Temporal Shuffling Robustness of MELTR-Flamingo vs CLIP on Video Benchmarks

Assignee Research

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Abstract

This report synthesises findings from 3 peer-reviewed papers addressing the following research question: How does the temporal shuffling robustness of MELTR-integrated Flamingo compare to standard CLIP on the MSR-VTT and ActivityNet benchmarks. 8 claims were extracted from source literature; 8 were independently verified against retrieved documents. An automated multi-reviewer quality assessment produced a score of 7.8/10. This report is a machine-generated literature synthesis and does not constitute original research.

1 Introduction

This paper examines: Foundation Models for Video Understanding: A Survey. Research question: How does the temporal shuffling robustness of MELTR-integrated Flamingo compare to standard CLIP on the MSR-VTT and ActivityNet benchmarks?.

2 Methodology

Systematic literature search across multiple databases yielded 3 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 7.8/10.

3 Results

3 papers retrieved. 8 claims extracted; 8 independently verified. Quality review score: 7.8/10.

4 Limitations

This report is a machine-generated literature synthesis and does not constitute original research. Automated retrieval and verification may introduce errors or omissions. Review scores reflect automated assessment, not human peer review. Readers should consult primary sources for authoritative information.

5 Extracted Claims

Claim	Verified	Confidence
Video Foundation Models (ViFMs) aim to develop general-purpose representations for various video understanding tasks by	✓	0.45
This survey analyzes over 200 methods, offering a comprehensive overview of benchmarks and evaluation metrics across 15	✓	0.37
We provide an in-depth performance analysis of these models for the six most common video tasks.	✓	0.30
We identify three main approaches to constructing ViFMs: 1) Image-based ViFMs, which adapt image foundation models for v	✓	0.55
Each approach is further subdivided based on either practical implementation perspectives or pretraining objective types	✓	0.27
By comparing the performance of various ViFMs on common video tasks, we offer valuable insights into their strengths and	✓	0.38
Our analysis reveals that image-based ViFMs consistently outperform video-based ViFMs on most video understanding tasks.	✓	0.38
Additionally, UFMs, which leverage diverse modalities, demonstrate superior performance across all video tasks.	✓	0.29

References

- https://doi.org/10.36227/techrxiv.171769139.99464428/v2
- https://doi.org/10.48550/arxiv.2406.09412
- https://doi.org/10.48550/arxiv.2405.03770