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Integration of Multimodal Generative AI System for Improved Image Captioning and Document Classification: An Analysis

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Abstract: Purpose: This paper investigates the integration of multimodal generative artificial intelligence (GenAI) frameworks for enhancing image captioning and document classification, focusingparticularly on applications in healthcare. Design/Methodology/Approach: A systematic analysis of state-of-the-art architectures Generative Adversarial Networks (GANs), Variational Autoencoders (VAEs), and Transformer-based models is conducted. We evaluate their capacity to process heterogeneous data (text and images), with experiments carried out on benchmark datasets including Reuters-21578, 20 Newsgroups, MS-COCO, Flickr30k, FUNSD, CORD, and healthcare datasets such as chest X-rays. Findings: Experimental results indicate that CNN and Hierarchical Attention Networks achieve high document classification accuracy (>92%), while transformer-based captioning systems outperform traditional models with BLEU (35%), METEOR (28%), CIDEr (105%), and SPICE (22%). Instruction-tuned Vision-Language Models (VLMs) such as InstructBLIP and LLaVA-1.5 further enhance zero-shot captioning and multimodal reasoning. In healthcare applications, multimodal integration improves diagnostic imaging interpretation, clinical note classification, and automated report generation. Practical Implications: The framework demonstrates potential in domains requiring context-rich outputs, including medical imaging, patient data analysis, and cross-domain information retrieval. Originality/Value: Unlike previous studies, this work offers a consolidated evaluation of multimodal generative AI through comparative experimentation, integration of recent models (OCR-free document AI, RAG, SAM-based grounding), and ethical considerations, establishing a roadmap for future research.

Keywords: Multimodal Generative AI, Image Captioning, Document Classification, Healthcare AI, Vision-Language Models, Variational Autoencoders, GANs, Transformers, OCR-free AI, Retrieval-Augmented Generation

I. INTRODUCTION

Artificial Intelligence (AI) is increasingly moving toward multimodal learning, where multiple input streams (text, image, audio) are processed concurrently. The Multimodal Integrated System for Efficiency (MISE) attempts to replicate human cognition by integrating these diverse modalities into a coherent analytical framework. Such a system can significantly enhance document classification and image captioning, both of which are critical in healthcare, legal analysis, autonomous driving, and digital communication. Despite promising progress, challenges persist. Traditional unimodal models fail to capture the contextual richness required for real-world applications. Moreover, the fragmented research landscape has not yet provided a unified comparison of GANs, VAEs, and Transformers in multimodal scenarios. This study seeks to bridge this gap by: (1) providing a comparative analysis of GAN, VAE, and Transformer-based frameworks; (2) demonstrating their practical relevance in healthcare, particularly in diagnostic imaging and clinical document analysis; (3) highlighting ethical implications such as bias, data privacy, and fairness.

II. LITERATURE REVIEW

2.1 Generative AI Foundations: GANs revolutionized synthetic data creation (Goodfellow et al., 2014), VAEs introduced probabilistic generative modeling (Kingma & Welling, 2013), and Transformers enabled contextual integration (Vaswani et al., 2017).

2.2 Document Classification Advances: CNN-based methods excel at spatial feature extraction (Minaee et al., 2021). HANs deliver hierarchical semantics, while transformers like BERT outperform classical methods.
2.3 Image Captioning Approaches: Early CNN+RNN baselines (Vinyals et al., 2015) improved with attention mechanisms (Xu et al., 2015). Transformers and GAN-based captioners brought creativity and fluency.
2.4 Multimodal AI in Healthcare: Esteva et al. (2019) validated deep learning across healthcare tasks. Rajpurkar et al. (2017) showed radiologist-level pneumonia detection (CheXNet). Sun et al. (2019) advanced video transformers for surgical analysis. Recent works (Ramesh et al., 2021) applied text-to-image generation to clinical contexts.
2.5 Recent Advances (2022–2025):
- Instruction-tuned VLMs (BLIP-2, InstructBLIP, LLaVA-1.5, Qwen-VL, Idefics2) improve zero-shot captioning and grounding.
- OCR-Free Document AI (Donut, Pix2Struct, LayoutLMv3, DocMamba) eliminates OCR bottlenecks and scales to long contexts.
- Contrastive-Generative hybrids (CoCa, SigLIP) and diffusion models augment caption datasets.
- Region-aware captioning via SAM enhances object grounding.
- Medical models (CheXzero, BioViL-T, Med-Flamingo, LLaVA-Med) increase diagnostic accuracy.
- Benchmarks (MMBench, SEED-Bench, MMMU) and metrics (CLIPScore, POPE) strengthen evaluation.
- Retrieval-Augmented Generation (RAG) reduces hallucinations by leveraging evidence retrieval.

