Multimodality in Large Language Models: State of the Art (February 2025)

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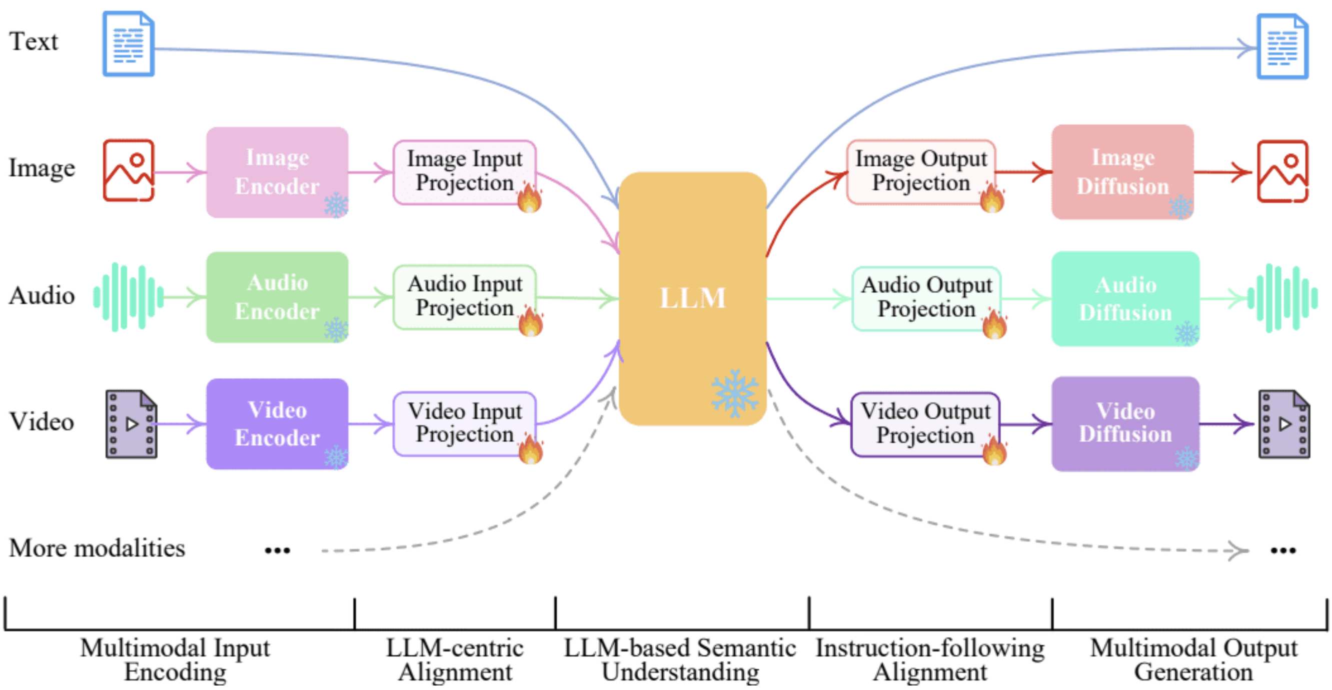
1. Introduction

Multimodality in large language models (MLLMs, as per its English acronym) represents a key frontier in artificial intelligence, integrating modalities such as vision, text, video, and audio to achieve a more human-like understanding. These systems, capable of *"seeing, listening, and speaking"*, accept diverse inputs (images, videos, sounds, and text) and produce natural language responses in either conversational or descriptive formats. This document offers an exhaustive investigation of the state of the art as of February 28, 2025, combining analysis of recent literature with practical perspectives. It addresses critical questions about **advances, trends, and challenges**, enriching the analysis with open resources that facilitate experimentation in the field.



2. Definition and Objectives

- **Theme:** Multimodality in large language models, that is, the integration of vision, text, audio, and video capabilities within a single language model.
- **Specific Objectives:**
  - **State of the Art:** Identify the most recent advances in multimodal models up to February 2025, highlighting milestones and outstanding examples.
  - **Trends and Challenges:** Analyze dominant techniques, emerging architectures, and persistent challenges such as visual hallucinations, biases, and computational costs.

