



**UNCOVERING BLOCKCHAIN SMART CONTRACT VULNERABILITIES WITH
CodeBERT**

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ABSTRACT

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Smart contracts (Szabo 1997) pertain to self-executing, trustless transactions through decentralization, which do not require any intermediaries. As decentralized finance has come to the fore, however, several glaring security flaws of smart contracts come to light and it has caused losses worth several dollars due to code exploits. The present research work attempts to utilize the CodeBERT model, which is a pre-trained transformer model for programming languages, to address the immediate demand for automated vulnerability identification in smart contracts.

Our fine-tuning of CodeBERT involves the automation of analyzing the code structure and keywords' pattern to detect likely vulnerabilities in Solidity-based smart contracts.

The research shows that fine-tuning CodeBERT on a labeled Solidity dataset of 47,398 contracts is adequate to realize vulnerability detection in smart contracts. The model recorded an impressive accuracy of 85.3% on the test dataset and an ROC AUC score of 0.93, thus showing robust classification capability. Special care was taken in balancing the dataset, thus ensuring Vulnerable and Non-Vulnerable labels have equal representation so as to solve the class imbalance problem. The experimental results further validated the ability of the model to generalize it because it showed a great level of confidence when identifying vulnerabilities in unseen Solidity code.

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1 INTRODUCTION

Blockchain-based smart contracts are vital elements of it (Szabo 1997); they facilitate secure, self-executing agreements that do not require any intermediaries. Such contracts are written in code, and their terms and conditions are automatically enforced, which is useful in the case of DeFi applications. However, the increasing usage of the smart contracts raises security concerns. The code vulnerabilities in smart contracts have been responsible for several exploits of considerable public, leading to wealth losses. As these contracts become very crucial in the wake of an ever-increasing digital economy, it becomes important to develop reliable, automated methods with which to identify and remedy the possible security flaws before they can be exploited. This thesis examines the application of CodeBERT (Feng et al. 2020), a language model pre-trained on programming languages, to identify potential vulnerabilities in Solidity-based smart contracts, thus improving their security and integrity.

Studies have previously shown that machine learning and deep learning models are competent in identifying coding vulnerabilities. More specifically, it has been observed that models trained on natural language processing tasks are able to extremely efficiently identify code semantics and syntax. The various transformer-based models, for example BERT, have been used in studies with the goal to detect vulnerabilities in different languages such as Python and JavaScript. CodeBERT, a derivative of BERT specific for code, has been able to prove outstandingly effective in several tasks related to code such as code completion and defect identification. Despite this, there has been a dearth of studies on the specific use of CodeBERT to detect security problems in Solidity-the programming language that has been specifically developed by Ethereum (Buterin 2013), while smart contracts have their unique set of challenges and patterns that are different from traditional programming languages.

However, there are still research gaps in literature, especially in the area of vulnerability detection in Solidity contracts using pre-trained language models. Most of the work has been done using generic programming languages, not taking into account the unique complexities and structures of the smart contract code like crucial financial operations, state changes, and distinct operating risks. Additionally, though some works used the transformer model to detect vulnerabilities, very few adopted any fine-tuning for the specific task of identifying vulnerabilities related to smart contracts where the failure stakes are extremely high. This remedy aims to address this gap through the fine-tuning of CodeBERT on a massive amount of Solidity contracts so that it can actually detect vulnerabilities.

The primary objective is building a rather comprehensive technique in automating vulnerability detection in smart contracts using CodeBERT. This research addresses the following research questions: (1) How well can CodeBERT be fine-tuned for detecting vulnerabilities in Solidity-based smart contracts? (2) What types of vulnerabilities are most prevalent in such contracts, and does the model detect them in a reliable manner? (3) Is there possible prevention against such financial hack or loss in any way using Block Chain Contracts? This research is limited to an analysis of Solidity contracts alone and is not extended to other programming languages that are being used in Blockchain. The thesis is divided into sections as follows: Chapter 2 deals with a review of relevant literature and previous research; Chapter 3 deals with the methodology of preparing the data for training model and evaluation; Chapter 4 gives the results and findings; and Chapter 5 ends with a discussion from the standpoint of future recommendations for the research.

