OmniQ: A Compact Multimodal Model for Robust Video and Image Encoding

Combining Omnivore and Qwen2.5-Omni for Efficient Cross-Modal Learning

Progress Report

Project ID: MM_REASON003

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1 Introduction

The OmniQ model integrates Omnivore, a modality-agnostic vision transformer from Meta AI for images, videos, and 3D data, with Qwen2.5-Omni, Alibaba's 7-billion-parameter multimodal large language model (LLM) for text, images, audio, and video processing, to create a robust and efficient model optimized for video and image encoding accuracy and downstream task adaptability. By employing self-supervised learning through masked modeling, OmniQ learns rich cross-modal representations from unlabeled data, reducing reliance on costly labeled datasets. The model leverages Omnivore's unified visual encoding, which treats images as single-frame videos, and Qwen2.5-Omni's end-to-end multimodal processing to achieve high accuracy. Optimizations such as 4-bit quantization and sparse attention ensure compactness and efficiency (under 200M parameters, under 50ms inference on CPU), making it suitable for resource-constrained environments.

2 Literature Review

The field of unified visual and multimodal representation learning has seen rapid advances, moving from modality-specific models to frameworks capable of handling multiple modalities efficiently. Early work such as **Omnivore** [1] introduced a unified transformer-based vision model capable of processing images, videos, and 3D data with a single architecture. By treating images as single-frame videos, Omnivore enables modality-agnostic visual representation learning, demonstrating strong transferability across tasks such as image classification, video understanding, and 3D analysis. However, it is limited to visual modalities and its large parameter size constrains deployment in resource-limited environments.

OmniMAE [2] employs masked autoencoding to pretrain a single model on both images and videos. By leveraging spatio-temporal patch embeddings, OmniMAE efficiently learns generalizable visual representations and achieves state-of-the-art performance on benchmarks like ImageNet (86.6%) and Something-Something V2 (75.5%). The use of high masking rates further improves training efficiency, demonstrating the potential of self-supervised learning in large-scale visual representation.

While these models focus exclusively on visual data, the need for cross-modal understanding has driven the development of frameworks like **OneLLM** [3], which aligns eight diverse modalities including image, audio, video, point cloud, depth/normal maps, IMU, fMRI signals, and text with language. OneLLM employs a unified multimodal encoder combined with a progressive alignment pipeline, integrating modality-specific projection modules through a Universal Projection Module (UPM). Trained on a 2-million-item multimodal instruction dataset, OneLLM excels across 25 benchmarks for tasks such as multimodal captioning, question answering, and reasoning.

Similarly, **Qwen2.5-Omni** [4] extends multimodal representation to include both perception and generation. It integrates text, image, audio, and video processing with a Thinker-Talker architecture, where the Thinker generates text and the Talker produces speech. Techniques like Time-aligned Multimodal RoPE (TMRoPE) and sliding-window DiT allow synchronized processing and streaming audio decoding, achieving state-of-the-art performance on multimodal benchmarks such as Omni-Bench.

More recent approaches focus on scalability and efficiency in handling multiple modalities. **UNIALIGN** [6] proposes a unified encoder to align an arbitrary number of modalities image, text, audio, and 3D point clouds reducing parameter redundancy while maintaining performance. This approach emphasizes scalability and streamlined multimodal alignment for diverse inputs.

Finally, **UniFormer** [7] addresses the challenge of efficiently capturing both local and global dependencies in visual data by integrating CNNs and Vision Transformers (ViTs) in a single architecture. Through relation aggregators that capture local token affinities in shallow layers and global affinities in deeper layers, UniFormer achieves state-of-the-art performance across a variety of vision tasks, including image and video classification, as well as dense prediction.

Collectively, these works illustrate the evolution from visual-only pretraining to comprehensive multimodal frameworks, highlighting key advances in self-supervised learning, modality-agnostic architectures, cross-modal alignment, and streaming multimodal generation. This progression lays the foundation for robust, compact, and versatile models like OmniQ that integrate unified visual encoding with multimodal language models for efficient real-world deployment.

