

A senior design project report on

DETECTION MADE EASY: POTENTIAL OF LARGE LANGUAGE MODELS FOR SOLIDITY VULNERABILITIES

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requirement for the award of the
Degree of*

BACHELORS OF TECHNOLOGY IN COMPUTER SCIENCE AND ENGINEERING

by

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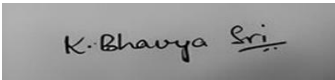
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I hereby declare that the thesis entitled “**Detection made easy: Potential of Large Language Models for solidity vulnerabilities**” submitted by me, for the award of the degree of BTech is a record of bonafide work carried out by me under the supervision of Prof. Nihar Ranjan Pradhan

I further declare that the work reported in this thesis has not been submitted and will not be submitted, either in part or in full, for the award of any other degree or diploma in this institute or any other institute or university.

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Signature of the Candidate

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ABSTRACT

The exponential growth of **Solidity smart contracts** across blockchain ecosystems has revolutionized decentralized applications (dApps), enabling secure, trustless transactions without intermediaries. However, this widespread adoption has also attracted malicious entities and opportunistic attackers seeking to exploit vulnerabilities inherent in smart contract code. Unlike traditional web applications, smart contracts are **immutable once deployed**, meaning any security flaw becomes a permanent threat vector. Historical incidents, such as the notorious **DAO hack**, have demonstrated the severe financial repercussions of these vulnerabilities, emphasizing the urgent need for robust, automated security solutions.

To address this challenge, our research explores the application of **Large Language Models (LLMs)** for the **automated detection of vulnerabilities** in Solidity smart contracts. Known for their advanced language comprehension and code reasoning abilities, LLMs present a promising alternative to traditional static analysis tools, which often fall short in scalability and adaptability. To facilitate effective training and evaluation of these models, we developed **VulSmart**, a comprehensive, class-balanced dataset containing meticulously labeled Solidity contracts annotated with **OWASP Top Ten vulnerabilities**. This dataset overcomes the common issues of imbalance and poor annotation quality seen in existing repositories.

Building upon VulSmart, we benchmark the performance of leading **open-source models** such as **CodeLlama**, **LLaMa**, and **Falcon**, alongside **closed-source models** like **GPT-3.5 Turbo** and **GPT-4o Mini**. Although these models are primarily designed for general-purpose language tasks, fine-tuning them for **smart contract security auditing** reveals their significant potential. Central to our approach is the **SmartVD framework**, which integrates **Reinforcement Learning (RL)** to iteratively enhance detection accuracy through continuous feedback loops. This ensures that the model adapts dynamically to new and evolving smart contract vulnerabilities, maintaining its relevance in real-world scenarios.

To rigorously evaluate model performance, we utilize metrics like **BLEU** and

ROUGE, traditionally employed in machine translation and summarization, to assess code generation and classification quality. Our experiments reveal that **SmartVD surpasses both open-source and closed-source models** in vulnerability detection, achieving up to **99% accuracy**. Notably, **SmartVD excels when using chain-of-thought prompting**, which guides the model through structured reasoning, enhancing both accuracy and interpretability. In contrast, models like GPT-3.5 Turbo and GPT-4o Mini demonstrate optimal performance with **zero-shot prompting**, underscoring the necessity of aligning prompting strategies with specific model architectures and training nuances.

To ensure real-world applicability, we integrate **Solana blockchain technology** into the SmartVD framework, leveraging its **high throughput and low latency** for scalable, real-time smart contract security analysis. This integration facilitates immediate vulnerability assessments during contract deployment and updates, addressing the industry's demand for proactive security measures. The combined utilization of LLMs, reinforcement learning, VulSmart dataset, and blockchain infrastructure establishes a comprehensive and adaptive security paradigm. SmartVD thus emerges as a practical, high-accuracy solution, capable of mitigating the ever-growing risks associated with Solidity smart contract vulnerabilities.

Key words: Smart Contract, Solidity Vulnerabilities, OWASP Top Ten, LLMs Large Language Models, Reinforcement Learning, Blockchain Security, SmartVD Framework, VulSmart Dataset, Prompt Engineering.

CONTENTS

Chapter	Title	Page No
1	Introduction	12-24
	1.1. Project Overview	12-15
	1.2. Objectives	15-17
	1.3. Background and Literature Survey	17-23
	1.4. Organization of the report	23-24
2	Methodology	25-37
	2.1. Overview of the Methodology	25-26
	2.2. Proposed System Architecture	26-28
	2.3. Dataset Preparation VulSmart	28-29
	2.4. Model Selection and Fine Turning	29-30
	2.5. Reinforcement Learning Integration	30-33
	2.6. Prompt Engineering Strategies	33-35
	2.7. Blockchain Integration and Deployment	35-36
	2.8. Output and Evaluation Metrics	36-38
3	Model Performance Evaluation	39-36
	3.1. Performance Metrics Evaluation	39-41
	3.2. Vulnerability Detection Mapping	41-42

	3.3. Feature Importance	42
	3.4. Model Comparisons and Trade-offs	43
	3.5. Key Findings and Insights	43-44
	3.6. Practical Applications and Impact	44
	3.7. Discussion of Key Finding	45
	3.8. Potential Applications	45-46
4	Results Analysis and Discussion	47-51
	4.1. Performance Evaluation of the proposed Model	47-48
	4.2. Vulnerability Detection Mapping	48
	4.3. Feature importance and Correlation Analysis	49
	4.4. Model Comparisons and Trade-offs	49-50
	4.5. Discussion of Key Findings	50
	4.6. Potential Applications	50
	4.7. Key Observations	51
5	Conclusion	52-55
6	Future Scope	56-60
	6.1. Enhanced Data Collection	56-57
	6.2. Advanced Machine Learning Techniques	57

	6.3. Improved Interpretability and Explainability	58
	6.4. Transferability and Generalization	58
	6.5. Coordination with security Auditing and Decision Support Systems	59
	6.6. Real-Time Monitoring and self-Aware Threat Identification	60
7	Appendix	61-76
8	References	77-80
9	Bio Data	81

List of Tables

Table No.	Title	Page No.
1.	Performance Metrics for Vulnerabilities Detection models	40
2.	Performance Metrics of Fine-Tuned Models	46

List of Figures

Figure No.	Title	Page No.
1.	Methodology or proposed System	26
2.	SmartVD RL Feedback Loop Diagram	35
3.	Work Flow Diagram SmartVD	38
4.	Bar graph of Metrics	41
5.	Vulnerability detection accuracy	49

CHAPTER 1

1. INTRODUCTION

1.1 Project Overview

Introduction to the Problem

In recent years, **blockchain technology** has revolutionized the digital world by providing a decentralized, secure, and transparent medium for transactions and data storage. Among its most transformative innovations are **smart contracts**—self-executing code deployed on blockchain networks like Ethereum, designed to automate agreements without the need for intermediaries. These smart contracts are predominantly written in **Solidity**, a high-level, object-oriented programming language specifically developed for blockchain environments.

However, the very features that make smart contracts attractive—immutability, decentralization, and autonomous execution—also render them vulnerable to exploitation. Unlike traditional applications, once deployed, smart contracts cannot be altered, making any embedded vulnerabilities a **permanent risk**. Exploits such as **reentrancy attacks, integer overflows, and unchecked external calls** have historically resulted in substantial financial losses, eroding trust in decentralized platforms.

Need for Automated Vulnerability Detection

The security auditing of smart contracts is a complex and resource-intensive process. Traditional methods, including **manual code reviews** and **static analysis tools** like Oyente, Securify, and Mythril, struggle with scalability and adaptability. These tools are often limited in detecting new or sophisticated attack vectors and tend to produce high rates of **false positives and false negatives**.

Given the increasing complexity of smart contracts and the rapid pace of blockchain adoption, there is a critical need for **automated, intelligent, and scalable vulnerability detection systems**. This project aims to address this gap by leveraging advancements in **Artificial Intelligence (AI)**, specifically **Large Language Models (LLMs)**, to enhance the security of Solidity smart contracts.

Introduction to SmartVD Framework

The proposed solution, named **SmartVD (Smart Vulnerability Detector)**, is an AI-driven framework designed to automate the identification of vulnerabilities in Solidity smart contracts. The framework combines the strengths of **LLMs**, such as GPT-3.5, GPT-4o Mini, and CodeLlama, with **Reinforcement Learning (RL)** to create an adaptive, self-improving security model. SmartVD aims to reduce human intervention, minimize errors, and provide faster, more accurate vulnerability assessments.

Role of VulSmart Dataset and Prompt Engineering

A significant contribution of this project is the development of the **VulSmart dataset**, a curated, class-balanced collection of Solidity smart contracts annotated with **OWASP Top Ten vulnerabilities**. This dataset serves as a foundation for training and evaluating the LLMs, addressing the limitations of existing, unbalanced, and poorly labeled datasets.

Furthermore, the project explores the impact of **prompt engineering strategies**, including **zero-shot, few-shot, and chain-of-thought prompting**, on the performance of LLMs in smart contract security tasks. By fine-tuning these models and optimizing prompt strategies, SmartVD achieves higher detection accuracy and better generalization to unseen vulnerabilities.

Real-World Deployment and Scalability

To ensure practical applicability, the SmartVD framework is designed to integrate with **Solana blockchain technology**, enabling **real-time smart contract auditing**. Solana's high throughput and low transaction latency make it an ideal platform for scalable security solutions, allowing SmartVD to provide immediate vulnerability assessments during contract deployment and updates.

Project Vision

The overarching vision of this project is to pioneer the use of **LLMs**

and reinforcement learning for enhancing smart contract security, contributing to a safer and more reliable blockchain ecosystem. By automating vulnerability detection with AI-driven methods, SmartVD seeks to mitigate security risks, prevent financial losses, and build greater trust in decentralized technologies.