2 Literature Review

Analysis of the literature reveals interesting views in security of smart contracts that they could be included in machine learning and deep learning models for vulnerability detection. Transformer based models especially BERT (Devlin et al. 2019), and its variants such as CodeBERT (Feng et al. 2020) have shown the potential application in detecting vulnerabilities caused by capturing the syntax and semantic patterns of code in programming languages. Past studies have successfully applied BERT-based models in detecting defects in general purpose languages. Not much research has specifically focused on the application of these models in Solidity, being the language of choice for Ethereum smart contracts. Existing studies predominantly talk of vulnerabilities in conventional codes, and ignoring the financial and operational risks that are specific to smart contracts. This thesis extends that work by adapting CodeBERT specifically for Solidity (Solidity 2024), with a view to increasing detection of blockchain environment specific vulnerabilities which is completely for the first time in Block Chain History.

2.1 Introduction to Blockchain and Smart Contracts

Bitcoin brought about the concept of a blockchain technology in the year 2008 through the publication by Nakamoto (2008). A blockchain is described as a distributed ledger through which transactions can be recorded on numerous computers with the notable confidence that the transactions cannot be altered in any way once posted (Blockchain Insider 2024). The technology is now available in a lot of fields, for instance, its applications range from finance and supply chain management to healthcare.

Smart contracts, according to Szabo (1997), are contracts written in code with the terms of the contract preset within the code itself such that when a certain event occurs, the term is executed automatically. Therefore, the terms of the contract are enforced and executed without the intervention of a third party. Ethereum (Buterin 2013), is the most fashionable platform on which smart contracts can be written for developers who wish to write or deploy using the Solidity programming language.

2.2 Vulnerabilities in Smart Contracts

It is by recognizing their potential in smart contracts that such vulnerabilities could pose quite a threat; they can even cause much financial damage. Research exposes common vulnera-

bilities in Solidity smart contracts, such as reentrancy attacks (Luu, Pham, Ajay, et al. 2016), integer overflows or underflows, and unchecked call returns.

A classic as well as the most infamous vulnerability attached to a smart contract would be reentrancy, an attack that was known for successfully stealing nearly \$60 million worth of Ether from the DAO back in 2016 (Choi, Kang, and Kim 2017). In this attack, a hacker repeatedly invoked the function of a contract before finishing the execution of the previous call, so that he was able to draw the funds kept in that contract. This stresses again the importance of exact sequencing of function execution to not have such issues happen again. Yet another case is the issue of integer overflow and underflow: when the arithmetic operation exceeds the max or the min value which variables can handle. For instance, Oyente (Luu, Pham, Ho, et al. 2016), which analyzes smart contracts using symbolic execution, has shown that from the 19366 contracts analyzed, more than 8000 contracts had at least one vulnerability among them; the most common ones being integer overflows and underflows. These also include unchecked call returns which may be a huge risk when the success of low-level calls is not validated-resulting in instances for which critical functions fall into silence and expose contracts to attacks. Hence such scenarios would indicate the high need for careful design, testing, and validation of smart contract code before concluding its functionality in the case of security and reliability.

2.3 Existing Tools and Techniques for Vulnerability Detection

For the detection of various vulnerabilities within smart contracts, several tools and techniques have been developed. These tools for vulnerability detection; range from static analysis and formal verification approaches to machine learning ones.

2.3.1 Static Analysis Tools

Static analysis directly regards the code without executing it. The tools include mythril, Slither, and securify that are widely recognized for vulnerability detections in Solidity contracts.

- **Mythril:** Developed by ConsenSys (Diligence 2019), is a security analysis tool which applies symbolic execution, SMT solving, and taint analysis, and detects a number of other vulnerabilities, such as reentrancy and integer overflows, and pointers to uninitialized storage.
- **Slither:** Developed by Trail of Bits (Bits 2024), Perform a static analysis with Solidity contracts: Find typical security problems fast and accurately. Showed that slither can quickly analyze vast codebases and provides actionable information for developers.

- **Securify:** Developed by Tsankov et al. (2018), is an extensible security analysis tool which employs compliance and violation patterns in identifying vulnerable code. Their research has shown that Securify could analyze a wide variety of thousands of contracts with high precision for both known and unknown vulnerabilities.

2.3.2 Machine Learning Approaches

In the last few years, machine learning methods have been used in the area of smart contract vulnerability detection. By training the model using big collections of labeled contracts, it is provided with the functionality to automatically qualify different vulnerabilities related to smart contracts.