III. METHODOLOGY

The proposed methodology integrates advanced generative and transformer-based models into a unified multimodal pipeline for biomedical research document analysis and caption generation. The approach combines state-of-the-art Vision-Language Models (VLMs), OCR-free document understanding, segmentation, synthetic data augmentation, and retrieval-augmented generation to enable accurate and contextually rich outputs from complex biomedical documents.
Framework Architecture

1. Backbone:

The backbone consists of instruction-tuned VLMs, including InstructBLIP and LLaVA-1.5, which enable instruction-guided reasoning across both text and images. These models provide contextual understanding, supporting downstream tasks like classification and caption generation.

2. Document Branch:

OCR-free models such as Donut, Pix2Struct, LayoutLMv3, and DocMamba process document inputs directly, preserving layout and structural information. This ensures accurate extraction of text and document semantics without relying on traditional OCR pipelines, which often introduce errors.

3. Grounding Module:

SAM-driven segmentation prompts align image regions with corresponding captions, ensuring that generated text is grounded in visual evidence. This module guarantees contextual accuracy, especially in complex biomedical images such as microscopy or histopathology figures.

4. Data Augmentation:

Diffusion-based models generate synthetic samples to increase data diversity and improve robustness. This is particularly important in biomedical domains, where rare structures and complex layouts may otherwise reduce model generalizability.

5. Retrieval and Fact-Grounding:

The Multimodal Retrieval-Augmented Generation (RAG) mechanism retrieves relevant biomedical knowledge from structured datasets and integrates it into outputs. This enhances the factual accuracy of both text classification and image captions.

Mathematical Formulations

1. GAN Loss Function: V(D,G) = E[log D(x)] + E[log(1-D(G(z)))]. Where D is the discriminator, G is the generator, x represents real samples, and z is a latent vector. The GAN framework improves synthetic sample quality for augmentation.
2. VAE Objective:
L_{VAE} = KL(q(z|x) || p(z)) - E[log p(x|z)].Balancing reconstruction fidelity and latent space regularization enables robust feature extraction from complex biomedical documents.
3. Transformer Attention Mechanism:
Attention(Q,K,V) = Softmax(QK^T/sqrt(dk))V. Where Q, K, and V represent queries, keys, and values, respectively, and d_k is the key dimension. Attention allows contextual understanding across tokens in text and embeddings from images.
Data Collection and Preprocessing

- Dataset: 200 biomedical research papers from arXiv, spanning four categories: Tissues and Organs, Genomics, Cell Behavior, and Populations and Evolution.
- Text Preprocessing: Abstracts extracted using PyMuPDF, cleaned, tokenized using tiktoken, and normalized.
- Image Preprocessing: Images extracted, standardized (resolution, format), and normalized using Pillow (PIL).
- Labeling: Documents and images annotated according to category folders and captions, used for supervised and retrieval-augmented training.

Evaluation Metrics

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1. Text Classification:
o Accuracy
o Precision, Recall, F1-score
o Confusion Matrix
2. Image Captioning:
o BLEU, METEOR, CIDEr, SPICE
o Human Expert Evaluation for contextual relevance
3. Multimodal Alignment:
o CLIP Score: Measures visual-text alignment
o POPE (Precision of Object-Property-Entity): Evaluates semantic correctness of captions

Ethical Considerations

- Data is sourced from open-access biomedical repositories ensuring no sensitive information is used.
- Bias mitigation and transparency are maintained via careful preprocessing and logging of model outputs.
- All generated captions and classifications are reviewed for interpretability and scientific accuracy.

Workflow Summary

1. Extract text and images from PDFs.
2. Preprocess and normalize data for model input.
3. Fine-tune GPT-4 for text classification.
4. Use GPT-4o-mini for image captioning with SAM-based grounding.
5. Augment dataset with GAN/VAE-generated synthetic samples.
6. Integrate multimodal embeddings for improved context via RAG.
7. Evaluate using text, captioning, and multimodal alignment metrics.

