Fine-Tuning Large Language Models for Software Vulnerability Detection

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I. INTRODUCTION

Security breaches pose significant threats to individuals, corporations, and society at large. For individuals, breaches often result in the loss of sensitive personal data such as credit card information, social security numbers, or medical records, which can be exploited for identity theft and financial fraud. For corporations, the consequences can be even more severe: data breaches can compromise intellectual property, damage customer trust, and lead to direct financial losses through theft or costly incident response efforts.

A leading cause of security breaches is unsafe or vulnerable code that traditional static analysis tools often fail to detect. With the rise of advanced machine learning, models such as VulDeePecker [5] and Devign [12] have demonstrated the feasibility of detecting vulnerabilities from source code using learned representations. These models illustrate the benefits of deep learning and graph-based approaches for capturing semantic and structural information in code, improving vulnerability detection beyond rule-based tools.

While these methods represent important advances, large language models (LLMs) offer unique advantages for software vulnerability detection. Pre-trained on massive corpora of code, LLMs can learn rich syntactic and semantic patterns across programming languages and project types. They are capable of zero- or few-shot reasoning, enabling vulnerability detection even in codebases that were unseen during training. Additionally, LLMs can potentially generalize to new vulnerability types and provide contextual insights to developers, complementing traditional static analysis and specialized ML models. These properties make LLMs a promising tool for building more robust, scalable, and adaptable vulnerability detection systems.

Recent research has begun to explore the use of LLMs for software security, investigating both their capabilities and limitations. Studies have applied LLMs to tasks such as vulnerability detection, patch generation, code summarization, and secure coding suggestions. Early results indicate that fine-tuned LLMs can achieve performance comparable to or exceeding specialized models for certain types of vulnerabilities, while prompted LLMs show potential in zero- and few-shot scenarios. However, challenges remain, including sensitivity to prompt design, varying performance across programming languages, and limited interpretability of the model's reasoning. Additionally, systematic benchmarks comparing LLM-based approaches to traditional static analyzers and graph-based models are still scarce, leaving important questions about their generalizability, reliability, and practical deployment in real-world development workflows.

In this paper I focus on a critical, unanswered question regarding the generalization of fine-tuned LLMs for security vulnerability detection. While previous work has shown that LLMs can find vulnerabilities, it is unclear whether these models are understanding the underlying concepts of these vulnerabilities or simply overfitting to the patterns of a given dataset. To address this gap, I will conduct a cross-dataset generalization study. I will fine-tune a model on "real-world" vulnerabilities (found in the Big-Vul dataset) and test its ability to find "textbook" vulnerability examples (found in the Juliet Test Suite) and vice-versa. This analysis will assess the robustness of these models and their suitability for real-world applications.

This project aims to address these gaps through the following research question:

- **RQ:** To what extent do fine-tuned Large Language Models for vulnerability detection generalize across different data domains (i.e., from "textbook" code to "real-world" code and vice-versa)?

II. RELATED WORK

The task of automatically detecting software vulnerabilities has been addressed through a variety of approaches, ranging from traditional static analysis tools to recent machine learning and deep learning models. In this section, I will review existing work within these three domains: static analysis techniques, machine learning-based detection, and large language model approaches.

A. Static Analysis Tools

Static analysis tools are widely used in practice to detect coding errors that could lead to vulnerabilities. These tools examine source code without executing it, following a set of predefined rules to map control and logic flows. They can be highly effective at catching security flaws such as buffer

overflows, SQL injection risks, or improper input validation. However, their effectiveness is often limited by the scope of their rule sets and their sensitivity to different language-specific and framework-specific constructs.

Tools such as CodeQL [4], semgrep [7], ITS4 [10], SPLINT [1], and FindBugs [8] perform rule-based analysis of source code to identify potential weaknesses. While effective at catching certain low-level issues, these tools often suffer from high false positive and false negative rates and are limited by the coverage and specificity of their rule sets. Moreover, they generally do not capture higher-level design or architectural flaws, which can propagate vulnerabilities in a system-wide manner.