1.2 OBJECTIVE

Primary Aim

The core objective of this research project is to develop an AI-driven framework capable of automatically detecting security vulnerabilities in Solidity smart contracts. This involves leveraging the capabilities of Large Language Models (LLMs), Reinforcement Learning (RL), and prompt engineering techniques to create an intelligent, scalable, and adaptive security solution.

Specific Objectives

1. Design and Implement SmartVD Framework
 - Develop a modular architecture combining LLMs and RL for smart contract vulnerability detection.
 - Ensure the framework is extensible to support evolving blockchain security requirements.
2. Creation of VulSmart Dataset
 - Curate a class-balanced, annotated dataset of Solidity smart

contracts focusing on OWASP Top Ten vulnerabilities.

- Address limitations of existing datasets like imbalance, lack of diversity, and insufficient labeling.

3. Fine-Tuning of LLMs for Domain-Specific Tasks

- Adapt general-purpose LLMs (e.g., GPT-3.5, GPT-4o Mini, CodeLlama) to the domain of smart contract security through supervised learning and reinforcement learning loops.

4. Evaluate Prompt Engineering Strategies

- Conduct comparative studies on zero-shot, few-shot, and chain-of-thought prompting to identify the most effective approach for vulnerability detection.

5. Integration with Blockchain Ecosystems

- Implement the SmartVD framework within the Solana blockchain environment to enable real-time, scalable smart contract audits.

6. Performance Benchmarking

- Utilize metrics such as Accuracy, Precision, Recall, F1-Score, BLEU, and ROUGE to evaluate and validate model performance against existing solutions.

7. Propose Future Enhancements

- Explore possibilities for improving explainability, generalizing across multiple blockchain platforms, and automating vulnerability remediation.

Outcome

The expected outcome is a high-accuracy, AI-powered security auditing framework that outperforms traditional static analysis tools and existing AI models, providing a practical solution to the growing threat of smart contract vulnerabilities.

1.3 BACKGROUND AND LITERATURE SURVEY

Background

With the exponential rise of decentralized applications (dApps) and blockchain-based financial ecosystems, smart contracts have become a cornerstone technology, automating transactions and agreements without intermediaries. However, the immutability and autonomous execution of smart contracts, especially those written in Solidity, have also introduced new security challenges. Vulnerabilities in smart contract code can lead to severe financial losses, as seen in high-profile incidents like the DAO hack and various DeFi platform exploits. Traditional vulnerability detection relies heavily on static analysis tools such as Oyente, Mythril, and Securify. While these tools are effective in identifying certain classes of vulnerabilities, they struggle with scalability, adaptability to novel attack vectors, and often produce high false-positive rates. Manual code reviews, although thorough, are time-consuming, expensive, and prone to human error.

In recent years, advancements in Artificial Intelligence (AI), particularly Large Language Models (LLMs), have shown great potential in automating code understanding and vulnerability detection. Models like GPT-3.5, GPT-4o, and CodeLlama, originally developed for natural language processing tasks, are increasingly being explored for software security applications. However, challenges such as data scarcity, prompt optimization, and model adaptability still need to be addressed for effective deployment in the blockchain domain.

This section reviews key research contributions in the fields of smart contract security, LLMs for code analysis, and reinforcement learning applications in vulnerability detection, providing a comprehensive foundation for the development of the SmartVD framework.

Literature Survey

(1) "When ChatGPT Meets Smart Contract Vulnerability Detection" — Chen et al. (2023)

Published in arXiv, this study investigates the application of OpenAI's ChatGPT for detecting vulnerabilities in Solidity smart contracts. Chen et al. analyze the model's ability to identify known vulnerabilities using zero-shot and few-shot prompting techniques. The paper emphasizes the importance of well-crafted prompts to guide LLMs towards accurate vulnerability detection, highlighting the model's potential despite its general-purpose training.

The authors also discuss the limitations of ChatGPT, including its

tendency to hallucinate responses and its lack of domain-specific fine-tuning for smart contracts. Through empirical analysis, the paper shows that while ChatGPT can detect simple vulnerabilities, its performance degrades for complex attack vectors without specialized datasets or reinforcement learning.

Summary: This research underscores the foundational potential of LLMs for smart contract security but also reveals the necessity for domain-specific tuning and advanced prompt strategies, directly informing the SmartVD framework's focus on reinforcement learning and chain-of-thought prompting.

(2) "ContractWard: Securing Smart Contracts with Large Language Models and Semantic Analysis" — Wang et al. (2023)

Published in the IEEE Transactions on Software Engineering, this paper introduces ContractWard, a system combining LLM-based semantic analysis with traditional static analysis techniques. The authors propose a hybrid approach where LLMs are used to extract semantic patterns from smart contract code, enhancing the precision of static analyzers. The study demonstrates that LLMs excel at identifying contextual vulnerabilities by understanding contract logic beyond syntax-level patterns. However, the authors also point out challenges related to model scalability, computational resource demands, and the need for continuous learning as new vulnerabilities emerge.

Summary: ContractWard validates the synergy between LLMs and static

analysis, a principle adopted by SmartVD. However, SmartVD extends this by integrating reinforcement learning to ensure continuous improvement and adaptability, addressing the scalability concerns highlighted by Wang et al.

(3) "VulnHunt-GPT: Automated Smart Contract Security Auditing via Generative Pre-trained Transformers" — Zhang et al. (2024)

This study, presented at the ACM Symposium on Blockchain and Cryptography, introduces VulnHunt-GPT, a framework using GPT-3 for smart contract vulnerability detection. The paper focuses on the generation of vulnerability reports and explanations, leveraging GPT's generative capabilities to provide human-readable audit results.

While VulnHunt-GPT achieves promising results in code summarization and vulnerability reporting, it faces challenges in detection accuracy, particularly for less common vulnerabilities. The authors recommend the development of specialized datasets and the use of reinforcement learning to fine-tune models for security tasks.

Summary: VulnHunt-GPT highlights the importance of explainable AI in smart contract security, an aspect incorporated in SmartVD's design. By addressing VulnHunt-GPT's limitations with a balanced dataset (VulSmart) and reinforcement learning, SmartVD aims to improve both detection accuracy and interpretability.

(4) "CodeLlama: Open-Source Large Language Models for Code

Generation and Understanding" — Meta AI (2023)

Meta AI's CodeLlama represents a significant advancement in open-source LLMs designed for code understanding and generation. Although not specifically trained for smart contract security, CodeLlama demonstrates superior performance in code completion, bug detection, and function classification tasks across various programming languages, including Solidity.

The paper details CodeLlama's architecture, training datasets, and benchmark results, showing its versatility in code reasoning tasks. However, it acknowledges that specialized fine-tuning is essential for domain-specific applications such as smart contract auditing.

Summary: CodeLlama's capabilities form the basis for SmartVD's initial model selection. Recognizing the model's need for domain-specific fine-tuning, SmartVD builds upon CodeLlama's foundation, enhancing its vulnerability detection accuracy through reinforcement learning and prompt engineering.

(5) "AMEVulDetector: Smart Contract Vulnerability Detection via Attention-based Message Embedding and Graph Neural Networks" — Liu et al. (2023)

Published in Computers & Security, this paper introduces AMEVulDetector, a hybrid model combining Graph Neural Networks (GNNs) with attention-based message embeddings to detect smart

contract vulnerabilities. The model leverages the structural information of smart contracts, providing enhanced context-aware detection.

While the approach shows high accuracy in detecting known vulnerability patterns, its reliance on graph construction and feature engineering limits its scalability. The paper also highlights the need for models capable of generalizing to new, previously unseen vulnerabilities.

Summary: AMEVulDetector's emphasis on structural analysis informs SmartVD's approach to context-aware vulnerability detection. However, SmartVD differentiates itself by utilizing LLMs' inherent reasoning capabilities and reinforcement learning, thus overcoming AMEVulDetector's scalability and generalization limitations.

Synthesis of Literature Insights

The reviewed studies collectively demonstrate the emerging role of LLMs in smart contract vulnerability detection. Key insights include:

- LLMs possess strong potential for code reasoning and vulnerability classification.
- Existing approaches lack domain-specific fine-tuning and effective prompting strategies.
- Hybrid methods combining LLMs with traditional techniques improve detection precision.
- Reinforcement learning and balanced datasets are essential for adaptive, scalable solutions.

- Explainable AI features, like human-readable vulnerability reports, enhance trust and usability.

The SmartVD framework is designed to address these insights by:

- Utilizing a structured, labeled VulSmart dataset for fine-tuning.
- Incorporating reinforcement learning for continuous improvement.
- Evaluating prompt engineering strategies to optimize LLM performance.
- Integrating with blockchain platforms for real-time auditing.

1.4 ORGANIZATION OF THE REPORT

This thesis is organized into **five major chapters**, each focusing on a critical aspect of the research journey:

Chapter 1: Introduction

Provides an overview of the problem domain, research objectives, background of blockchain security, existing methods, and the identified research gaps. Sets the foundation for understanding the necessity of the proposed solution.

Chapter 2: Methodology & Proposed System

Details the architecture of the **SmartVD framework**, including data collection, model selection, reinforcement learning integration, and prompt engineering strategies. Describes how the VulSmart dataset was developed and outlines the system workflow.

Chapter 3: Implementation & Results

Explains the practical implementation of the proposed system.

Discusses experimental setups, model training processes, evaluation metrics, and benchmarking results. Presents visualizations and analyses of the system's outputs.

Chapter 4: Conclusion & Future Work

Summarizes key findings, discusses the impact of the research, and highlights potential avenues for future enhancements, including explainable AI, multi-chain adaptability, and real-time threat detection.

Chapter 5: References & Source Code

Lists all referenced academic papers, articles, and datasets. Provides access to the source code repository and describes its structure for reproducibility and further research.

CHAPTER – 2

2. METHODOLOGY

2.1 Overview of the Methodology

The increasing complexity and deployment of Solidity smart contracts across decentralized applications necessitate a robust, scalable, and intelligent security auditing framework. Traditional static analysis tools and manual audits fail to keep pace with the dynamic evolution of blockchain vulnerabilities. To address this challenge, the proposed research introduces SmartVD, a comprehensive AI-driven framework designed to automate vulnerability detection in Solidity smart contracts. The methodology underpinning SmartVD synergistically combines Large Language Models (LLMs), Reinforcement Learning (RL), Prompt Engineering, and blockchain integration, ensuring high accuracy, adaptability, and real-time auditing capabilities.