- **Practical Application:** Provide open resources and practical lessons (models, repositories, *benchmarks*) to facilitate fieldwork and experimentation.

3. Research Methodology

The collection of information was based on official, academic, and community sources. The **Hugging Face Daily Papers** summaries from 2024 and early 2025 [1] were reviewed, complemented with searches on **arXiv** and official documentation from developers such as Hugging Face and Alibaba.

Selection Criteria: Publications from 2024 and 2025 were prioritized, focusing on models with public implementations (e.g., Hugging Face Hub) for practical experimentation. Technical articles, corporate reports, and blogs were analyzed, cross-checking quantitative data between sources to ensure accuracy.

4. State of the Art (Feb. 2025)

In early 2025, MLLMs have achieved **surprising capabilities** in visual understanding and visuo-linguistic reasoning, evolving from prototypes to robust systems that integrate multiple modalities. A foundational milestone was **GPT-4 with vision (GPT-4V)** from OpenAI (2023), which interpreted complex images and reasoned about diagrams without explicit OCR [2]. In parallel, *DeepMind* introduced **Flamingo** (2022), a pioneering model in processing interleaved sequences of images and text with few-shot learning [3]. These advances laid the groundwork for a trend toward foundational multimodal models.

A key approach is the **convergence of pre-trained vision models with existing LLMs**, avoiding costly training from scratch. Flamingo combined an NFNet visual encoder with **Chinchilla** (70B parameters) using cross-attention layers [3], while OpenAI integrated vision into GPT-4 built on GPT-3.5 [2]. Google advanced with **PaLI** and **PaLM-E**, applying vision to tasks ranging from VQA to robotics [5], and Microsoft developed **Kosmos-1** (2023) for visual IQ tests and OCR, followed by **Kosmos-2** with visuo-linguistic fusion [6].

The **explosion of open-source efforts** between 2023 and 2024 democratized the field. Models such as **LLaVA**, **MiniGPT-4**, **BLIP-2**, **OpenFlamingo**, and **IDEFICS** replicated GPT-4V's capabilities on a smaller scale [7]. **IDEFICS (80B)** from Hugging Face (2023), trained with public data, rivaled Flamingo in vision-text tasks [8]. The **fine-tuning with visual instructions** (*visual instruction tuning*), using datasets generated by GPT-4, improved visual dialogue and reduced hallucinations [10].

By 2025, MLLMs have transcended static images, integrating **video and audio**. Models such as **Qwen2.5VL** and **Baichuan-Omni-1.5** (detailed later) process long videos and omni-modal inputs, marking a step toward truly comprehensive systems [11][22][23].

5. Recent Multimodal Models (2024–2025)

The period 2024–2025 saw the emergence of models that expanded the state of the art:

- **IDEFICS2 (Hugging Face, 2024):** With 8B parameters, this open model improves OCR and high-resolution image handling, trained with ~6 TB of scanned documents [12]. Its visuo-textual fusion uses a *Perceiver* module to project visual embeddings into the LLM's space [13].

- **ShareGPT4Video (Shanghai AI Lab, 2024):** Extends LLMs to video with temporal understanding, achieving leadership in Video QA with 8B parameters and only ~5 hours of training on 8 A100 GPUs [14]. Its dataset includes ~40K videos annotated by GPT-4V and ~4.8M generated by *ShareCaptioner-Video* [15].

- **DeepSeek-V3 (DeepSeek AI, Dec. 2024):** A Mixture-of-Experts (MoE) language model with **671B** total parameters (37B active per token) trained with **14.8T** high-quality tokens. With **open weights** and a multimodal vocation (simultaneously processes text and images), it achieves performance comparable to the best closed models through remarkably efficient computational training [27][28].

- **Qwen2.5VL (Alibaba, Feb. 2025):** Introduces dynamic resolution processing and long video understanding, with precise object localization and robust document analysis [22]. It surpasses previous models in complex visual tasks.

- **Long-VITA (Feb. 2025):** Scales to 1M tokens, processing more than 4,000 frames with parallel distributed inference, leading in Video-MME [23].

- **Baichuan-Omni-1.5 (Jan. 2025):** Supports text, image, video, and audio, with both text and audio outputs, outperforming GPT-4o mini in multimodal tasks thanks to an advanced audio tokenizer [24].

