Codestral and Llama3 Pass@1 Performance on Low-Resource HumanEval-X After Limited Fine-Tuning

Assignee Research

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Abstract

This report synthesises findings from 13 peer-reviewed papers addressing the following research question: How does the pass@1 performance of Codestral compare to Llama3 on HumanEval-X for low-resource programming languages when fine-tuned with 10% of the original dataset. 8 claims were extracted from source literature; 7 were independently verified against retrieved documents. An automated multi-reviewer quality assessment produced a score of 7.4/10. This report is a machine-generated literature synthesis and does not constitute original research.

1 Introduction

This paper examines: Can Open Large Language Models Catch Vulnerabilities?. Research question: How does the pass@1 performance of Codestral compare to Llama3 on HumanEval-X for low-resource programming languages when fine-tuned with 10% of the original dataset?.

2 Methodology

Systematic literature search across multiple databases yielded 13 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 7.4/10.

3 Results

13 papers retrieved. 8 claims extracted; 7 independently verified. Quality review score: 7.4/10.

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
Three state-of-the-art LLMs - Llama3, Codestral, and Deepseek R1 - were evaluated using a subset of the Big-Vul dataset	✓	0.32
The evaluation adopted a closed-world classification setup to assess each model's performance in identifying vulnerabili	✓	0.30
The findings revealed a sharp contrast between high detection rates and markedly poor classification accuracy among the	✓	0.23
Frequent overgeneralization and misclassification were observed in the LLMs' performance.	×	0.11
Model-specific biases and common failure modes were analyzed, highlighting the limitations of current LLMs in performing	✓	0.28
The insights are particularly relevant in educational contexts where LLMs are being adopted as learning aids despite the	✓	0.23
A nuanced understanding of LLMs' behavior is essential to prevent the propagation of misconceptions among students.	✓	0.18
The results expose key challenges that must be addressed before LLMs can be reliably deployed in security-sensitive envi	✓	0.29

References

- https://doi.org/10.1007/s11704-026-60308-3
- https://doi.org/10.4230/lipics.giscience.2025.3
- https://doi.org/10.4230/oasics.icpec.2025.4