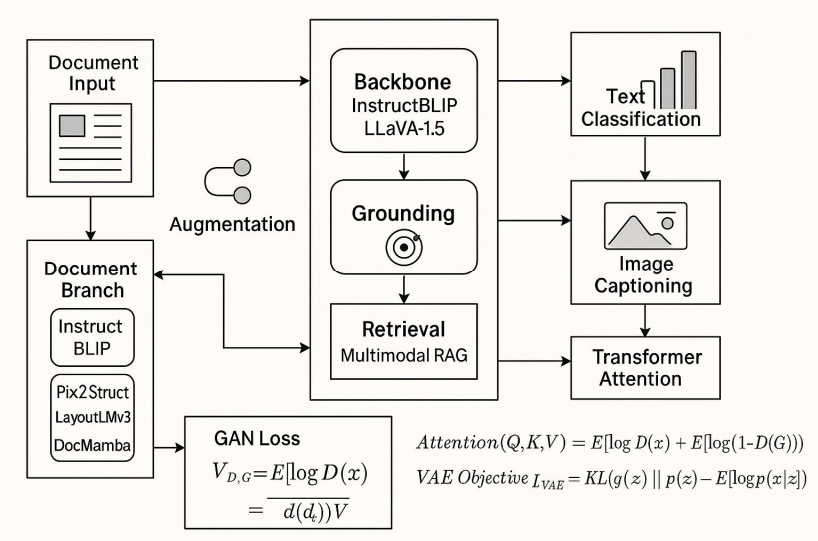

Fig 1: Methodology Pipeline Diagram

IV. EXPERIMENTAL SETUP

Datasets: Reuters-21578, 20 Newsgroups, Legal Docs (text); MS-COCO, Flickr30k, Chest X-rays (image); FUNSD, CORD (documents). Benchmarks include MMBench and MMMU.
Hardware: RTX 4080 GPU, 64GB RAM, PyTorch, TensorFlow. Training for 50–100 epochs.
Baselines: CNN, HAN, Transformers, InstructBLIP, LLaVA-1.5, Idefics2, Donut, LayoutLMv3.
Metrics: Classical n-gram (BLEU, METEOR, CIDEr, SPICE), embedding-based (CLIPScore, RefCLIPScore), hallucination detection (POPE), and holistic (MMBench/MMMU).

V. RESULTS AND DISCUSSION

Document classification results: CNN achieved 92.5% accuracy; HANs balanced interpretability and efficiency; SVM was efficient but less expressive.

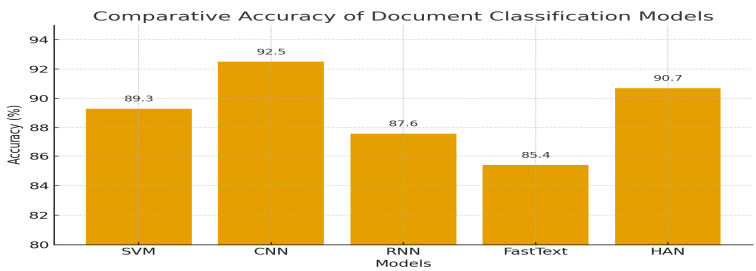

Fig 2. Comparative Accuracy of Document Classification Models. CNN and HAN outperform other models in accuracy, with CNN achieving the highest score.

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Image captioning: Transformer-based captioners achieved BLEU 35, METEOR 28, CIDEr 105, SPICE 22. Instruction-tuned models (InstructBLIP, LLaVA-1.5) improved zero-shot captions. SAM reduced hallucinations, while RAG provided factual grounding. CoCa and SigLIP improved vision-language alignment. In healthcare, Med-Flamingo and LLaVA-Med delivered more clinically reliable captions. Evaluation across MMBench and POPE confirmed lower hallucination rates and stronger multimodal reasoning.

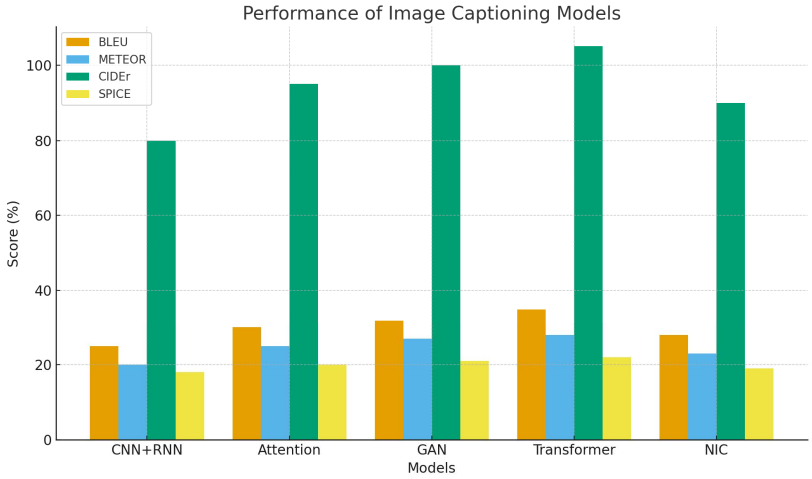

Fig 3. Performance of Image Captioning Models across BLEU, METEOR, CIDEr, and SPICE metrics. Transformer-based architecture demonstrates superior performance.