- **Qwen2.5-Max (Alibaba, Jan. 2025):** A large-scale MoE architecture pre-trained with over **20T** tokens, refined through supervised fine-tuning and reinforcement learning from human feedback [29]. It demonstrates superior results to open models like DeepSeek-V3 in tests of knowledge, programming, and human preference [30], rivaling the most advanced closed systems in various tasks.

Other advances include **Qwen-VL**, **LLaVA-1.5**, and **VITA-1.5**, whose open weights have boosted industrial adoption [16][25].

6. Multimodal Techniques and Architectures

Large multimodal language models (MLLMs) are built upon three fundamental components:

1. A **visual (or multimodal) encoder** that transforms images, videos, or audio into high-quality latent representations.
2. A **large language model (LLM)** responsible for processing text and generating coherent natural language responses.
3. A **fusion module** that effectively integrates the representations from different modalities into a unified space for the LLM [17].

This design is illustrated in *Figure 1*, which presents a clear diagram of the typical MLLM architecture. In this diagram, available at `img/mllm_architecture_diagram.png`, one can see how multimodal inputs — such as images or video sequences — flow from the visual encoder to the fusion module, and then are processed by the LLM to generate text as output [18]. This graphical representation highlights the interaction between the components, emphasizing the importance of efficient integration.