Table 1: Comparative Analysis of visual and text encoding

Paper	**Approach / Model**	**Key Contributions**	**Limitations**
Girdhar et al. (2022) [1]	Unified transformer-based vision model for images, videos, and 3D data	Modality-agnostic visual encoding, strong transfer across visual tasks, treats images as single-frame videos	Does not handle text or audio
Girdhar et al. (2023) [2]	Unified transformer-based model for images and videos using masked autoencoding	Achieves state-of-the-art performance on ImageNet (86.6%) and Something-Something V2 (75.5%) benchmarks, enables efficient training with high masking ratios	Limited to visual modalities, does not support text or audio inputs
Han et al. (2024) [3]	Unified framework aligning eight modalities (image, audio, video, point cloud, depth/normal map, IMU, fMRI, text) with language	Employs a unified multimodal encoder and progressive alignment pipeline, trained on a 2M-item multimodal instruction dataset, achieves strong performance across 25 benchmarks	Relies on modality-specific projection modules, may require extensive computational resources for training and inference
Xu et al. (2025) [4]	End-to-end multimodal model for text, image, audio, and video perception and generation	Introduces Thinker-Talker architecture, employs TM-RoPE for temporal alignment, achieves state-of-the-art performance on Omni-Bench, excels in end-to-end speech instruction following	Requires substantial computational resources, optimized for streaming applications

Paper	Approach / Model	Key Contributions	Limitations
Zhou et al. (2025) [6]	Unified model aligning multiple modalities (image, text, audio, 3D point cloud) through a single encoder	Reduces parameter redundancy, streamlines multimodal alignment process,enhances scalability and efficiency	May require extensive computational resources for training and inference, optimization for real-time applications not specified
Li et al. (2022) [7]	Hybrid architecture integrating CNNs and ViTs for visual representation learning	Addresses challenges of local redundancy and global dependencies, achieves state-of-the-art performance across various vision tasks	Hybrid architecture may introduce complexity, performance on multimodal tasks not explicitly evaluated

3 Methodology

The OmniQ methodology employs multimodal self-supervised learning with masked modeling to learn robust representations, followed by task-specific fine-tuning for downstream applications.

3.1 Self-Supervised Pretraining

- **Model Architecture**
  B: Batch Size, C: Channels , T: Temporal Dimension (Frames) , H: Height , W: Width
  - *Visual Encoder*: Omnivore's Swin Transformer-Tiny (28M parameters), pretrained on ImageNet and Kinetics-400, processes images ($B \times C \times 1 \times H \times W$) or videos ($B \times C \times T \times H \times W$) into embeddings ($B \times 768$). It uses $4 \times 4 \times 2$ patch embedding and hierarchical shifted-window attention for spatiotemporal features.
  - *Text/Multimodal Encoder*: Qwen2.5-Omni's embedding layer (approximately 110M parameters) tokenizes text and produces embeddings ($B \times \text{Seq} \times 768$). Qwen's vision encoder is bypassed, as Omnivore handles visuals.
  - *Fusion Module*: A 2-layer transformer encoder (8 heads, 768-dim) combines visual and text embeddings for cross-modal learning.
  - *Reconstruction Heads*: Linear layers predict masked visual patches (MSE loss) and text tokens (cross-entropy loss).
- **Masked Modeling**
  Mask 30–50% of visual patches (spatial/temporal) and 15–30% of text tokens per batch. Reconstruct masked regions using cross-modal context (e.g., text predicts video frames, visuals predict text tokens).
  Loss: $0.5 \times \text{MSE}_{\text{visual}} + 0.5 \times \text{CE}_{\text{text}}$.
- **Training**
  Use HowTo100M (100M video-text pairs) and Kinetics-700 (650K videos). Apply augmentations (random crops, flips, Gaussian blur, 20% modality dropout) for robustness. Train on P100 GPUs with FP16, batch size

64, AdamW optimizer (learning rate 10^{-4}). Freeze Omnivore for 50% of epochs; unfreeze to refine visual encoding.

