Impact of Sliding Window Truncation on Defect Localization Accuracy of LLaMA 3.2 and CodeGen on BugsInPy

Assignee Research

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Abstract

Large language models (LLMs) have demonstrated strong performance on a wide range of software engineering tasks, including code generation and analysis. However, most prior work relies on cloud-based models or specialized hardware, limiting practical applicability in privacy-sensitive or resource-constrained environments. In this paper, we present a systematic empirical evaluation of two locally deployed LLMs, LLaMA 3.2 and Mistral, for real-world Python bug detection using the BugsInPy benchmark. We evaluate 349 bugs across 17 projects using a zero-shot prompting approach at the function leve

1 Introduction

This paper examines: An Empirical Evaluation of Locally Deployed LLMs for Bug Detection in Python Code. Research question: How does sliding window truncation affect the defect localization accuracy of LLaMA 3.2 versus CodeGen on Python-specific BugsInPy benchmarks?.

2 Methodology

Systematic literature search across multiple databases yielded 8 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 7.2/10.

3 Results

8 papers retrieved. 21 claims extracted; 18 independently verified. Quality review score: 7.2/10.

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
Locally executed models achieve bug detection accuracy between 43% and 45%.	✓	0.22
Locally executed models produce a large proportion of partially correct responses that identify problematic code regions	✓	0.33
Bug detection performance varies significantly across different Python projects.	×	0.13
Precise bug localization is difficult for locally executed LLMs when handling complex and context-dependent bugs.	✓	0.24
Chen et al. introduced Codex, a GPT-based model fine-tuned on publicly available code.	✓	0.26
Codex was evaluated on its ability to generate functional Python programs from natural language descriptions using the H	✓	0.25
Feng et al. proposed CodeBERT, which was trained jointly on natural language and programming language data.	✓	0.28
CodeBERT enables tasks such as code search and documentation generation.	×	0.13
Kang et al. proposed AutoFL, which uses LLMs for fault localization while generating natural language explanations.	✓	0.31
Mhatre et al. found that defect complexity is the primary factor governing detection accuracy in their evaluation of clo	✓	0.23
Prior studies converge on the observation that LLM performance degrades when bugs require cross-function reasoning.	✓	0.18
Santana et al. reported variation in LLM performance across model families and task complexity when detecting and refact	✓	0.17
Acharya and Ginde found that open-weight models can approach proprietary system performance in converting unstructured b	✓	0.21
Widyasari et al. released BugsInPy, a curated set of real Python bugs with reproducible test cases drawn from well-known	✓	0.31
Aguilar et al. identified reproducibility issues in the BugsInPy dataset and proposed revisions.	✓	0.20
Pushkar et al. showed that model performance drops systematically as the number of co-occurring defects increases. 4	✓	0.21
The availability of open-weight models such as LLaMA and Mistral has made local deployment a practical option.	✓	0.20
Local deployment of open-weight models eliminates cloud dependencies and usage costs.	×	0.15
Prior work has largely evaluated large cloud-hosted models rather than locally deployed ones	✓	0.16

References

- http://arxiv.org/abs/2604.23361v1
- http://arxiv.org/abs/2305.17384v2
- http://arxiv.org/abs/2102.10014v1