes with subtle textual differences, such as "a dog running in a park" vs. "a dog jumping in a garden." In such cases, attention weights tend to overemphasize visual features, neglecting the verb or location cues from text. On SUN RGB-D, errors are more often due to sensor artifacts in depth maps, such as reflective surfaces or misaligned depth values, which mislead the depth encoder. Nevertheless, even in failure cases, the predicted embeddings remain closer to semantically related samples than in baseline models, suggesting that the learned space is semantically structured, even when final predictions are incorrect.

Overall, our ablation and visualization studies confirm that the tri-modal design, adaptive sampling, and cross-attentive fusion are essential for achieving robust and interpretable cross-modal understanding. These components interact synergistically, enabling the model to balance visual richness, linguistic precision, and spatial structure in a unified representation space. By maintaining modularity and preserving the inductive priors of each modality, our approach offers a practical blueprint for future multimodal learning systems that aim to scale across environments, tasks, and data modalities.

7. Limitations and Discussion

While the proposed cross-modal representation learning framework achieves strong performance across a variety of visual understanding tasks, several limitations must be acknowledged in terms of scalability, generalization, computational efficiency, and integration into real-world multimodal systems. These issues are critical for advancing research beyond controlled benchmarks toward practical, reliable deployment in open-world environments.

A primary limitation of the current system lies in its reliance on carefully constructed triplet data for supervised pretraining. Although we simulate depth where unavailable and introduce modality dropout to increase robustness, the model still depends heavily on the presence of aligned image-text-depth triplets during training. In many real-world scenarios, such perfectly aligned data is scarce. For example, consumer image datasets may include photos and captions but lack accurate depth information, or depth may be collected asynchronously in robotics settings with no corresponding text descriptions. While our difficulty-aware contrastive loss helps

mitigate this problem by learning from weak correlations, the model's reliance on multi-modal synchrony imposes a data bottleneck. Future work should explore weakly supervised or self-supervised tri-modal training objectives, perhaps using pseudo-labeling for missing modalities or cycle consistency across modality pairs.

Another challenge involves generalization to unseen modalities or domain shifts. Although we test the model's robustness under controlled corruption—such as depth dropout or caption perturbation—it is unclear how well the learned representations extend to entirely new domains, such as satellite imagery, medical scans, or low-light environments. The current training pipeline uses a frozen vision backbone (ViT-B/16) pretrained on ImageNet-style data, which may encode biases that limit adaptability. For broader applicability, especially in cross-domain transfer learning or domain-invariant representation tasks, future systems may require meta-learning strategies or dynamically composable encoders that can adjust modality weights or attention heads depending on context.

Computational cost is also a relevant concern. Our multi-stream architecture, while effective in preserving modality-specific features, introduces nontrivial memory and compute overhead due to maintaining separate encoders and multiple attention layers per modality. Although we employ techniques such as weight sharing in the upper transformer blocks and activation checkpointing to reduce memory usage, training remains slow and sensitive to batch size. In practice, a full pretraining run on the COCO+SUN hybrid corpus requires approximately 170 GPU-hours on A100 hardware. This restricts rapid iteration and may hinder accessibility for smaller research groups. Exploring lightweight fusion strategies, such as adapter layers, knowledge distillation from tri-modal teachers, or dynamic pruning mechanisms could significantly reduce model size and inference latency, making deployment on edge devices or mobile platforms feasible.

From a modeling standpoint, we also observe that tri-modal fusion introduces representational entanglement when modalities are weakly informative or inconsistent. For example, in scenes where the depth map contains strong occlusion artifacts or where captions contain stylistic or idiomatic language, the model may struggle to resolve semantic conflicts across streams. While our late-fusion design allows for independent stream refinement prior to merging, it does not include any explicit modality confidence estimation. In future iterations, incorporating uncertainty modeling, such as Bayesian attention masks or reliability scores per modality, could help the fusion mechanism assign appropriate weights depending on input quality. This would be especially useful in real-time human-robot interaction, where sensor quality can vary dramatically from frame to frame.

Another practical concern is the difficulty of interpreting model decisions, particularly under failure cases. Although we provide attention visualizations and t-SNE plots, these are primarily diagnostic tools that require manual inspection. For deployment in high-stakes applications such as autonomous vehicles or medical triage systems, more formal interpretability and safety guarantees are needed. Integrating formal reasoning modules, causal inference layers, or counterfactual explanation engines into the tri-modal transformer could provide not only greater transparency but also opportunities for human oversight and post-hoc correction.

Lastly, there remains an open question about how such cross-modal systems scale beyond three modalities. While our architecture supports image, text, and depth, modern multimodal systems often include video, audio, pose estimation, tactile sensing, and symbolic knowledge graphs. Extending our framework to a general multi-N-modal learning paradigm would require rethinking the interaction structure in the transformer: a naive approach would increase memory quadratically with modality count. Efficient interaction patterns, such as hierarchical fusion, attention routing, or sparse entanglement matrices, could provide a path forward. Furthermore, designing benchmarks that evaluate real-world task compositionality — such as robotic manipulation with vision, language, and force input — would help contextualize the benefits of adding new modalities versus improving core alignment in existing ones.

In conclusion, although our model presents a robust and flexible approach to cross-modal representation learning, there are substantial challenges to address before it can be considered universally deployable. These include removing the need for triplet-aligned data, improving generalization and interpretability, reducing compute costs, handling modality-specific noise, and scaling the architecture to broader input formats. Addressing these challenges will not only refine the proposed method but also lay foundational work for building truly general-purpose AI systems that can perceive, reason, and act in the complex, multimodal world we inhabit.

8. Conclusion

In this paper, we proposed a unified cross-modal representation learning framework that effectively integrates vision, language, and depth information through a multi-stream transformer architecture and a tri-modal contrastive learning objective. By preserving modality-specific inductive biases and encouraging robust semantic alignment through difficulty-aware negative sampling, our system achieves state-of-the-art performance across a wide spectrum of tasks, including image-text retrieval, zero-shot classification, and visual question answering. Extensive experiments on COCO, Flickr30k, VQAv2, and SUN RGB-D datasets validate the benefits of including geometric modality, as well as the importance of our contrastive loss design and fusion strategy. The system demonstrates strong generalization, resilience to noise and occlusion, and interpretable behaviors as evidenced by attention maps and embedding analysis.

Nevertheless, we acknowledge several limitations, such as reliance on triplet-aligned training data, computational overhead, and sensitivity to domain shifts. We discussed

potential improvements including lightweight architecture variants, uncertainty-aware fusion, and extensions to multi-N-modal scenarios. Our findings contribute to the growing field of multimodal AI and offer a scalable foundation for building next-generation visual systems capable of real-world understanding and reasoning.

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