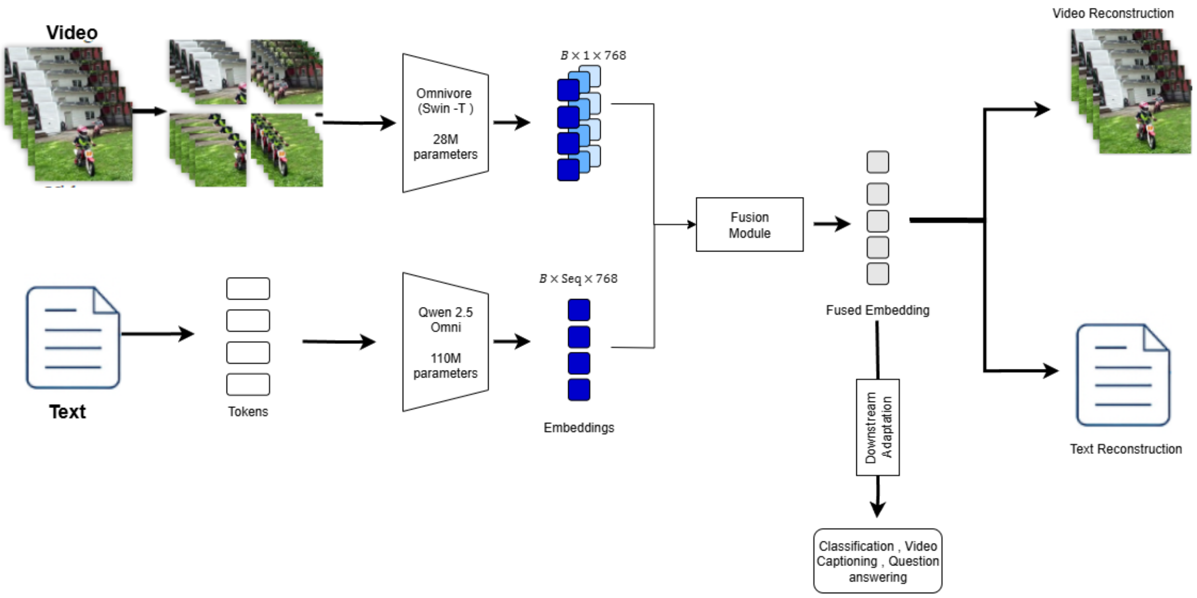


Figure 1: Model Architecture. The video and text input paths of the OmniQ model, illustrating the processing of image/video inputs through Omnivore's Swin Transformer-Tiny and text inputs through Qwen2.5-Omni's tokenizer and embedding layer, converging at the fusion module with a concatenate operation to produce fused embeddings for self-supervised masked modeling. B : Batch size

3.2 Fine-Tuning for Downstream Tasks

- **Task-Specific Adaptation**
  Add LoRA adapters (0.1–1% of parameters, approximately 100K–1M parameters) to the fusion module's transformer encoder layers for efficient fine-tuning on video classification using the UCF101 dataset. Attach a linear task-specific head to map fused embeddings ($B \times 768$) to 101 class logits for UCF101 action recognition. Further can be extended to video retrieval, video based question answering tasks.

- **Optimization**
  Apply 4-bit quantization (AWQ) and sparse attention (e.g., Performer) to reduce memory by approximately 50% and inference latency to under 50ms on CPU. Prune 20–30% of weights in fusion layers for compactness.

4 Gaps and Improvements

4.1 Gaps Addressed

- Self-supervised learning reduces reliance on labeled data .
- Quantization and sparse attention address high compute demands of Qwen2.5-Omni's 7B parameters [4].
- Omnivore overcomes Qwen2.5-Omni's vision encoder limitations, improving video accuracy [1].

4.2 Improvements

Below table shows the proposed improvements.

