Integrating Retrieval-Augmented Prompting with Instruction Fine-Tuning for Zero-Shot Low-Resource Language Performance

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: Can combining retrieval-augmented prompting with instruction fine-tuning (e.g., using XTREME-R benchmarks) improve zero-shot performance for low-resource languages, and how does it compare to pure retrieval-augmented approaches?.

2 Methodology

Systematic literature search across multiple databases yielded 14 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 7.6/10.

3 Results

14 papers retrieved. 11 claims extracted; 9 independently verified. Quality review score: 7.6/10.

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 and may require access to model weights, with non-trivial traini	✓	0.22
Few-shot prompting avoids the need for model retraining by embedding labeled input-output examples directly into the pro	✓	0.18
Few-shot prompting suffers from high variance depending on the quality and relevance of in-context examples.	✓	0.24
Retrieval-augmented prompting with 20 shots achieves an F1 score of 74.05% and a partial match accuracy of 83.90%.	✓	0.37
Fine-tuning Gemini-1.5-Flash achieves an F1 score of 59.31% and a partial match accuracy of 53.10%.	✓	0.32
Retrieval-augmented prompting surpasses fine-tuned Gemini-1.5-Flash without any training overhead.	✓	0.20
Fine-tuning smaller open-source models like DistilBERT and DistilGPT2 achieves lower performance compared to retrieval-a	×	0.14
Semantic retrieval of in-context examples significantly enhances few-shot prompting effectiveness.	✓	0.19
Retrieval-augmented prompting achieves substantial gains over other prompting strategies and fine-tuned LLMs like Gemini	✓	0.22
Retrieval-augmented prompting requires no model training.	×	0.09
Retrieval-augmented prompting is a practical alternative to fine-tuning in real-world settings where resources may not a	✓	0.25

References

- http://arxiv.org/abs/2309.06089v3
- http://arxiv.org/abs/2512.04106v1
- http://arxiv.org/abs/2506.15415v1