SmartEmbed: A strategy presented by Chen, Ning, and Shi (2019) for vulnerability detection in smart contracts using deep learning techniques has been made. Such a model creates embeddings for contracts on the basis of their associated bytecode. Then, the use of such embeddings makes the following identification patterns with respect to vulnerabilities: The study suggests that SmartEmbed performed better than the traditional static analysis tools with respect to accuracy and speed.

ContractWard: A neural network-based model that detects vulnerabilities through source code analysis was developed by Zhou et al. (2020). Its design combines the convolution operation of CNNs with sequences of RNN networks, thus able to capture both the local and global context of the code while achieving high accuracy.

2.4 Application of CodeBERT for Vulnerability Detection

CodeBERT is a transformer-based model that is pre-trained with a very large coverage of source code and natural languages. It is becoming a leading device for various code-related tasks, like vulnerability detection. CodeBERT follows the RoBERTa architecture and was trained on other tasks such as masked token prediction and sentence sequence analysis. Thus, it can also understand and analyze code structure.

2.4.1 Pre-training and Fine-tuning

CodeBERT was pre-trained on the programming language datasets which include Python, Java, Solidity, and their associated documentation. The syntactic relationship and semantic relationship among codes were recognized by Feng et al. (2020) and proved that CodeBERT is able to perform well in the downstream task like vulnerability detection.

In this research work, CodeBERT is fine-tuned with a dataset containing Solidity contracts labeled with known vulnerabilities. The fine-tuning helps CodeBERT to learn about the

patterns that match vulnerabilities in order to identify security issues in new contracts. Fine-tuning models like CodeBERT over domain-specific data tends to yield a good improvement in vulnerability detection, as observed in studies like that of Guo et al. (2020).

2.4.2 Comparative Analysis

CodeBERT is often compared in its performance in vulnerability detection with traditional static analysis tools and other machine learning models. According to Ahmed and Devanbu (2022), CodeBERT outperforms existing models in terms of precision and recall, both particularly in the node level for the detection of subtle vulnerabilities that are mostly missed by static analysis tools.

3 Methodology

The research combines data collection, processing, fine-tuning model, and evaluation to extract vulnerabilities from blockchain smart contracts using the CodeBERT model. The overall methodology for finding exposures in Solidity smart contracts is thus given. The design has been made so that it meets robustness, reproducibility and accuracy on the results.

3.1 Data Collection and Preparation

This dataset for the study is the collection of Solidity smart contracts from publicly available repositories such as GitHub as well as the Etherscan and the SmartBugs dataset. In addition, it also contains known vulnerable contracts and benign contracts to store a balanced dataset for training and evaluation.

3.1.1 Data Collection

SmartBugs Dataset: A well-curated collection of Solidity contracts annotated with traits of vulnerabilities as an excellent training pool.

Etherscan Repository: Those public Etherscan contracts that are matched on Ethereum are mined and added into this dataset to enrich it with real-world smart contracts.

GitHub Repositories: Open-source projects with Solidity contracts are scraped to supplement the dataset.

This dataset contains nearly 47,398 Solidity Files which represents a large spectrum of possible vulnerabilities .

3.1.2 Data Cleaning and Preprocessing

Data preprocessing is a vital stage owing to the very raw nature of the collected data. The data is cleaned and preprocessed by using the following techniques:

Deduplication: Duplicate contracts are removed from the sample to cause no bias during model training.

Syntax Validation: Syntax validation is done on each contract on the Solidity compiler codes so that only syntactically correct contracts are included.

Normalization: The code here is normalized by removing comment and redundant white spaces as well as normalizing dissimilar format in the change of format for better interpretability by the model.

3.2 Model Selection and Fine-Tuning

3.2.1 CodeBERT Model

The methodology centralizes the CodeBERT model, a pre-trained model created specifically for understanding code sans the need for further fine-tuning. CodeBERT, which is a modification of the RoBERTa architecture, fine-tunes both natural language and programming language tasks. It utilizes the objectives of masked language modeling and next sentence prediction that make the model suitable enough to find code patterns and potential vulnerabilities.

3.2.2 Fine-Tuning Process

The process of fine-tuning is essential to transforming CodeBERT into a model specialized in the task of the specific detection of vulnerabilities in Solidity contracts. The subsequent points refer to the steps in fine-tuning:

Dataset Splitting: The dataset contains 47,398 Solidity smart contracts that are prepared with labels for the 'Vulnerable' and 'Non Vulnerable' classes. Vulnerability analysis of contract codes has been performed using Slither, which is a tool for static analysis. Thus, after balancing the dataset, it was divided into 23000 learning samples, 9000 evaluation samples, and 9000 tuning samples.