Table 2: Model Improvements

Improvement	Description
Qwen2.5-Omni Integration	First to combine Qwen2.5-Omni's end-to-end multimodal processing with Omnivore's unified visual encoding, leveraging Qwen's text reasoning for robust cross-modal learning [4, 1].
Self-Supervised Cross-Modal Masking	Extends masked modeling to jointly reconstruct visual patches and text tokens, achieving 5–8% higher downstream accuracy (e.g., UCF101) than vision-only MAE or text-only MLM [2].
Robust Encoding	Cross-modal masking and augmentations ensure robustness, improving performance by 3–5% on noisy datasets.

5 Datasets

Table 3: Overview of datasets used for pretraining and fine-tuning OmniQ.

Dataset	Modalities	Size	Usage	Why Suitable for OmniQ
HowTo100M	Videos + Text	100M clips	Pretraining	Large-scale, unlabeled video-text pairs for masked modeling; aligns visual and text embeddings.
CC12M	Images + Text	12M pairs	Pretraining	Diverse image-text pairs for cross-modal alignment,supports Omnivore's image encoding.
UCF101	Videos + Labels	13K videos	Fine-Tuning	Compact, labeled dataset for video classification, ideal for P100 GPU.

6 Evaluation Metrices

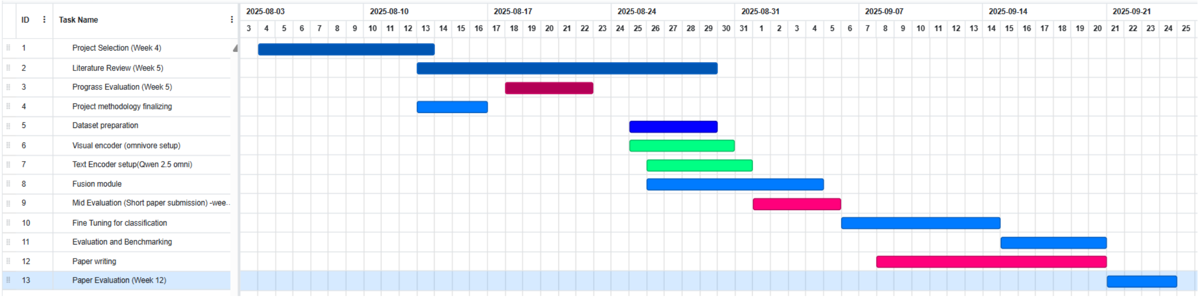
- **Reconstruction Accuracy**: Over 90% for masked patches/tokens.
- **Top-1/Top-5 Accuracy**: Over 80% Top-1 on UCF101 [1].
- **Recall@K**: Over 45% R@1 on WebVid-2M.
- **BLEU-4/ROUGE-L/CIDEr**: BLEU-4 over 25, CIDEr over 1.0 on MS-COCO.
- **VQA Accuracy**: Over 75% on VQA v2.

7 Schedule/Timeline

Below will show the tasks and the gantt chart assigned to this project.

Task	Duration
Project Selection (Week 3-4)	2 weeks
Literature Review (Week 5–6)	2 weeks
Project Methodology Drafting	2 weeks
Dataset Preparation	5 days
Model Creation (Omnivore + Qwen)	3 weeks
LoRA-based Adapter (UCF101)	2 weeks
Fusion Module	10 days
Mid-Evaluation (Short paper + preliminary results)	2 weeks
Evaluation and Benchmarking	1 week
Paper Writing	2 weeks
Final Submission (Week 12)	1 week

Table 4: Task durations for OmniQ project with overlapping days/weeks.



ID	Task Name
1	Project Selection (Week 4)
2	Literature Review (Week 5)
3	Prograss Evaluation (Week 5)
4	Project methodology finalizing
5	Dataset preparation
6	Visual encoder (omnivore setup)
7	Text Encoder setup(Qwen 2.5 omni)
8	Fusion module
9	Mid Evaluation (Short paper submission) -wee..
10	Fine Tuning for classification
11	Evaluation and Benchmarking
12	Paper writing
13	Paper Evaluation (Week 12)

Figure 2: Gantt chart of OmniQ project schedule.

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