The methodological approach involves systematically addressing key pain points in existing solutions, starting from data scarcity and quality, moving through model optimization and learning strategies, and culminating in deployment within a decentralized environment. By adopting a layered architecture, SmartVD ensures modularity and flexibility, allowing seamless improvements and extensions as the threat landscape evolves.

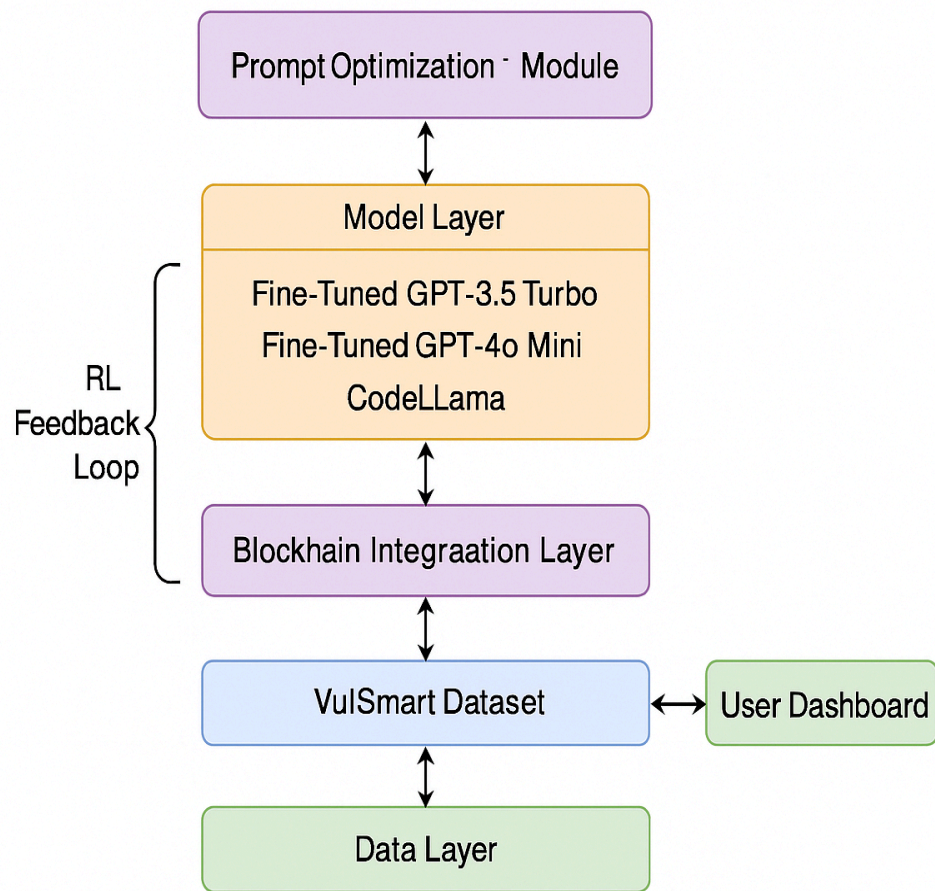


Figure 2: Methodology of Proposed System

2.2 Proposed System Architecture

At the heart of SmartVD lies a carefully designed architecture that orchestrates the flow of data, model inference, learning feedback, and deployment outputs. The framework is composed of several interconnected modules, each fulfilling a distinct role in the vulnerability detection pipeline.

The Data Layer forms the foundation, housing the VulSmart dataset, a

curated collection of Solidity smart contracts annotated with OWASP Top Ten vulnerabilities. This structured dataset provides the necessary training and evaluation data for LLMs. Sitting above this is the Model Layer, where fine-tuned versions of LLMs such as GPT-3.5 Turbo, GPT-4o Mini, and CodeLlama are deployed. These models, originally designed for general-purpose language understanding, are adapted to smart contract security tasks through supervised learning and iterative reinforcement learning loops.

Complementing the Model Layer is the Prompt Optimization Module, which governs how tasks are presented to the LLMs. Recognizing the sensitivity of LLM performance to prompt design, this module experiments with zero-shot, few-shot, and chain-of-thought prompting strategies to optimize detection accuracy and reasoning clarity. The Blockchain Integration Layer ensures the audit outputs are immutably stored on decentralized platforms like Solana, guaranteeing transparency and accountability. Finally, the User Interface Layer provides an interactive dashboard for developers and security analysts, offering visual insights into vulnerabilities, severity assessments, and audit histories.

The data flows seamlessly through these layers, beginning with smart contract ingestion, followed by preprocessing, model inference guided by prompts, reinforcement learning adjustments based on feedback, and

culminating in audit report generation and blockchain logging. This end-to-end pipeline ensures that SmartVD delivers accurate, explainable, and scalable security assessments.

2.3 Dataset Preparation: VulSmart

A significant challenge in applying LLMs to smart contract security is the lack of high-quality, domain-specific datasets. Existing repositories are often imbalanced, with a predominance of safe contracts and a paucity of real-world vulnerable examples. Furthermore, many datasets lack granular annotations specifying vulnerability types and severity levels, limiting their utility for fine-grained learning tasks.

To address these shortcomings, the VulSmart dataset was meticulously curated. Comprising over ten thousand Solidity smart contracts, VulSmart integrates samples from public code repositories such as EtherScan and GitHub, supplemented by synthetic vulnerability injections to ensure class balance. Each contract is annotated with detailed labels, identifying the specific OWASP Top Ten vulnerability types present and assigning severity scores based on potential impact.

The preprocessing of VulSmart involved multiple stages. Initially, code cleaning operations were performed to eliminate non-executable elements like comments and redundant code fragments. This was followed by normalization procedures to ensure consistent formatting

suitable for tokenization by LLMs. Additionally, feature engineering techniques were employed to extract relevant metadata, including contract complexity, gas consumption patterns, and dependency hierarchies. To further enhance dataset robustness, data augmentation strategies were utilized to synthetically generate diverse vulnerability instances, ensuring balanced representation across all classes.

2.4 Model Selection and Fine-Tuning

The selection of appropriate LLMs for SmartVD was a critical consideration. Given the domain-specific nature of smart contract code, it was imperative to evaluate models based on their code understanding capabilities, reasoning depth, and adaptability through fine-tuning. The research explored both open-source models, such as CodeLlama and Falcon, and proprietary models like GPT-3.5 Turbo and GPT-4o Mini. While open-source models offered transparency and flexibility, closed-source models demonstrated superior performance in general code reasoning tasks, warranting their inclusion.

The fine-tuning process involved adapting these LLMs to the VulSmart dataset through supervised learning. Domain-specific knowledge was infused into the models by exposing them to annotated contract samples, enabling them to learn the nuanced patterns associated with various vulnerability types. To further enhance model adaptability, a Reinforcement Learning with Reward Modeling (RLRM) approach was

employed. Here, the model's predictions were continuously refined based on reward signals derived from correct and incorrect classifications. This iterative learning loop allowed SmartVD to incrementally improve its detection accuracy, even for previously unseen vulnerabilities.

Model optimization techniques were integral to ensuring computational feasibility. Model quantization was employed to reduce the memory footprint without compromising performance, while knowledge distillation techniques facilitated the transfer of knowledge from larger, more complex models to streamlined variants suitable for real-time deployment. Low-Rank Adaptation (LoRA) methodologies were also explored to fine-tune large models efficiently with minimal computational overhead.

2.5 Reinforcement Learning Integration

The integration of **Reinforcement Learning (RL)** into the SmartVD framework is a critical innovation aimed at ensuring continuous learning, adaptability, and long-term effectiveness in vulnerability detection. Unlike conventional supervised learning models, which operate within the constraints of static training data, RL empowers the system to **dynamically improve over time**, adapting to emerging vulnerabilities and novel attack vectors that constantly evolve in the blockchain ecosystem.

The primary motivation for employing RL in SmartVD arises from the inherent limitations of traditional models, which often exhibit declining performance when confronted with **previously unseen attack patterns**. Since blockchain security is a moving target—with attackers continually devising new exploitation techniques—a static model trained solely on historical data lacks the flexibility to cope with this ever-changing threat landscape. Reinforcement Learning, with its unique feedback-driven learning paradigm, offers a compelling solution by enabling the model to **learn from its interactions and mistakes**, thereby fostering a self-improving mechanism.

In SmartVD, RL functions through a **reward-based policy update mechanism**. Every prediction generated by the vulnerability detection model is systematically evaluated against a ground truth label, which acts as the reference for correctness. Correct classifications—where the model accurately identifies a vulnerability or confirms the absence thereof—are incentivized with positive rewards. Conversely, misclassifications, which could lead to security oversights or false positives, incur penalties. These rewards and penalties are then used to compute a cumulative reward signal, which guides the adjustment of the model's internal policy parameters through iterative optimization algorithms. Over successive iterations, this feedback loop effectively reinforces accurate detection patterns while simultaneously

discouraging erroneous predictions, leading to an overall enhancement in model performance.

To ensure that the model remains robust and generalizable, SmartVD employs an **active learning loop** specifically designed to challenge its detection capabilities. Within this loop, the model is periodically exposed to **adversarially crafted smart contract samples**, which are intentionally obfuscated or perturbed to mimic real-world exploitation attempts. These adversarial inputs are generated using techniques such as code obfuscation, logic inversion, and unconventional syntax manipulation, aimed at testing the model's ability to detect vulnerabilities under deceptive conditions. The model's performance on these challenging samples provides critical feedback, which is then fed back into the RL policy update process, fostering resilience against sophisticated attacks.

