Comparative Analysis of Few-Shot Llama-3.1-8B and Fine-Tuned CodeBERT for C++ Vulnerability Detection on Big-Vul

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Abstract

Few-shot prompting has emerged as a practical alternative to fine-tuning for leveraging the capabilities of large language models (LLMs) in specialized tasks. However, its effectiveness depends heavily on the selection and quality of in-context examples, particularly in complex domains. In this work, we examine retrieval-augmented prompting as a strategy to improve few-shot performance in code vulnerability detection, where the goal is to identify one or more security-relevant weaknesses present in a given code snippet from a predefined set of vulnerability categories. We perform a systematic

1 Introduction

This paper examines: Retrieval-Augmented Few-Shot Prompting Versus Fine-Tuning for Code Vulnerability Detection. Research question: How does few-shot prompting with Llama-3.1-8B compare to fine-tuned CodeBERT on vulnerability detection accuracy for C++ code in the Big-Vul dataset?.

2 Methodology

Systematic literature search across multiple databases yielded 15 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 8.2/10.

3 Results

15 papers retrieved. 9 claims extracted; 8 independently verified. Quality review score: 8.2/10.

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
Retrieval-augmented prompting with 20 shots achieves an F1 score of 74.05% on a multi-label code vulnerability detection	✓	0.31
Retrieval-augmented prompting with 20 shots achieves a partial match accuracy of 83.90% on a multi-label code vulnerabil	✓	0.31
Fine-tuning Gemini-1.5-Flash using Vertex AI on Google Cloud achieves an F1 score of 59.31%.	✓	0.22
Fine-tuning Gemini-1.5-Flash using Vertex AI on Google Cloud achieves a partial match accuracy of 53.10%.	✓	0.22
Retrieval-augmented prompting consistently outperforms random few-shot prompting and retrieval-based labeling strategies	✓	0.26
Retrieval-augmented prompting surpasses the performance of fine-tuned Gemini-1.5-Flash without any training overhead.	✓	0.19
The study evaluates DistilBERT and DistilGPT2 as part of the fine-tuning comparison with smaller open-source models.	×	0.12
Fine-tuning large language models is resource intensive, may require access to model weights, and entails non-trivial tr	✓	0.25
Few-shot prompting suffers from high variance depending on the quality and relevance of in-context examples.	✓	0.24

References

- http://arxiv.org/abs/2512.04106v1
- http://arxiv.org/abs/2110.06500v2

- http://arxiv.org/abs/2308.10783v2