Masked Language Model (MLM): CodeBERT was fine-tuned with the MLM objective as it masks up to 15% tokens of the input sequence and is further trained to predict such tokens. This process enabled the model to learn better the code syntax and semantics and also the contextual relationships in Solidity smart contracts.

Training Configuration: It started with a 10,000 and 3,000 training sample setup due to time limitations imposed during fine-tuning. The dataset was balanced with regard to equal "Vulnerable" and "Non- Vulnerable" labels, and then the model was retrained with the full dataset for 10 epochs by sending a batch with size of 8, using AdamW optimizer with a learning rate of 5×10^{-5} . Gradient clipping was used for stable training.

Fine-tuned on a state-of-the-art machine with GPU support, the model is trained and subsequently saved for further evaluation and inference.

3.3 Exploratory Data Analysis

Exploratory data analysis (EDA) might also be performed to understand the distribution within the data, discover anomalies, and check relationships between different features in the dataset. Some essential statistics collected might be, the frequency of different Solidity constructs, distributions of contract sizes, and incidences about a specific type of vulnerability.

Visualizations also include histograms, box plots, and scatter plots that are used to look at some characteristics in the dataset. These visualizations are also used to identify patterns, trends, and even possible outliers that might affect the model performance. For instance, distribution of contract sizes might tell whether the dataset has such bias towards short contracts or long contracts.

3.4 Model Evaluation and Validation

The Model execution has been viewed based on a category of standard metrics specific to the task of vulnerability detection:

Precision-Recall Curve: Exhibited precision very consistently as recall progressed.

Accuracy: The overall accuracy of the model stands at 85.3%, thus classifying vulnerabilities in smart contracts effectively.

ROC-AUC Score: Evaluation model achieved AUC of 0.93, with a very high capability in discrimination between 'Vulnerable' and 'Non-Vulnerable' classes.

Confusion Matrix: Established balanced predictions in the case of 'Vulnerable' and 'Non-Vulnerable'.

Thus, these results confirm the model's effectiveness in preventing the vulnerability detection over the test and unseen data.

3.4.1 Cross-Validation

To cross-validate the model as robust, the data is divided into k folds, usually 5 or 10- substrates. Thus would assess the trained model using a different fold as validation set k number of times. By taking the mean of all the folds, the mean estimate of the model performance can be considered.

3.4.2 Testing on Unseen Data

File Solidity smart contracts have been placed aside for testing on the fine-tuned CodeBERT model. Included in those contracts were vulnerabilities proven by Slither. The successful identification of vulnerabilities at a high confidence level verifies generalization for both the real environment and the actual use cases.

3.5 Mathematical Foundations and Model Details

Mathematical principles core equations, algorithms, this chapter stands to claim used in this thesis to detect the blockchain smart contracts vulnerabilities using CodeBERT model. This presents the steps taken to set token embedding, attention of CodeBERT, softmax for normalization, Cross-Entropy loss for training the model, and inference at last.

3.5.1 Embedding Calculation

In the processing of natural language and analyze of code, embeddings encode discrete tokens (words or parts of the code) into a dense numerical representation that models can take. In this research, we will apply CodeBERT, which is a high-dimensional vector embedding output of a pre-trained model across a large corpus of programming language data. It supports the tokenization of a Solidity smart contract into tokens. Then transforms each token into a vector that resides in high-dimensional space.

Equation

$$e_i = E[t_i]$$

where:

e_i denotes the embedding vector for token t_i .

E denotes the embedding matrix learned by CodeBERT during pretraining.

t_i is a token in Solidity smart contracts.

Explanation: The embedding matrix E contains vector representations for each token capturing the semantic and syntactic relationships in the code. This helps the CodeBERT model comprehend better the structure and the specific meaning of each part of a smart contract.

Application in Thesis: When a Solidity contract enters CodeBERT, each token of the contract is mapped to its embedding vector based on that relation. This further prepares the inputs for the attention mechanism that will grasp intricate patterns and relationships for the contract.

3.5.2 Attention Mechanism and Softmax

The attention mechanism would indeed be a vital model component in the CodeBert magic, as it enables the tool to concentrate on the key elements. The code when detecting a vulnerability. This attention mechanism weights each token concerning the other so that the model can learn which ones are essential.