B. Machine Learning Approaches for Vulnerability Detection

Recent research has explored machine learning models to automatically detect vulnerabilities from code. VulDeePecker [5] was one of the first deep learning approaches to do so, introducing the concept of *code gadgets*—semantically related lines of code extracted from a program. These gadgets are tokenized and fed into a Bidirectional Long Short-Term Memory (BiLSTM) network, which learns to classify each *gadget* as vulnerable or not. VulDeePecker was evaluated on both benchmark datasets and real-world projects, demonstrating reduced false negatives compared to traditional static analysis tools. The model was able to detect previously unknown vulnerabilities that were later confirmed in 3 upstream software projects, illustrating its practical effectiveness. This work highlighted the importance of capturing semantic information in code for automated vulnerability detection.

Devign [12] extended the deep learning paradigm by modeling program semantics as graphs and applying Graph Neural Networks (GNNs) for function-level vulnerability detection. Using program dependence graphs (PDGs), Devign represents both the control-flow and data-flow dependencies in a function, capturing structural relationships that sequential models cannot easily learn. A graph convolutional module aggregates node-level information into function-level embeddings, which are then classified as vulnerable or not. Devign was trained on large-scale real-world C projects and demonstrated higher accuracy and F1 scores than VulDeePecker and prior approaches. This showed that leveraging structural and semantic information in code significantly improves vulnerability detection performance. Furthermore, Devign's use of graphs enables it to generalize better across diverse code patterns and vulnerability types.

Together, VulDeePecker and Devign illustrate the benefits of using learned representations of code for automated vulnerability detection. They show that deep learning and graph-based models can capture semantic and structural information that static analysis tools often miss, reducing false negatives and improving the detection of both known and previously unseen vulnerabilities.

C. Large Language Models (LLMs) for Code Analysis

Large language models pre-trained on code, such as Codex, CodeT5, and CodeBERT, have recently been explored for vulnerability detection. These models leverage vast amounts of source code data to learn syntactic and semantic patterns, enabling zero- or few-shot detection of vulnerabilities in novel codebases. Fine-tuned LLMs have been shown to perform comparably or better than specialized models on certain tasks, but systematic comparisons with GNN-based methods and traditional static analyzers remain limited. Moreover, the relationship between the scale of code pre-training and detection performance has not been thoroughly investigated, leaving open questions about how much pre-training data is necessary for robust vulnerability detection.

Fine-tuning LLMs for vulnerability detection is important for several reasons. First, it enables models to specialize in identifying security vulnerabilities by training them on labeled datasets containing examples. This specialization can lead to improved performance over general-purpose models. For instance, Shestov et al. [9] demonstrated that fine-tuning the WizardCoder model on vulnerability datasets resulted in significant improvements in detection accuracy, outperforming CodeBERT-like models. They also explored techniques to handle class imbalance and accelerate training, further enhancing model performance.

Second, fine-tuning enables models to adapt to specific programming languages and coding styles prevalent in different development environments. This adaptability is essential for detecting vulnerabilities in diverse codebases. Yang et al. [11] introduced the MSIVD framework, which combines self-instructed fine-tuning over multiple tasks with program control flow graphs encoded as GNNs. Their approach achieved superior performance on the BigVul dataset, which highlighted the importance of tailoring models to the nuances of specific programming languages and frameworks.

In summary, fine-tuning LLMs for vulnerability detection is a promising direction that leverages the strengths of large-scale pre-trained models while adapting them to the specific challenges of software security. By specializing models through fine-tuning, researchers and practitioners can develop more effective tools for identifying and mitigating vulnerabilities in software systems.

D. Work Novelty

While prior work has established that fine-tuned LLMs cna be effective at detecting software vulnerabilities, the depth of their understanding is not well understood. The novelty of this project lies in its specific, empricial focus on cross-domain generalization.