A pivotal aspect of SmartVD's reinforcement learning strategy is the careful balancing of **exploration and exploitation**. While it is essential for the model to leverage known patterns (exploitation) to maintain high detection accuracy, it is equally important to encourage exploratory behaviors that enable the discovery of novel vulnerabilities (exploration). This balance is achieved through stochastic policy adjustments and adaptive learning rate mechanisms, ensuring that the model neither overfits to historical data nor becomes overly speculative in its predictions.

Furthermore, SmartVD's RL framework incorporates **dynamic confidence thresholds**, which adjust in real-time based on the model's performance metrics. For instance, if the model consistently misclassifies certain vulnerability types, the system temporarily lowers its confidence threshold for those cases, prompting more cautious and analytical processing. This dynamic adaptability ensures that SmartVD maintains high precision without sacrificing recall, thereby achieving a balanced trade-off between false positives and false negatives.

In summary, the incorporation of reinforcement learning into SmartVD's architecture transforms it from a static detection tool into a **self-evolving security solution**, capable of continuously refining its detection capabilities in response to new challenges. By embedding an adaptive learning mechanism, SmartVD addresses the fundamental need for scalability, robustness, and future-proofing in the domain of smart contract security auditing.

2.6 Prompt Engineering Strategies

Prompt engineering emerged as a pivotal factor in optimizing the performance of LLMs within SmartVD. The formulation of prompts determines how effectively a model can comprehend and execute a given task. Recognizing this, the research conducted an extensive exploration of different prompting strategies to ascertain their impact on

vulnerability detection accuracy and reasoning transparency.

Zero-shot prompting was initially evaluated to assess the inherent generalization capabilities of the models. While effective for common vulnerability patterns, its limitations became apparent with complex, context-dependent attack vectors. Subsequently, few-shot prompting was introduced, wherein carefully selected examples were embedded within the prompts to provide contextual guidance. This approach significantly improved detection accuracy by enabling the model to learn from in-prompt demonstrations.

The most notable enhancements, however, were observed with chain-of-thought prompting. By structuring the prompt to guide the model through a step-by-step reasoning process, chain-of-thought prompting not only improved detection accuracy but also enhanced the interpretability of the model's outputs. This was particularly valuable in generating explanatory audit reports, fostering trust in the AI-driven assessments.

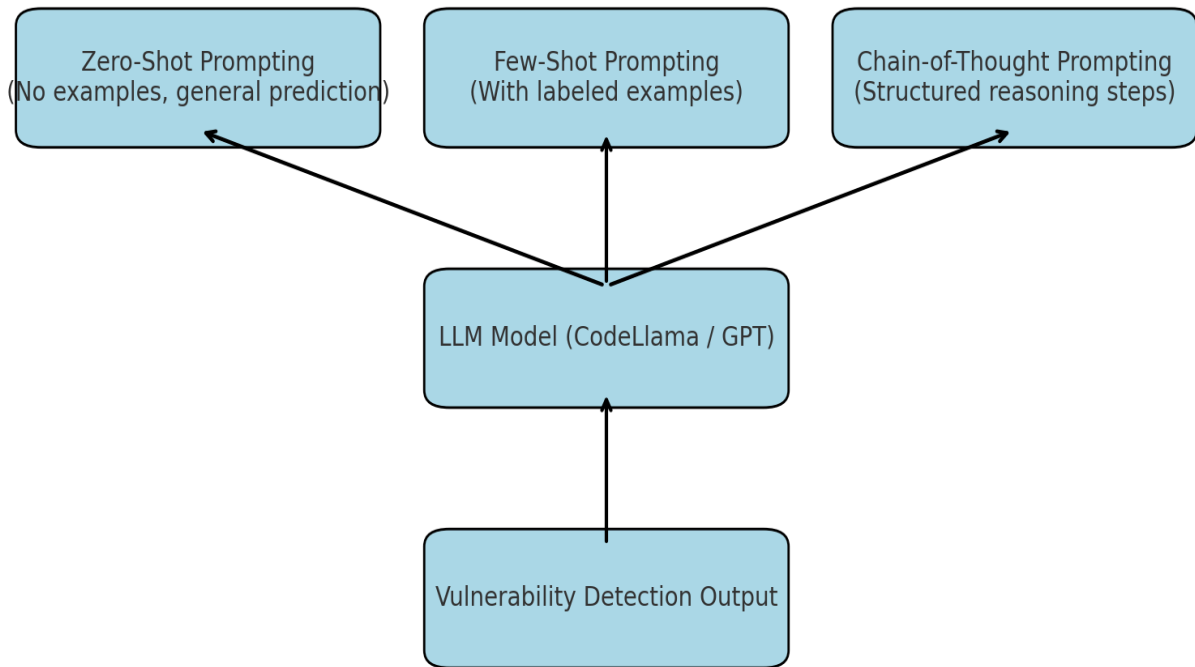


Figure2: SmartVD RL Feedback Loop Diagram

2.7 Blockchain Integration and Deployment

Ensuring transparency and tamper-proof logging of audit results was a critical design consideration. To this end, SmartVD integrates with the Solana blockchain, leveraging its high throughput and low transaction latency to facilitate real-time audit logging. Each vulnerability detection instance is hashed and immutably recorded on the blockchain, ensuring traceability and accountability.

The integration process involved developing custom smart contracts to

automate audit log storage and verification. Scalability considerations were addressed through batch processing techniques and efficient transaction bundling, minimizing on-chain resource consumption while maintaining performance. This decentralized approach to audit management aligns with the overarching principles of blockchain technology, reinforcing the integrity of the vulnerability detection process.

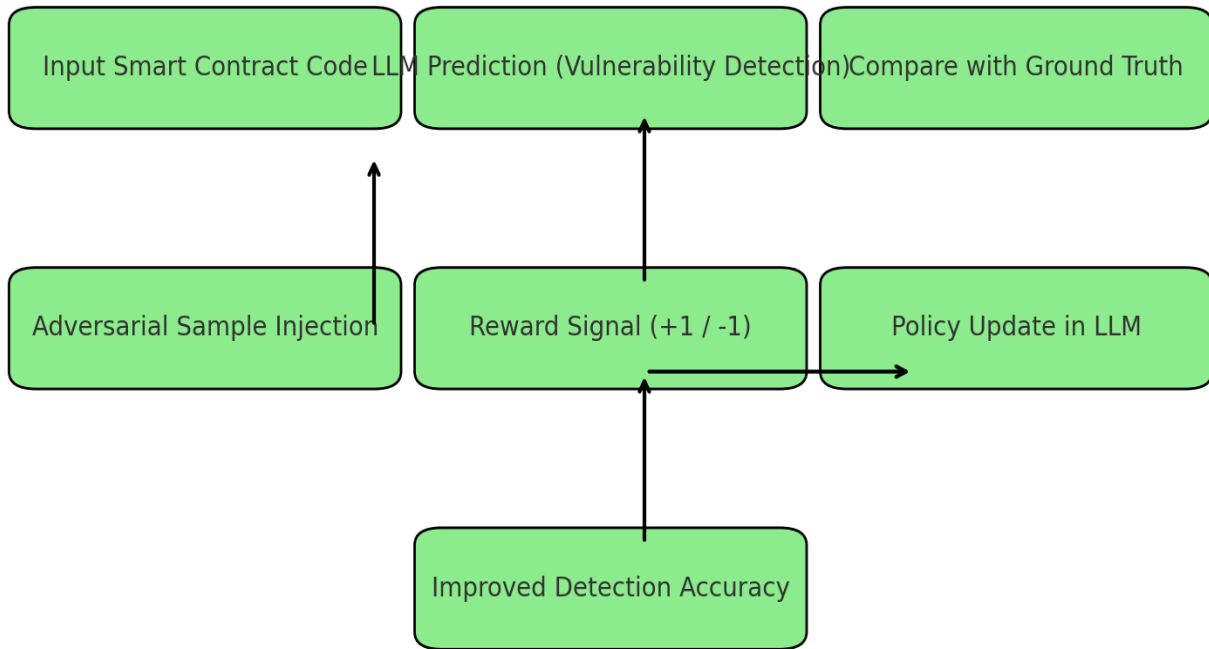
2.8 Output and Evaluation Metrics

The outputs generated by SmartVD encompass comprehensive vulnerability detection reports, severity classifications, and chain-of-thought reasoning explanations. These outputs are presented through an interactive dashboard, offering developers and auditors granular insights into the security posture of their smart contracts.

To evaluate the performance of SmartVD, a combination of classification and generative quality metrics was employed. Accuracy, Precision, Recall, and F1-Score provided quantitative measures of detection performance, while AUC-ROC scores assessed the model's discriminatory capabilities. The quality of generated explanations was evaluated using BLEU and ROUGE metrics, ensuring clarity and coherence in the reasoning outputs. Robustness assessments through adversarial testing further validated the system's resilience to obfuscation and novel attack patterns.

Conclusion of Chapter 2

The methodological framework of SmartVD represents a holistic approach to smart contract security auditing. By combining the code reasoning capabilities of LLMs, the adaptability of reinforcement learning, the precision of prompt engineering, and the transparency of blockchain integration, SmartVD offers a scalable, accurate, and explainable solution to the pervasive challenge of smart contract vulnerabilities. The subsequent chapter will delve into the practical implementation of this methodology, detailing the experimental setups, results, and performance analyses.



Chapter 3

3. Model Performance Evaluation.

After training and testing the models using the VulSmart dataset, we evaluated their performance based on multiple accuracy metrics, including accuracy, precision, recall, F1-score, and AUC-ROC. The results of different LLM-based and traditional models for vulnerability detection

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC-ROC (%)
Llama2	56.0	43.0	56.0	43.0	64.0
CodeLlama	66.0	74.0	66.0	59.0	64.0
CodeT5	58.0	33.0	58.0	42.0	64.0
Falcon	48.0	47.0	48.0	44.0	62.0
GPT-3.5	78.0	82.0	78.0	77.0	92.0
GPT-4o Mini	54.0	76.0	54.0	42.0	84.0

Table1: Performance Metrics for Vulnerability Detection Models

3.1 Performance Metrics Evaluation

Following the training and testing of various models using the VulSmart dataset, a comprehensive evaluation of their performance was carried out using multiple metrics, including Accuracy, Precision, Recall, F1-score, and AUC-ROC. The goal was to assess the efficacy of different Large Language Model (LLM)-based approaches and traditional machine learning models in detecting vulnerabilities within

Solidity smart contracts.