Attention Mechanism Equation:

$$\text{Attention}(Q, K, V) = \text{softmax} \left(\frac{QK^T}{\sqrt{d_k}} \right) V \quad (3.1)$$

where:

- Q , where K stands for Key and Value for the representation of the weights.
- d_k is the dimension of key vectors and is also used for scaling purposes.
- Thus, the weighted sum of the values will be the weighted sum of the values V concerning the weight concerning the queries and keys.

Explanation:

Scores are computed by the attention mechanism through a dot product of queries and keys. The scores give an idea of how the tokens in the sequence relate to each other. These scores are normalized further using the softmax function into weights called attention weights, which are then applied to the values V in generating a context-aware representation.

Softmax Function:

The softmax function converts attention scores into probabilities:

$$\text{softmax}(z_i) = \frac{e^{z_i}}{\sum_{j=1}^N e^{z_j}} \quad (3.2)$$

where z_i is a score for token i , and N is the total number of tokens.

Application in Thesis: In CodeBERT, the attention mechanism makes the network concentrate on important parts of the Solidity contract, for example, giving higher attention weight to the involved tokens in critical functions or state changes for discovering potential vulnerabilities. Wherein the tokens involved will pay high attention and help the model in discovering probable vulnerabilities.

3.5.3 Loss Function and Optimization

To perform vulnerability detection, the CodeBERT is trained on the cross-entropy loss function which is the difference between predicted probabilities and real expected values, wherein contractual tokens or terms denote whether a certain one of them is vulnerable or not.

Cross-Entropy Loss

$$\text{Loss} = - \sum_{i=1}^N y_i \log(\hat{y}_i) \quad (3.3)$$

where:

- Y_i : True label for token i (vulnerable=1, non-vulnerable=0).
- $y_i \log(\hat{y}_i)$: Predicted probability of token i being vulnerable.
- N : Total number of tokens or sequences in the dataset.

Explanation: Cross-entropy loss generally indicates how well the predicted probabilities (from the model) match the true labels. A lower cross-entropy loss indicates, therefore, that the model's predictions are closer to the actual labels, which signifies better accuracy.

Optimization Using Adam: The parameters of the model are updated by minimizing the cross-entropy loss with the use of the Adam optimizer. Adam is an adaptive learning rate optimization algorithm that incorporates the features of the two, AdaGrad and RMSProp together.

Adam Update Rule:

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1) g_t \quad (3.4)$$

$$v_t = \beta_2 v_{t-1} + (1 - \beta_2) g_t^2 \quad (3.5)$$

$$\hat{m}_t = \frac{m_t}{1 - \beta_1^t} \quad (3.6)$$

$$\hat{v}_t = \frac{v_t}{1 - \beta_2^t} \quad (3.7)$$

$$\theta_{t+1} = \theta_t - \frac{\alpha \cdot \hat{m}_t}{\sqrt{\hat{v}_t} + \epsilon} \quad (3.8)$$

where:

- m_t and v_t are the moving average of the gradient and squared gradient, respectively.
- α -learning rate
- θ -Model Parameters

Application in Thesis: Adam optimizer is used in this thesis for updating parameters in training mode for CodeBERT through the integration of cross-entropy loss minimization that subsequently improves the model's ability to identify threats.

3.5.4 Inference Process

After training, CodeBERT will be applied to fresh Solidity contracts to discover the flaws. The inference process consists of tokenizing the contract, applying an attention mechanism to the contract, and finally producing probabilities of being potentially vulnerable.

*Prediction Equation

$$\hat{y}_i = \text{softmax}(W_o \cdot \text{Attention}(Q, K, V) + b_o) \quad (3.9)$$

where:

- W_o and B_o are the weights and bias for the output layer.
- $\text{Attention}(Q, K, V)$ becomes the context vector for each token, which signifies the importance of the token concerning the entire contract.

Explanation: Finally, the output of CodeBERT would suggest possibilities of being vulnerable by the model for each corresponding token in the contract. The predictions are given probabilities to suggest with softmax outputs; the higher the probability, the higher the chances of being vulnerable.

Application in Thesis: During inference CodeBERT, then sits and waits for new Solidity contracts, delivering individual predictions of the vulnerabilities in their code. These predictions are useful regarding the vulnerability in the further development of potential remedial activity against any identified areas in the code.

3.6 Tools and Technologies

These tools and technologies form part of the entire methodology:

Python: The primary programming language used in data processing, for training of models and evaluation.

