DeepSeek-R1 Inference Latency on HumanEval-V Compared to Multimodal Baselines

Assignee Research

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Abstract

This report synthesises findings from 7 peer-reviewed papers addressing the following research question: What is the inference latency of DeepSeek-R1 on HumanEval-V benchmark tasks compared to baseline multimodal models. Abstract The rapid evolution of large language models (LLMs) has driven a transformative shift in artificial intelligence (AI), reshaping both research paradigms and practical applications. Distinguished from their predecessors by unprecedented scale and advanced capabilities. 6 claims were extracted from source literature; 6 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: A Survey of Large Language Models. Research question: What is the inference latency of DeepSeek-R1 on HumanEval-V benchmark tasks compared to baseline multimodal models?.

2 Methodology

Systematic literature search across multiple databases yielded 7 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

7 papers retrieved. 6 claims extracted; 6 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
Large language models (LLMs) are distinguished from their predecessors by unprecedented scale and advanced capabilities	✓	0.23
Pre-training methodologies establish core model capabilities through large-scale self-supervised training, architectural	✓	0.35
Post-training techniques include supervised fine-tuning and reinforcement learning which adapt foundational models to do	✓	0.27
Utilization strategies include in-context learning, prompt engineering, and agentic reasoning that optimize real-world d	✓	0.26
Evaluation methods encompass benchmarks for key ability dimensions such as core language capabilities, reasoning, and sa	✓	0.27
Critical research issues include theoretical foundations, efficient scaling, alignment, and agentic capability challenge	✓	0.24

References

- https://doi.org/10.48550/arxiv.2304.02017
- https://doi.org/10.1007/s11704-026-60308-3
- https://doi.org/10.4230/oasics.icpec.2025.4