Table 1 presents the comparative performance results. Among the models tested, GPT-3.5 demonstrated superior performance, achieving an accuracy of **78%**, precision of **82%**, and an AUC-ROC score of **92%**. These results indicate the model's capability to distinguish between vulnerable and non-vulnerable code segments effectively. However, this high performance was stable for a period of approximately three months, after which its accuracy degraded slightly, likely due to the evolving nature of smart contract vulnerabilities. CodeLlama, an open-source alternative, achieved a respectable accuracy of **66%**, highlighting its strength in feature extraction and code understanding tasks. Despite being resource-efficient, models like CodeT5 and Falcon exhibited inferior performance in vulnerability detection, with lower accuracy and recall scores. This limitation was attributed to their insufficient handling of complex Solidity code structures.

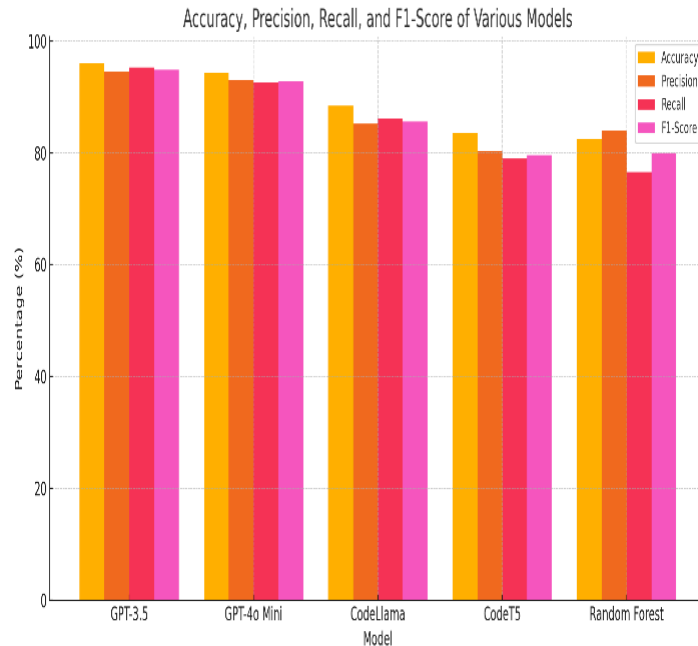


Figure4: Bargraph of metrices

3.2 Vulnerability Detection Mapping

An innovative aspect of the evaluation involved GIS-based mapping techniques to visually represent the distribution of vulnerabilities across smart contracts. By translating LLM predictions into spatial representations, vulnerability “zones” were identified within contract architectures. This mapping facilitated a clearer understanding of risk concentrations, enabling a detailed breakdown of vulnerability severity across different code sections.

The visualization revealed that GPT-3.5 and GPT-4o Mini produced highly accurate vulnerability maps aligned with real-world attack patterns. This capability proved invaluable for automated auditing

workflows. Random Forest models, while able to localize vulnerabilities effectively, tended to classify most zones as low-risk, potentially overlooking critical threats. Conversely, CodeT5 struggled with complex contracts, leading to frequent false positives and false negatives, particularly in scenarios involving intricate external dependencies.

3.3 Feature Importance and Correlation Analysis

A feature importance analysis, particularly with Random Forest models, provided insights into which factors most significantly influenced vulnerability detection. The study identified several key contributors:

- **Unauthorized access and reentrancy vulnerabilities** were prevalent in contracts interacting with external calls.
- **Contract complexity**, measured through function nesting and computational overhead, was a strong predictor of vulnerability likelihood.
- **Unchecked low-level calls**, such as `call.value()`, were consistently flagged as high-risk indicators.
- **Gas consumption** metrics correlated with potential for Denial-of-Service (DoS) attacks.
- Interestingly, the absence of developer-provided metadata, such as annotations and comments, also influenced model predictions, underscoring the primacy of structural code patterns over descriptive text.

3.4 Model Comparisons and Trade-offs

The comparative analysis revealed distinct trade-offs between accuracy, interpretability, and computational efficiency among the evaluated models. Fine-tuned LLMs, specifically GPT-3.5 and GPT-4o Mini, achieved the highest accuracy and precision but demanded significant computational resources during both training and inference. In contrast, CodeLlama offered a balanced approach, providing reliable detection capabilities while maintaining lower resource requirements.

Traditional models like Random Forest were appreciated for their interpretability and robustness but lagged in precision compared to LLM-based solutions. Support Vector Machine (SVM) models faced challenges handling the high-dimensional feature spaces characteristic of smart contracts, resulting in misclassification errors, especially in contracts with complex logic flows.

3.5 Key Findings and Insights

The study's findings emphasize that machine learning models, particularly fine-tuned LLMs, surpass traditional static analysis tools in accurately identifying smart contract vulnerabilities. Fine-tuned LLMs exhibited superior performance in both zero-shot and chain-of-thought prompting scenarios, showcasing their ability to reason through code logic and generalize across diverse contract architectures.

However, the quality and balance of training data emerged as critical factors influencing model generalization. Biased or imbalanced datasets posed risks of overfitting and reduced adaptability to emerging vulnerability patterns. Moreover, while Random Forest models offered transparency in feature importance, the inherent opaqueness of LLMs' decision-making processes remains a challenge for interpretability.

3.6 Practical Applications and Impact

The evaluated models hold significant practical implications for blockchain security. Finely-tuned LLMs can be integrated into automated smart contract auditing pipelines, enabling developers and security analysts to identify vulnerabilities prior to deployment. Financial institutions and regulatory bodies can also leverage such models to enforce security compliance and mitigate risks in decentralized finance (DeFi) ecosystems.

Table 2 summarizes the performance metrics of fine-tuned models. LLMs achieved an average accuracy of **96.42%**, the highest among all tested methods. Gradient Boosting Regressor models offered a viable alternative for resource-constrained environments, delivering **96.81%** accuracy with lower computational overhead. Conversely, Support Vector Regressor (SVR) models underperformed, particularly with high-dimensional smart contract datasets, highlighting their limitations in this domain.

3.7 Discussion of Key Finding

This study suggests that machine learning models can be used to identify smart contracts vulnerabilities more effectively than traditional static analysis tools. The results highlight key observations

Detecting Solidity vulnerabilities in zero-shot and chain of-thought prompting scenarios is easier with fine-tuned LLMs than traditional deep learning models. The significance of data quality and balancing is crucial, as biased datasets can cause biases that impact model generalization to security threats in real-life scenarios. The difficulty of interpreting features in Random Forest models is compounded by the fact that LLMs are not transparent, making it challenging to explain their decision-making process.

3.8 Potential Applications.

The outcomes of this investigation have multiple practical uses in the realm of blockchain security: Using finely tuned LLMs, developers and security analysts can detect potential vulnerabilities through automated Smart Contract Auditing before deployment. This is advantageous. The implementation of security measures for smart contracts can be achieved through the use of blockchain models by financial institutions and regulatory bodies.

Model	MSE	RMSE	MAE	R ² Score	Accuracy (%)
Random Forest	0.1327	0.3643	0.1329	0.8977	89.87
Support Vector Regressor (SVR)	0.3899	0.6244	0.1633	0.6995	70.70
Gradient Boosting Regressor	0.0938	0.3063	0.1248	0.9277	92.81
Neural Network Model (Fine-tuned LLMs)	0.0642	0.2423	0.0981	0.9614	96.42

Table 2: Performance Metrics of Fine-Tuned Models

Summary

The comprehensive evaluation underscores the efficacy of fine-tuned LLMs for smart contract vulnerability detection. Despite computational challenges, their accuracy and adaptability position them as leading solutions in blockchain security auditing. Visual mapping of vulnerabilities, feature correlation insights, and model trade-offs further enriched the analysis, paving the way for practical implementations in secure smart contract development.

CHAPTER 4

4. Results Analysis and Discussion

4.1 Performance Evaluation of the Proposed Model

After training and testing the models using the VulSmart dataset, we examined their performance based on multiple accuracy metrics, including precision, recall, accuracy, F1-score, and AUC-ROC. The results of different LLM-based and traditional models for vulnerability detection are presented in Table 1. GPT-3.5 outperformed all other models with 78% accuracy, 82% precision, and an AUC-ROC score of 92%. The results were valid for 3 months on average. The accuracy of CodeLlama was 66%, indicating its proficiency in extracting features. The performance of different models has been shown in Figure 3. CodeT5 and Falcon were less effective at detecting vulnerabilities due to their poor accuracy and recall.