I am not merely benchmarking a model's performance on a single dataset. Instead, I am investigating whether these models are learning the underlying concept of a security vulnerability. I will train on a "real-world" dataset (Big-Vul) and test on a "synthetic" one (Juliet Test Suite), and then I will reverse the process. Through this testing, I aim to be the first to provide a clear analysis of this generalization gap. This

addresses a major open question, as a model that only performs well on data that looks similar to its training set cannot be used effectively in other settings.

III. METHODOLOGY

This study proposes fine-tuning a large language model (LLM) for software vulnerability detection and systematically comparing its performance against prior machine learning methods, few-shot prompted LLMs, and conventional static analysis tools.

A. Datasets

I will use two publicly available datasets for evaluation:
- **Big-Vul**: Real-world C/C++ functions linked to CVEs [2].
- **Juliet Test Suite**: Synthetic CWE-labeled programs for controlled testing [6].

Both datasets are freely accessible for research purposes. They provide a combination of real-world and synthetic vulnerabilities, enabling robust evaluation and cross-dataset generalization experiments.

B. Proposed Model

For this study, I will use a single, pre-trained model: CodeBERT-Base [3]. This is a RoBERTa-style model pre-trained on a large corpus of code data.

I will fine-tune the model for sequence classification (0 for non-vulnerable, 1 for vulnerable) with a learning rate of 2×10^{-5}, a batch size of 8, and for one epoch, as this is the standard for fine-tuning tasks. I use the `RobertaForSequenceClassification` class from the Hugging Face `transformers` library.

C. Evaluation Metrics

Performance will be measured using standard metrics:
- Precision
- Recall
- F1-score

These metrics are standard for binary classification tasks. They will show me an interpretable depiction of the model's ability to detect vulnerabilities.

D. Experimental Procedure

The experiments will proceed as follows:
1) Real-to-Synthetic
   - **Training:** The pre-trained `codebert-base` model will be fine-tuned exclusively on the `Big-Vul` training split. This is the "real world" dataset.
   - **Evaluation:** The resulting fine-tuned model will be tested on the `Julet Test Suite` test split.
   - **Purpose:** This measures the model's ability to apply knowledge learned from "real-world" examples to "textbook" vulnerability examples.
2) Synthetic-to-Real
   - **Training:** The pre-trained `codebert-base` model will be fine-tuned exclusively on the

`Juliet Test Suite` training split. This is the "synthetic/textbook" dataset.
   - **Evaluation:** The resulting fine-tuned model will be tested on the Big-Vul test split.
   - **Purpose:** This measures the model's ability to apply knowledge learned from "textbook" examples to "real-world" vulnerability examples.

The precision, recall, and F1-scores from these two cross-domain evaluations will be compared to directly answer the reserach question.

IV. EARLY RESULTS

I do not have any results yet for my models. However, I have been working on the code for fine-tuning the models. There was a lot of set up involved in getting this code to run. Here are some of the things I have done so far:
- Downloaded `Big-Vul` and `Juliet Test Suite` datasets
- Downloaded `CodeBERT-Base model`
- Installed CUDA on my laptop for fine-tuning
- Tokenized `Big-Vul` and `Juliet Test Suite`
- Begin fine-tuning the Big-Vul model

As this is my first time fine-tuning an LLM, this took some time to figure out how all of these processes worked. As of turning this paper in, I am in the process of fine-tuning `Big-Vul` on the `Juliet Test Suite`.

V. NEXT STEPS

Fine-tuning on the `Big-Vul` training set should take, I presume, around 3-4 hours. I assume fine-tuning on the `Juliet Test Suite` training set should take around that much time as well. I should be able to get both models fine-tuned using my own laptop over a couple days. For context, I have a RTX 3060 in my laptop, which allows me to fine-tune the model locally rather than relying on university resources.

The next step will be evaluating both of these models. I will test each fine-tuned model on the dataset opposite of the one it was fine-tuned on. I will then calculate precision, recall, and F1-scores for these tests. The final part of this project will be to analyze this data and answer the proposed research question.

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