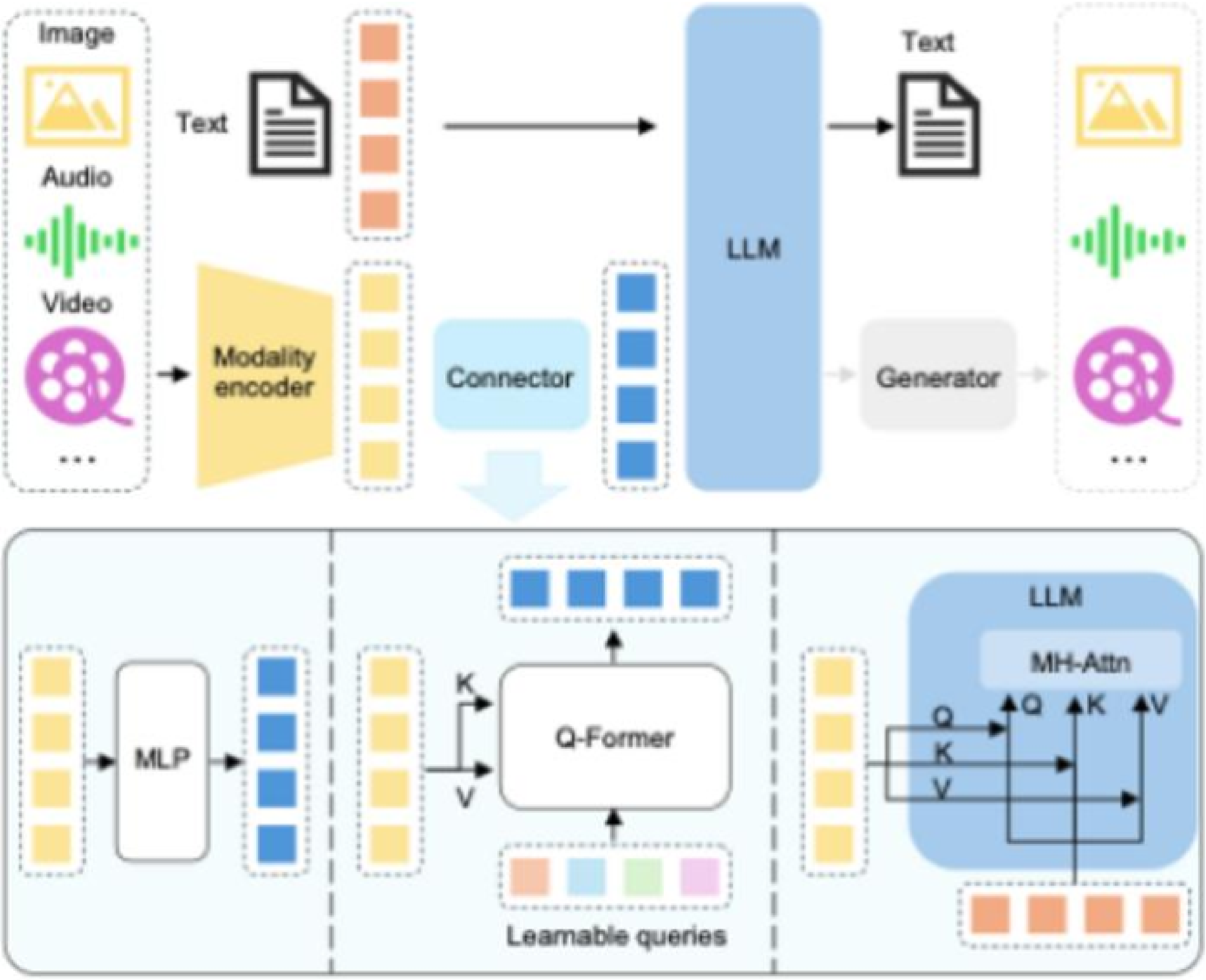


Figure 1: Diagram of an MLLM architecture, illustrating the data flow from multimodal inputs (images, video, audio) through the visual encoder and fusion module, to the LLM that produces the textual output.

Multimodal Fusion Strategies:

- **(A) Late Fusion:** Visual features are converted into embeddings that are directly concatenated to the text tokens before entering the LLM, simplifying the training process [17].
- **(B) Cross-Attention:** Specialized cross-attention layers, implemented in models such as Flamingo [3] and BLIP-2 [19], allow a deeper integration by dynamically connecting visual and textual information at multiple stages of processing.

Both approaches offer advantages: late fusion reduces computational complexity, whereas cross-attention enhances the model's ability to capture complex relationships between modalities.

Emerging Techniques:

- **Dynamic Resolution Processing (Qwen2.5VL):** Adapts images of different sizes without fixed resizing, optimizing precision and efficiency [22].
- **Parallel Distributed Inference (Long-VITA):** Accelerates the handling of long contexts, such as extended videos, through distributed computing [23].
- **Audio Tokenization (Baichuan-Omni-1.5):** Simultaneously captures semantics and acoustic properties, facilitating the integration of audio with other modalities [24].

- **Multivisual Chain-of-Thought:** Decomposes reasoning about visual inputs into intermediate textual steps, improving accuracy in complex tasks [20].
- **Mixture-of-Experts (MoE):** Architectures such as those in LLaVA-MoD selectively activate specialized experts, reducing costs and scaling efficiently [21].

These innovations reflect an ongoing effort to overcome traditional limitations and advance toward more robust and versatile multimodal systems.

7. Key Benchmarks and Multimodal Evaluation

The evaluation of MLLMs is based on a combination of classic vision-language benchmarks and modern datasets specifically designed for their multimodal capabilities:

- **Image Captioning:** The *MS COCO Captions* benchmark measures the quality of generated descriptions using metrics such as BLEU, ROUGE, METEOR, and CIDEr. For example, PaLI-X (55B) achieved a CIDEr score of ~149 [5].
- **Visual Question Answering (VQA):** *VQAv2*, with ~80K images and ~444K questions, evaluates answer accuracy, where the best models achieve ~85% [6].
- **Text-in-Image QA:** Tasks such as *TextVQA* and *DocVQA* test the comprehension of text within images; IDEFICS2 obtained ~74% accuracy on DocVQA [12].
- **Visual Reasoning:** Benchmarks such as *NLVR2*, *Visual Entailment*, and *CLEVR* analyze the ability to reason about relationships and visual attributes [20].
- **Video Evaluation:** Datasets such as *MSRVTT-QA*, *ActivityNet-QA*, *VideoBench*, and *TempCompass* assess temporal and causal understanding, with Long-VITA excelling in VideoBench [14][23].
- **Holistic Benchmarks:** *MMBench* and the recent *MMStar* (2025) provide comprehensive evaluations, covering perception, reasoning, and essential vision tasks [16][26].

These benchmarks provide a comprehensive view of the performance of MLLMs, highlighting both their strengths and areas for improvement in multimodal contexts.