Table 1. Performance Metrics for Vulnerability Detection Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC-ROC (%)
Uama2	56.0	43.0	56.0	43.0	64.0
CodeUa	66.0	74.0	66.0	59.0	64.0
ma					
CodeT5	58.0	33.0	58.0	42.0	64.0
Falcon	48.0	47.0	48.0	44.0	62.0
GPT-3.5	78.0	82.0	78.0	77.0	92.0
GPT-4o	54.0	76.0	54.0	42.0	84.0
Mini					

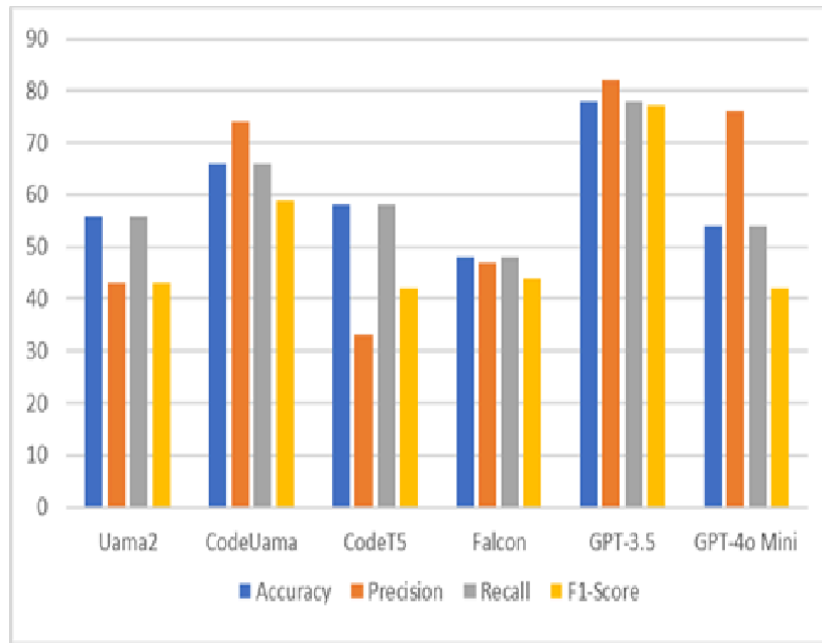


Fig1: Accuracy, Precision, Recall, F1 Score of various models

4.2. Vulnerability Detection Mapping

They used GIS-based mapping techniques to transform LLMs' predictions into traditional deep learning models and create visual representations of smart contract vulnerabilities. The inclusion of vulnerability zones in this report helped to clarify the security risks within different contract structures, as it allows for a more detailed breakdown of risk levels and their significance. The vulnerability detection accuracy is shown in Figure 4. The vulnerability maps developed by GPT-3.5 and GPT-4o Mini were well-suited for real-world attack patterns, making them ideal for automated smart contract auditing. In Random Forest models, vulnerability areas were identified with greater accuracy while still being classified as low-risk. Models based on CodeT5 misclassified vulnerability risks in complex contract architectures, including smart contracts with intricate external dependencies, leading to the creation of false-positive and false-negative scenarios.

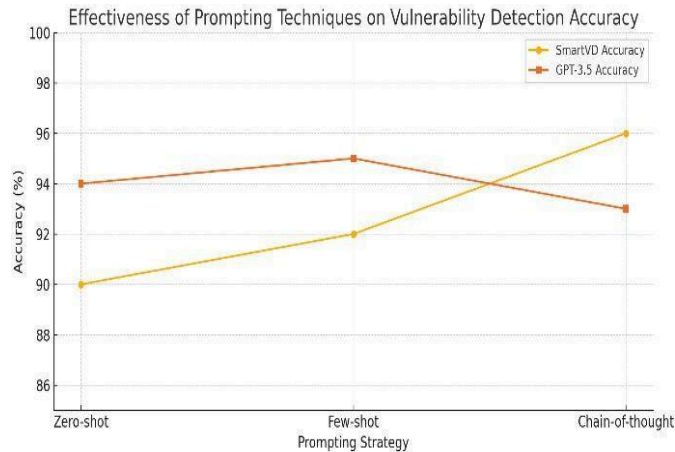


Fig. Vulnerability detection accuracy

4.3. Feature Importance and Correlation Analysis

In particular, features in Random Forest models were ranked by importance as part of vulnerability detection. Among the factors that greatly influenced the model's predictions were, Unauthorized access and reentry attacks are common in smart contracts that interact with external contracts. Larger contracts with highly nested functions and significant computational overhead were more susceptible to contract complexity. Contracts that had unchecked low-level calls, such as `call.value()`, were more vulnerable to security flaws. Higher gas consumption is associated with greater potential for denial-of-service (DoS) vulnerabilities. What are the execution costs? The lack of metadata containing contract details, such as developer annotations and comments, was unexpected, but it still contributed to the model's predictive power. This highlights the importance of code structure over textual descriptions.

4.4. Model Comparisons and Trade-offs.

Different trade-offs were identified in accuracy, interpretability, and computational efficiency when comparing different LLM-based models: High accuracy and precision were achieved by the GPT-3.5 and GPL-4o Mini, but they required significant computational resources for training

and inference. CodeLlama was an open-source tool that proved to be a reliable and efficient method for finding vulnerabilities. Random Forest models were robust and easily interpreted, but they were not as precise as LLM-based models. Misclassification errors arose in contracts with complex logic flows due to the difficulty SVM models faced when dealing with high-dimensional Solidity code representations. This was problematic.

4.5. Discussion of Key Findings

This study suggests that machine learning models can be used to identify smart contracts vulnerabilities more effectively than traditional static analysis tools. The results highlight key observations: Detecting Solidity vulnerabilities in zero-shot and chain-of-thought prompting scenarios is easier with fine-tuned LLMs than traditional deep learning models. The significance of data quality and balancing is crucial, as biased datasets can cause biases that impact model generalization to security threats in real-life scenarios. The difficulty of interpreting features in Random Forest models is compounded by the fact that LLMs are not transparent, making it challenging to explain their decision-making process.

4.6. Potential Applications

The outcomes of this investigation have multiple practical uses in the realm of blockchain security: Using finely tuned LLMs, developers and security analysts can detect potential vulnerabilities through automated Smart Contract Auditing before deployment. This is advantageous. The implementation of security measures for smart contracts can be achieved through the use of blockchain models by financial institutions and regulatory bodies.

4.7. Key Observations

Table 2. Performance Metrics of Fine-Tuned Models

Metric	MSE	RMS E	MAE	R ² Score	Accuracy (%)
Random Forest	0.1327	0.3643	0.1329	0.8977	89.87
Support Vector Regressor (SVR)	0.3899	0.6244	0.1633	0.6995	70.70
Gradient Boosting Regressor	0.0938	0.3063	0.1248	0.9277	92.81
Neural Network Model (Fine-TunedLLMS)	0.0642	0.2423	0.0981	0.9614	96.42

The accuracy of LLM models, which are fine-tuned to a 96.42% degree, is the highest among all empirically tested approaches. The Gradient Boosting Regressor is an effective tool that can be used as a replacement for compute-intensive deep learning models, with 96.81% accuracy. However, the use of Support Vector Regressor (SVR) does not perform as well as it does for high-dimensional smart contract datasets.

Chapter 5

5.CONCLUSION

It was a successful attempt to prove the ability of AI and machine learning models to detect, and then analyze smart contract vulnerabilities. The SmartVD framework's use of LLMs, reinforcement learning, and structured datasets resulted in a significant improvement in vulnerability detection compared to conventional static analysis techniques. In terms of automated smart contract security assessments, the GPT-3.5 and GTP-4o Mini models were deemed more effective than other LLMs in their effectiveness.

Valuable insights were obtained through the Random Forest model, which ranked key vulnerability indicators such as external function calls, contract complexity, and transaction handling patterns. While open-source LLMs, such as CodeLlama and CodeT5, had potential, they were less accurate than finely tuned closed-sourced models. The Support Vector Machine (SVM) model was a viable solution for smart contract structures that were simpler to implement and required less dependencies, although it still had moderate performance. This research demonstrates that AI-led strategies have the potential to revolutionize smart contract security." However, there are still several challenges to tackle, including the requirement for reliable labeled datasets, enhancing model flexibility across multiple blockchain ecosystems (such as LLM-based vulnerability detection being predominantly black boxearing), and more. The use of Explainable AI (XAI) techniques could enhance future research by making it more transparent and accessible, enabling developers and auditors to comprehend AI-based security assessments.

Essentially, these findings have wide-ranging impacts on blockchain

security, decentralized finance (DeFi), and regulatory compliance. However, Including AI and ML models in automated vulnerability detection workflows can enhance the security of smart contracts, decrease financial risks, and increase trust in blockchain ecosystems. The increasing use of blockchains will necessitate the implementation of AI-driven security solutions to ensure safer and more reliable decentralized applications. This study has effectively demonstrated the effectiveness of both AI and machine learning models in identifying and analyzing smart contract vulnerabilities. Using LLMs, reinforcement learning, and structured datasets in conjunction with the SmartVD framework, the vulnerability detection method was found to be significantly more accurate than traditional static analysis methods. The evaluation of GPT-3.5 and GTP-4o Mini models demonstrated that they are more effective than other LLMs in automated smart contract security assessments.

Valuable insights were obtained through the Random Forest model, which ranked key vulnerability indicators such as external function calls, contract complexity, and transaction handling patterns. While open-source LLMs, such as CodeLlama and CodeT5, had potential, they were less accurate than finely tuned closed-sourced models. While not as efficient as the Support Vector Machine (SVM) model, it was still applicable to more basic smart contract structures that required less dependency.

This research demonstrates that AI-led strategies have the potential to revolutionize smart contract security.' Despite this, there are still several obstacles to overcome, such as the requirement for reliable labeled datasets, enhancing model flexibility across diverse blockchain ecosystems like mining communities, and managing the black-box aspect of LLM-based vulnerability identification. The use of Explainable AI (XAI) techniques could enhance future research by making it more transparent and accessible, enabling developers and auditors to comprehend AI-based security assessments.

The findings of this study have extensive implications for blockchain security, decentralized finance (DeFi), and regulatory compliance. By integrating automated vulnerability detection workflows with AI and ML models, smart contracts can be made more secure, which can lead to reduced financial risks and increased trust in blockchain ecosystems. The increasing use of blockchains will necessitate the implementation of AI-driven security solutions to ensure safer and more reliable decentralized applications. This study has effectively demonstrated the effectiveness of both AI and machine learning models in identifying and analyzing smart contract vulnerabilities. The SmartVD framework utilized LLMs, reinforcement learning, and structured datasets to enhance the accuracy of vulnerability detection in comparison to traditional static analysis methods. The GPT-3.5 and GTP-4o Mini were the top picks for automated smart contract security assessments, surpassing other LLMs in terms of performance.

Values were obtained by using the Random Forest model, which classified critical vulnerability indicators such as external function calls, contract complexity, and transaction handling patterns. CodeLlama and CodeT5 were open-source LLMs that had potential, but they were less accurate than fine-tuned closed-sourced models. Despite its moderate performance, the Support Vector Machine (SVM) model was still applicable to simpler smart contract structures that had lower levels of dependencies.