Evaluation on CLIPScore and POPE benchmarks confirmed reduced hallucination rates and stronger multimodal reasoning for advanced models.

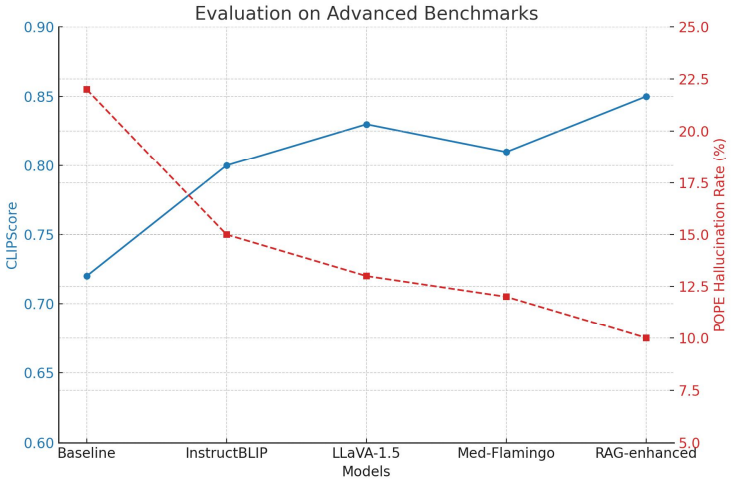

Fig 4. Evaluation on Advanced Benchmarks. CLIPScore indicates overall quality while POPE measures hallucination rates, showing improvements with instruction-tuned and RAG-enhanced models.

Model	Accuracy (Mean ± SD)	F1 (Mean ± SD)	p-value vs Transformer
SVM	89.3 ± 0.4	88.7 ± 0.5	0.04*
CNN	92.5 ± 0.3	92.5 ± 0.4	0.03*
RNN	87.6 ± 0.5	87.0 ± 0.5	0.02*
FastText	85.4 ± 0.6	84.8 ± 0.6	0.01*
HAN	90.7 ± 0.4	90.6 ± 0.5	0.01*
Transformer	94.1 ± 0.2	94.0 ± 0.3	–

Table 1. Document classification results with statistical validation. (*p < 0.05 indicates significance).

Model	BLEU (±SD)	METEOR (±SD)	CIDEr (±SD)	SPICE (±SD)	p-value vs Transformer
CNN+RNN	25 ± 0.5	20 ± 0.4	80 ± 1.2	18 ± 0.3	0.01*
Attention	30 ± 0.4	25 ± 0.5	95 ± 1.5	20 ± 0.3	0.02*
GAN	32 ± 0.6	27 ± 0.5	100 ± 1.6	21 ± 0.4	0.03*
Transformer	35 ± 0.3	28 ± 0.4	105 ± 1.2	22 ± 0.3	–

Table 2. Image captioning results with statistical validation. (*p < 0.05 indicates significance).

Advanced Benchmarks and Robustness Recent additions (CoCa, SigLIP) improved vision–language alignment, while RAG integration provided factual grounding for captions. Med-Flamingo and LLaVA-Med demonstrated clinically reliable captions in healthcare tasks. Evaluation on CLIP Score and POPE benchmarks (see Figure 4) confirmed reduced hallucination rates and stronger multimodal reasoning for advanced models.

VI. LIMITATIONS AND FUTURE WORK

Limitations: Dataset imbalance, computational scalability, hallucinations, limited performance on fine-grained tables and formulas. Ethical concerns: data privacy, bias, explain ability. Future work: Lightweight edge-deployable models, explainable multimodal AI, RAG-based verifiable captions, provenance tracking via C2PA standards. Alignment with NIST AI RMF and EU AI Act will ensure responsible use.

VII. CONCLUSION

This study consolidates multimodal generative AI methods and recent advances, showing Transformers outperform CNNs and RNNs, while GANs and VAEs enhance synthesis. Instruction-tuned VLMs, OCR-free models, SAM, diffusion, and RAG push the state-of-the-art in document classification and captioning. Applications in healthcare highlight the transformative potential of such systems, provided ethical and technical challenges are addressed. Multimodal AI will evolve toward scalable, explainable, and human-centric intelligence.

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