8. Computational Costs and Current Limitations

MLLMs inherit the high computational demands of text-based LLMs, amplified by the integration of additional modalities. Models such as Flamingo required hundreds of thousands of GPU-hours for their training [3], which has spurred strategies to mitigate these costs:

- **Efficient Fine-Tuning:** LLaVA-1.5 demonstrates that fine-tuning existing models significantly reduces the need for resources [9].
- **Architecture Optimization:** IDEFICS2 simplifies its fusion module [12], while MoE approaches, such as in LLaVA-MoD, allow smaller models to compete with larger ones [21].
- **High-Quality Synthetic Data:** Datasets such as ShareGPT4Video, generated with GPT-4V, reduce the cost of obtaining training data [15].
- **Advanced Infrastructure:** Distributed inference in Long-VITA optimizes hardware usage, accelerating the processing of extensive inputs [23].

Despite these advances, challenges such as visual hallucinations, data biases, and the difficulty of processing information in real time persist. However, innovations such as the dynamic processing of Qwen2.5VL are improving efficiency in complex visual tasks [22].

9. Code Implementations and the Open Ecosystem

The rise of MLLMs is closely linked to the open-source ecosystem, which has democratized their development and application:

- **Hugging Face Hub:** Hosts pre-trained models such as IDEFICS2 and Qwen2.5VL, ready for immediate use or customization [12][22].
- **Development Frameworks:** Projects such as OpenFlamingo and LAVIS offer standardized tools for training and evaluating MLLMs [7].
- **Multimodal Integrations:** The combination of tools such as Whisper (speech recognition) with visual models expands potential applications [16].
- **Permissive Licenses:** Models such as Long-VITA and Baichuan-Omni-1.5, released under open terms, accelerate their adoption in industry and academia [23][24].

This ecosystem fosters collaborative innovation and reduces barriers to accessing advanced multimodal technologies.

10. Conclusions and Outlook

In just a few years, MLLMs have evolved from systems with limited visual capabilities to comprehensive solutions that rival human understanding in certain tests [2]. Recent models such as Qwen2.5VL, Long-VITA, and Baichuan-Omni-1.5 are leading the advance in vision, video, and audio comprehension, opening new possibilities in fields such as healthcare, education, and robotics. Nevertheless, challenges such as computational efficiency, robustness against biases, and real-time integration require ongoing attention.

The future of MLLMs envisions the incorporation of more modalities —such as haptic or sensory data— and the development of mechanisms such as long-term memory or contextual knowledge retrieval. Driven by the open-source ecosystem, these systems promise to get ever closer to general artificial intelligence, combining versatility and efficiency.

11. References

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12. Table of Models and Sources

Model	Ref.	Main Source
GPT-4V	2	https://arxiv.org/abs/2303.08774
Flamingo	3	https://arxiv.org/abs/2206.00364
PaLI	5	https://arxiv.org/abs/2302.13971
PaLM-E	5	https://arxiv.org/abs/2302.13971
Kosmos-1	6	https://arxiv.org/abs/2304.09876
Kosmos-2	6	https://arxiv.org/abs/2306.14824
LLaVA	9	https://arxiv.org/abs/2304.08485
MiniGPT-4	-	https://arxiv.org/abs/2304.10592
BLIP-2	19	https://arxiv.org/abs/2301.12597
OpenFlamingo	7	https://arxiv.org/abs/2308.01390
IDEFICS	8	https://arxiv.org/abs/2308.01390
IDEFICS2	12	https://huggingface.co/blog/idefics2
ShareGPT4Video	14	https://arxiv.org/abs/2406.04325

Model	Ref.	Main Source
Qwen-VL/QwenVL-Chat	16	https://arxiv.org/abs/2308.12966
Qwen2.5VL	22	https://arxiv.org/abs/2502.13923
Long-VITA	23	https://arxiv.org/abs/2502.05177
Baichuan-Omni-1.5	24	https://arxiv.org/abs/2501.15368
VITA-1.5	25	https://arxiv.org/abs/2408.01319
MMStar	26	Hugging Face Datasets, 2025
DeepSeek-V3	27, 28	https://arxiv.org/abs/2412.19437 / AMD Instinct GPUs
Qwen2.5-Max	29, 30	https://qwenlm.github.io/blog/qwen2.5-max/