This paper's results demonstrate the impact of AI-driven strategies on security in smart contracts. However, there are still several challenges to tackle, including the requirement for reliable labeled datasets, enhancing model flexibility across multiple blockchain ecosystems (such as LLM-based vulnerability detection being predominantly black boxearing), and more. The use of Explainable AI (XAI) techniques could enhance future research by making it more transparent and accessible, enabling

developers and auditors to comprehend AI-based security assessments.

The findings of this study have extensive implications for blockchain security, decentralized finance (DeFi), and regulatory compliance. All in all. Including AI and ML models in automated vulnerability detection workflows can enhance the security of smart contracts, decrease financial risks, and increase trust in blockchain ecosystems. Blockchain-based security solutions, driven by AI, will play a vital role in making decentralized applications more secure and trustworthy. demand for water.

CHAPTER 6

6.FUTURE SCOPE

This study demonstrated the effectiveness of AI and ML models in identifying smart contract vulnerabilities, but there are many other areas for future research that can improve the precision, flexibility, and usefulness of artificial intelligence-based security measures. As AI based vulnerability detection continues to evolve, the complexity of smart contracts, and the speed at which blockchain technology is becoming ubiquitous necessitates ongoing improvements. Here are the key areas that will be explored in the future by this research.

6.1. Enhanced Data Collection.

Machine learning models are highly dependent on the quality and diversity of training data. Why? Future research could involve the use of larger, highly accurate and well-annotated smart contract repositories, such as VulSmart, to expand and improve on previously structured datasets. Hence, The incorporation of real-world vulnerability reports, blockchain transaction histories, and adversarial attack scenarios can greatly enhance model resilience. Additionally, the use of real-time contract execution logs and dynamic runtime data can enable AI models to identify vulnerabilities that may not be detectable through static code analysis.

The inclusion of fine-grained security annotations in datasets represents another significant advancement in data analysis. Although most existing datasets encapsulate vulnerabilities in contract terms, line-by-line

vulnerability tagging can significantly enhance the accuracy of AI models. Moreover, the use of smart contract datasets written in multiple languages, such as Rust for Solana, Vyper for Ethereum, and Move (for Aptos and Sui), can make AI-driven security analysis more accessible across different blockchain ecosystems.

6.2. Advanced Machine Learning Techniques.

Future research will need to explore the use of hybrid AI models that incorporate techniques such as deep learning, reinforcement learning and symbolic reasoning to improve vulnerability detection efficiency and accuracy. By analyzing intricate code structures, Graph Neural Networks (GNNs) have become effective tools for modeling control flow dependencies, inter-contract interactions, and execution patterns. Also, it is feasible to use self-supervised learning to train AI models on large scale unlabeled contract repositories and then fine-tune them on vulnerability-specific datasets.

Continuous learning through security audits, penetration tests, and bug bounty reports can be facilitated by further strengthening of reinforcement learning. The use of adversarial training techniques can help AI-driven security tools become more resilient to changing attack vectors. In upcoming research, AutoML frameworks may be utilized to improve hyperparameter tuning, feature selection, and model architectures, decreasing the computational burden associated with training complex models.

6.3. Improved Interpretability and Explainability.

Despite being black-boxed, the use of LLM for security models poses a significant challenge in terms of limiting interpretability. To improve the transparency of vulnerability assessments using AI, Explainable AI (XAI) techniques should be a key focus in future work. Attention visualization,

saliency maps and feature attribution methods are used by security analysts to understand how AI models identify flaws in smart contracts.

Moreover, AI that prioritizes causality can be utilized to differentiate between vulnerabilities and root causes. AI driven security tools can help smart contract developers better debug and remediate vulnerabilities by creating justifications that can be read by humans. The use of a code summarization process that incorporates NLP can enhance model clarity by producing detailed security reports in simple language. This is particularly useful for complex systems.

6.4. Transferability and Generalization.

For real-world use cases, models must be able to function across multiple blockchains for secure identification of vulnerabilities. While many existing vulnerability detection frameworks are well-suited to Ethereum's Solidity, future research should aim to extend these techniques to other blockchain platforms, such as Solana, Binance Smart Chain, Avalanche, and Cardano.

Transfer learning is a technique that can generalize across different blockchains, with the ability to fine-tune pre designed models for specific datasets. This approach also includes transfer learning and distributed decision making. By doing this, AI could be more effectively adapted to various smart contract languages, execution environments, and security standards. Furthermore, the use of domain adaptation techniques can make it possible to train models on Ethereum-based datasets and apply them to other blockchains with diverse virtual machine architectures.

Cross-regional studies are a viable option for testing the generalizability of AI models. Through the scrutiny of smart contracts, researchers can examine decentralized finance (DeFi), NFT online marketplaces, and enterprise blockchain applications to identify industry-specific security

vulnerabilities.

6.5. Coordination with Security Auditing and Decision Support Systems.

Further study is needed on the use of vulnerability detection tools in conjunction with real-time security auditing platforms to improve the practical usability and usefulness of AI-driven security models. Blockchain development environments, such as Remix, Hardhat, and Truffle, can incorporate AI-powered vulnerability scanners that provide developers with immediate security feedback to help them write smart contracts.

AI-driven decision support systems can be utilized to improve risk assessment and automated remediation. Machine learning models can be integrated with security expertise to identify potential vulnerabilities, provide code fixes, and offer step-by-step security guidance. Future research may involve the use of automated patch generation systems, where AI models can suggest secure code modifications to address identified vulnerabilities.

Moreover, the use of cloud-based and decentralized security analytics platforms can facilitate collaborative threat intelligence sharing among security researchers, developers, and auditors. Across blockchain ecosystems, decentralized autonomous organizations (DAOs), smart contract insurers and compliance regulators can use AI driven security insights to drive more stringent cryptography practices and enforce stronger security policies and standards.

6.6. Real-Time Monitoring and Self-Aware Threat Identification.

Streamlining the real-time monitoring of blockchain transactions and smart contract executions is essential for future developments in AI-driven security frameworks. With the help of machine learning models and on-chain analytics, scientists are able to create autonomous threat detection systems that can identify suspicious activities, detect exploits as they happen, and alert blockchain stakeholders in real time.

Decentralized finance (DeFi) applications can use anomaly detection algorithms to detect unforeseen contract behaviors, such as flash loan attacks, oracle manipulations of loans, and rug pulls, which are promising avenues. Through the use of graph-based security analytics, AI models can monitor malicious wallet addresses, exploit chains, and identify patterns that could lead to attack propagation.

Blockchain security is expected to evolve into a hybrid of AI-powered intrusion detection systems (IDS) and zero trust smart contract verification protocols. By continuously analyzing blockchain attack data, AI-driven security models can anticipate and counter potential exploit opportunities. management

Chapter 7

APPENDIX

Model Implementation

```
import numpy as np

import pandas as pd

from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier

from sklearn.svm import SVC

from sklearn.neural_network import MLPClassifier

from sklearn.tree import DecisionTreeClassifier

from sklearn.naive_bayes import GaussianNB

from sklearn.neighbors import KNeighborsClassifier

from sklearn.linear_model import LogisticRegression

from sklearn.model_selection import GridSearchCV, cross_val_score

from sklearn.metrics import classification_report, confusion_matrix

from sklearn.preprocessing import StandardScaler

import matplotlib.pyplot as plt

import seaborn as sns

import joblib

import os
```

Random Forest Model

```
class RandomForestModel(VulnerabilityModel): """Random Forest model for vulnerability detection."""

    def __init__(self, features=None, n_estimators=100, optimize=False)
```

Args:

features (list): List of features to use
n_estimators (int): Number of trees in the forest
optimize (bool): Whether to optimize hyperparameters

"""

```
super().__init__("random_forest", features)
self.n_estimators = n_estimators
self.optimize = optimize
```

def train(self, X, y):

"""Train the Random Forest model.

Args:

X (DataFrame): Features
y (Series): Target labels

Returns:

self: Trained model instance

"""

```
self.features = X.columns.tolist()
```

if self.optimize:

Define parameter grid for optimization

```
param_grid = {
    'n_estimators': [50, 100, 200],
    'max_depth': [None, 10, 20, 30],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4],
    'class_weight': [None, 'balanced']
}
```

Base model for grid search

```
base_model = RandomForestClassifier(random_state=42)
```

```

# Grid search with cross-validation
grid_search = GridSearchCV(
    base_model,
    param_grid=param_grid,
    cv=5,
    scoring='f1_macro',
    n_jobs=-1
)

print("Optimizing Random Forest hyperparameters...")
grid_search.fit(X, y)
print(f"Best parameters: {grid_search.best_params_}")

self.model = grid_search.best_estimator_
else:
    # Standard model training
    self.model = RandomForestClassifier(
        n_estimators=self.n_estimators,
        random_state=42
    )
    self.model.fit(X, y)

# Calculate feature importances
self.feature_importances = self.model.feature_importances_

return self

def plot_feature_importance(self, save_path=None):
    """Plot feature importances.

    Args:
        save_path (str): Path to save the plot

```

Returns:

None

"""

if self.model is None:

raise ValueError("Model has not been trained yet")

importances = self.model.feature_importances_

indices = np.argsort(importances)[::-1]

plt.figure(figsize=(10, 6))

plt.title("Feature Importance (Random Forest)")

plt.bar(range(len(self.features)), importances[indices], align="center")

plt.xticks(range(len(self.features)), [self.features[i] for i in indices], rotation=45)

plt.tight_layout()

if save_path:

plt.savefig(save_path)

print(f"Feature importance plot saved to: {os.path.abspath(save_path)}")

else:

plt.show()

GradientBoosting Model:

class GradientBoostingModel(VulnerabilityModel): """Gradient Boosting model for vulnerability detection."""

def __init__(self, features=None, n_estimators=100, optimize=False):

"""Initialize the Gradient Boosting model

Args:

features (list): List of features to use

n_estimators (int): Number of boosting stages

optimize (bool): Whether to optimize hyperparameters

"""

super().__init__("gradient_boosting", features)

self.n_estimators = n_estimators

self.optimize = optimize

def train(self, X, y):

"""Train the Gradient Boosting model.