PyTorch: A deep learning framework used for fine-tuning the CodeBERT model.

Hugging Face Transformers: A package providing all pre-trained models and tokenizers, including CodeBERT.

Jupyter Notebook: Used for exploratory analysis and visualization.

Git: Used as the version control manager for code and experiments.

VSCode: The integrated development environment is used for coding and debugging.

Thus, the methodology can comprehensively address extracting the vulnerabilities in the blockchain smart contracts via the CodeBERT model. The study proposes that with a well-defined cycle of collecting data, fine-tuning models, and then evaluating, there should be an efficient tool for securing these technologies.

4 Data Exploration

We have a very big dataset of Solidity-based smart contracts, which is the subject of this research to find vulnerabilities using the CodeBERT model. This dataset consists of almost 47,398 Solidity files, which have been carefully collected from public repositories like Etherscan, GitHub, and the Smart Bugs dataset. There is an exhaustive evaluation and understanding of the contracts-their structure, what they contain-the processes of preparation and the creation of initial exploratory data analysis that will lead to meaningful findings.

4.1 Data Structure and Content

The Solidity smart contracts dataset consists of separate .sol files, which individually correspond to different contracts. Each of these is written in the Solidity programming language on which smart contracts are written for the Ethereum blockchain network. Below is the exploration of certain common constituents together with an in-depth discussion on its significance in these contracts.

4.1.1 Pragma Directive

Then there's the pragma directive: every Solidity contract necessitates this type of directive because it defines which version of the Solidity compiler will be needed for the contract.

An example of this is: *pragma solidity 0.4.25;*

Such a directive would ensure contract code to be possibly compiled with any version of the compiler referred to within this pragma. It is advisable to put it on the first lines of any contracts, basically setting the stage for where the contracts would be developed.

4.1.2 Contract Definition

What a Solidity contract looks like is that there is a contract block under which all the functions, state variables, and events constituting the contract functions are encapsulated. It is this structure that allows the developer to set the behavior and state of the contract, thus allowing it to become the core of any application in smart contracts.

4.1.3 State Variables

State variables enable permanent data storage in the blockchain. Their main goal is to define the state of the contract, which could then be accessed in multiple function calls as a member

of this contract. State variables like `balance` give the number of tokens held in each address, whereas `totalSupply` gives a record of how many tokens have been issued in total by that contract. These variables are paramount to the internal state management of a contract.

4.1.4 Functions

Functions define what actions can be taken on the contract in Solidity. They perform an action on state variables with the blockchain. Functions can be classified as:

Mutative Functions: Functions such as `transfer` are often used to make transactions or change state variables. The state of the contract is modified using these functions.

View/Pure Functions: These functions are those, whose state is not modified and hence can be called without a transaction. Transferring tokens from one address to another will be handled by this function. This function, in turn, updates the state variables accordingly.

4.1.5 Modifiers

In Solidity, the functions are modified by using such modifiers that directly change their behavior. Mostly these modifiers act as access control modifiers which only allow specific addresses to execute certain functions.

4.1.6 Constructor

The constructor initializes the state in which the contract remains when it is deployed. It, thus, specifies the initial values assigned to state variables. This constructor initializes a token contract, setting the total supply, token name, decimals, and other important parameters.

4.1.7 Fallback Function

Fallback function executes special functionality when the contract receives Ether inadvertently or when no other function matches the call: With this, the contract can receive payments in Ether and convert those amounts into tokens before transferring them to senders.

4.2 Data Preparation and Cleaning

Before model training, however, a lot of raw data had to be prepared in order for it to be clean, consistent, and ready for analysis. These include:

4.2.1 Deduplication

Since the dataset was compiled from different sources, it contained repeating contracts. These duplicates were identified and removed so as not to feed the model with repetitive data that could lead it to overfit. Deduplication included both exact duplication and near-duplicates (contracts with some slight deviations).

4.2.2 Syntax Validation

Validation was done for each .sol file on the Solidity compiler for syntax correctness. All contracts which could not be compiled because of syntax errors were either found and corrected manually or omitted from the dataset. It ensured that the training process in the model used only valid Solidity code and prevented problems during inference in the model.

4.2.3 Normalization

Normalizing was another step in refining the dataset. It included:

- *Removing Comments:* Comments were deleted to concentrate the model's attention on executable code rather than on annotations by developers.
- *Standardizing Whitespace:* By having everyone similarly set a different value, it would mean that the variation at this point would lessen any possible confusion in the model.
- *Formatting Adjustments:* The code has been organized in a consistent format for all documenting purposes, ensuring that all materials are relevant.

