Retrieval-Augmented Revision Versus Adversarial Training for Big-Vul Detection in Llama-3.1-8B Without Retraining

Assignee Research

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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 retrieval-augmented revision compare to adversarial training in improving Big-Vul detection accuracy for Llama-3.1-8B without requiring model retraining?.

2 Methodology

Systematic literature search across multiple databases yielded 16 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 8.8/10.

3 Results

16 papers retrieved. 12 claims extracted; 12 independently verified. Quality review score: 8.8/10.

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
Fine-tuning large language models is resource intensive, may require access to model weights, and entails non-trivial tr	✓	0.25
Few-shot prompting avoids the need for model retraining by embedding labeled input-output examples directly into the pro	✓	0.18
The study evaluates three strategies: Random Few-Shot Prompting, Retrieval-Augmented Few-Shot Prompting, and Retrieval-B	✓	0.21
The evaluation was conducted using the Gemini-1.5-Flash model on a multi-label code vulnerability detection dataset.	✓	0.21
Retrieval-augmented prompting with 20 shots achieves an F1 score of 74.05%.	✓	0.29
Retrieval-augmented prompting with 20 shots achieves a partial match accuracy of 83.90%.	✓	0.30
Retrieval-augmented prompting consistently outperforms random prompting and retrieval-based labeling.	✓	0.24
Fine-tuning Gemini-1.5-Flash using Vertex AI on Google Cloud achieves an F1 score of 59.31%.	✓	0.23
Fine-tuning Gemini-1.5-Flash using Vertex AI on Google Cloud achieves a partial match accuracy of 53.10%.	✓	0.23
Retrieval-augmented prompting surpasses the performance of the fine-tuned Gemini-1.5-Flash model without any training ov	✓	0.21
The study fine-tuned smaller open-source models including DistilBERT and DistilGPT2.	✓	0.16
Semantic retrieval of in-context examples significantly enhances few-shot prompting effectiveness compared to zero-shot	✓	0.23

References

- http://arxiv.org/abs/2512.04106v1
- http://arxiv.org/abs/2604.23361v1
- http://arxiv.org/abs/2601.08691v1