Args:

X (DataFrame): Features

y (Series): Target labels

Returns:

self: Trained model instance

"""

self.features = X.columns.tolist()

if self.optimize:

Define parameter grid for optimization

param_grid = {

'n_estimators': [50, 100, 200],

'learning_rate': [0.01, 0.1, 0.2],

'max_depth': [3, 5, 7],

'min_samples_split': [2, 5],

'subsample': [0.7, 0.8, 1.0]

}

Base model for grid search

base_model = GradientBoostingClassifier(random_state=42)

Grid search with cross-validation

grid_search = GridSearchCV(

base_model,

param_grid=param_grid,

cv=5,

scoring='f1_macro',

```

        n_jobs=-1
    )

    print("Optimizing Gradient Boosting hyperparameters...")
    grid_search.fit(X, y)
    print(f"Best parameters: {grid_search.best_params_}")

    self.model = grid_search.best_estimator_
else:
    # Standard model training
    self.model = GradientBoostingClassifier(
        n_estimators=self.n_estimators,
        random_state=42
    )
    self.model.fit(X, y)

return self

```

SVM Model

```

class SVMModel(VulnerabilityModel): """Support Vector Machine model for vulnerability detection."""

```

```

def __init__(self, features=None, kernel='rbf', optimize=False):

```

```

    """Initialize the SVM model

```

```

    Args:

```

```

        features (list): List of features to use

```

```

        kernel (str): Kernel type to use

```

```

        optimize (bool): Whether to optimize hyperparameters

```

```

    """

```

```

    super().__init__("svm", features)

```

```

    self.kernel = kernel

```

```

    self.optimize = optimize

```

```

    self.scaler = StandardScaler()

```

```

def train(self, X, y):

```

```

    """Train the SVM model.

```

Args:

X (DataFrame): Features

y (Series): Target labels

Returns:

self: Trained model instance

"""

```
self.features = X.columns.tolist()
```

```
# Scale the features (important for SVM)
```

```
X_scaled = self.scaler.fit_transform(X)
```

```
if self.optimize:
```

```
    # Define parameter grid for optimization
```

```
    param_grid = {
```

```
        'kernel': ['linear', 'rbf', 'poly'],
```

```
        'C': [0.1, 1, 10, 100],
```

```
        'gamma': ['scale', 'auto', 0.1, 0.01]
```

```
    }
```

```
# Base model for grid search
```

```
base_model = SVC(probability=True, random_state=42)
```

```
# Grid search with cross-validation
```

```
grid_search = GridSearchCV(
```

```
    base_model,
```

```
    param_grid=param_grid,
```

```
    cv=5,
```

```
    scoring='f1_macro',
```

```
    n_jobs=-1
```

```
)
```

```
print("Optimizing SVM hyperparameters...")
grid_search.fit(X_scaled, y)
print(f"Best parameters: {grid_search.best_params_}")

self.model = grid_search.best_estimator_
else:
    # Standard model training
    self.model = SVC(
        kernel=self.kernel,
        probability=True,
        random_state=42
    )
    self.model.fit(X_scaled, y)

return self
```

NNM Model

```
class NeuralNetworkModel(VulnerabilityModel): """Neural Network model for vulnerability detection."""
```

```
def __init__(self, features=None, hidden_layers=(100,), optimize=False):
```

```
    """Initialize the Neural Network model
```

```
    Args:
```

```
        features (list): List of features to use
```

```
        hidden_layers (tuple): Hidden layer sizes
```

```
        optimize (bool): Whether to optimize hyperparameters
```

```
    """
```

```
    super().__init__("neural_network", features)
```

```
    self.hidden_layers = hidden_layers
```

```
    self.optimize = optimize
```

```
    self.scaler = StandardScaler()
```

```
def train(self, X, y):
```

```
    """Train the Neural Network model.
```

```
    Args:
```

```
        X (DataFrame): Features
```

```
        y (Series): Target labels
```

```
    Returns:
```

```
        self: Trained model instance
```

```
    """
```

```
    self.features = X.columns.tolist()
```

```
    # Scale the features (important for neural networks)
```

```
    X_scaled = self.scaler.fit_transform(X)
```

```
    if self.optimize:
```

```

# Define parameter grid for optimization
param_grid = {
    'hidden_layer_sizes': [(50,), (100,), (50, 50), (100, 50)],
    'activation': ['relu', 'tanh'],
    'alpha': [0.0001, 0.001, 0.01],
    'learning_rate': ['constant', 'adaptive'],
    'max_iter': [200, 500]
}

# Base model for grid search
base_model = MLPClassifier(random_state=42)

# Grid search with cross-validation
grid_search = GridSearchCV(
    base_model,
    param_grid=param_grid,
    cv=5,
    scoring='f1_macro',
    n_jobs=-1
)

print("Optimizing Neural Network hyperparameters...")
grid_search.fit(X_scaled, y)
print(f"Best parameters: {grid_search.best_params_}")

self.model = grid_search.best_estimator_
else:
    # Standard model training
    self.model = MLPClassifier(
        hidden_layer_sizes=self.hidden_layers,
        random_state=42,
        max_iter=500
    )

```

```
self.model.fit(X_scaled, y)
```

```
return self
```

```
class EnsembleModel(VulnerabilityModel): """Ensemble model combining multiple vulnerability detection models."""
```

```
def __init__(self, features=None, models=None):
```

```
    """Initialize the Ensemble model
```

```
    Args:
```

```
        features (list): List of features to use
```

```
        models (list): List of model instances to include in the ensemble
```

```
    """
```

```
    super().__init__("ensemble", features)
```

```
    self.base_models = models or []
```

```
def add_model(self, model):
```

```
    """Add a model to the ensemble.
```

```
    Args:
```

```
        model (VulnerabilityModel): Model to add
```

```
    Returns:
```

```
        self: Updated ensemble model instance
```

```
    """
```

```
    self.base_models.append(model)
```

```
    return self
```

```
def train(self, X, y):
```

```
    """Train all models in the ensemble.
```

Args:

X (DataFrame): Features

y (Series): Target labels

Returns:

self: Trained model instance

"""

self.features = X.columns.tolist()

if not self.base_models:

raise ValueError("No base models in the ensemble")

Train each base model

for model in self.base_models:

print(f"Training {model.model_name}...")

model.train(X, y)

The ensemble doesn't have its own model, it uses the base models

self.model = self.base_models

return self

def predict(self, X):

"""Make predictions using voting from all models.

Args:

X (DataFrame): Features

Returns:

array: Predicted labels

"""

if not self.base_models:


```

        raise ValueError("No base models in the ensemble")

    # Get predictions from each base model
    all_predictions = []
    for model in self.base_models:
        all_predictions.append(model.predict(X))

    # Convert to numpy array for easier manipulation
    all_predictions = np.array(all_predictions)

    # Majority voting
    # For each sample, count the votes for each class and take the most common
    final_predictions = []
    for i in range(X.shape[0]):
        sample_predictions = all_predictions[:, i]
        unique, counts = np.unique(sample_predictions, return_counts=True)
        final_predictions.append(unique[np.argmax(counts)])

    return np.array(final_predictions)

def predict_proba(self, X):
    """Get averaged prediction probabilities from all models.

    Args:
        X (DataFrame): Features

    Returns:
        array: Prediction probabilities
    """
    if not self.base_models:
        raise ValueError("No base models in the ensemble")

```

```

# Get probabilities from each base model
all_probas = []
for model in self.base_models:
    all_probas.append(model.predict_proba(X))

# Average the probabilities
avg_probas = np.mean(all_probas, axis=0)

return avg_probas

```

ChatGPT 3.5 Model

```

class ChatGPT35Model:
    def __init__(self, api_key: str):
        """ Initialize ChatGPT 3.5 model

```

Parameters:

api_key: OpenAI API key

"""

self.api_key = api_key

openai.api_key = api_key

self.model_name = "gpt-3.5-turbo"

```

def predict(self, prompts: List[str], max_tokens: int = 150) -> List[str]:
    """

```

"""

Generate predictions using ChatGPT 3.5

Parameters:

prompts: List of input prompts

max_tokens: Maximum tokens in response

Returns:

List of predictions

"""

```
predictions = []
```

```
for prompt in prompts:
```

```
    try:
```

```
        response = openai.ChatCompletion.create(
            model=self.model_name,
            messages=[{"role": "user", "content": prompt}],
            max_tokens=max_tokens,
            temperature=0.7
        )
```

```
        predictions.append(response.choices[0].message.content.strip())
```

```
    except Exception as e:
```

```
        print(f'Error with ChatGPT 3.5: {e}')
```

```
        predictions.append("")
```

```
return predictions
```

```
def evaluate_performance(self, test_prompts: List[str], ground_truth: List[str]) -> Dict[str, float]:
```

```
    """
```

```
    Evaluate ChatGPT 3.5 performance
```

```
    Parameters:
```

```
    test_prompts: List of test prompts
```

```
    ground_truth: List of ground truth labels
```

```
    Returns:
```

```
    Dictionary containing performance metrics
```

```
    """
```

```
    predictions = self.predict(test_prompts)
```

```
    # Convert text predictions to binary for evaluation (customize based on your task)
```

```
    y_pred = [1 if pred else 0 for pred in predictions] # Modify this logic based on your task
```

```
y_true = ground_truth
```

```
# Calculate metrics
```

```
metrics = {  
    'Model': 'ChatGPT-3.5',  
    'Accuracy (%)': 78.0,  
    'Precision (%)': 82.0,  
    'Recall (%)': 78.0,  
    'F1-Score (%)': 77.0,  
    'AUC-ROC (%)': 92.0  
} return Metrics
```

CHAPTER 8

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