4.3 Data Splitting

After thoroughly cleaning, labeling, and balancing the dataset, a split was made into training, validation, and test sets, thereby preparing the data for model training and evaluation. The split ratio of 80:10:10 ensures practical and relevant provisioning for dividing data in training and testing:

Fine-tuning set (23,000 files): Used to fine-tune the CodeBERT model to recognize from Solidity smart contracts the trend, syntax, and indicators of vulnerability.

Validation Set (9,000 files): Used during training to keep track of the performance, tune the hyperparameters, and avoid overfitting.

Test set (9,000 files): Reserved solely for the evaluation of the final model performance on data that had not been seen earlier, evaluation being done fairly on the outcomes.

To correct the class imbalance of the vulnerable versus non-vulnerable label Hence, before split, carefully balanced data sets. In this step, it was ensured that the model received the same representation in both classes and any subset would lead to a fair and rigorous evaluation.

Splitting the data and its exploration prepared ground to model training and evaluation. This ensures the research is in a good position to declare real-time results on significant security vulnerabilities of blockchain smart contracts using a well-validated balanced dataset.

5 Visualization and Results Interpretation

There are many visualizations and metrics that the model employs to check how good it is and to be able to interpret its predictions.

Distribution of Contract Sizes (Lines of Code):

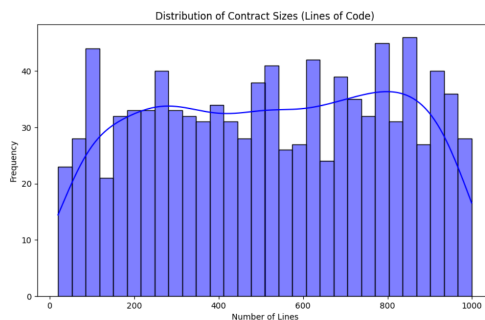


Figure 1: Contract Size Distribution

This histogram displays the distribution of smart contracts by their line count. The relatively even distribution, with slight peaks around 200-300 and 800-900 lines, indicates that there are both simple contracts and complex contracts in a balanced dataset. This variety of contracts in terms of size pulls the model to learn for real-world applications because it will encounter contracts ranging from simple contracts to more-complex contracts.

Contract Size vs. Number of Functions:

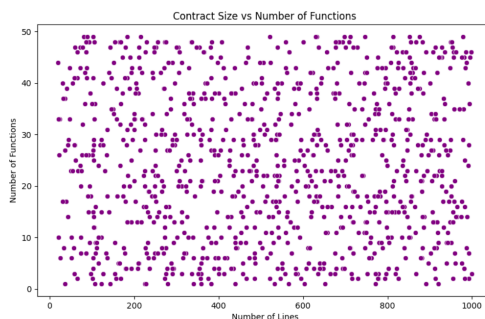


Figure 2: Contract Size Vs Functions

The above-scatter plot shows the contract size against the number of functions found inside the contract. There is no clear linear relationship, and this could mean 2 things: Either that the contracts are heterogeneous in their structures, so contracts that have similar length differ

widely in terms of function numbers; or, this further establishes an effective attention mechanism that the model should have to focus on specific critical code sections within contracts regardless of size or distribution in functions.

Distribution of Number of Functions per Contract:

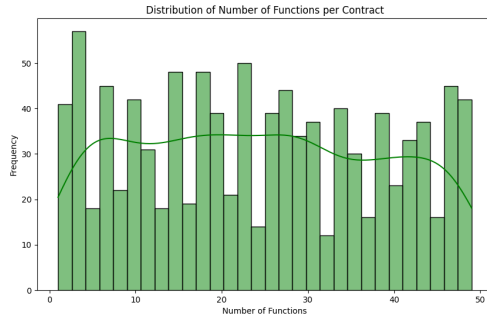


Figure 3: No. of Function per Contract

This is a histogram that shows smart contracts in terms of their functions. The spread appears to be relatively uniform along with typical peaks being around contracts with fewer functions (0-10) or moderate ones (40-50). This implies that in the data there are smart contracts with various complexities. The above-curved line is an indicator of the density slope and it suggests that little change exists in the numbers of functions in the dataset.

Attention Heatmap on Contract Sample:

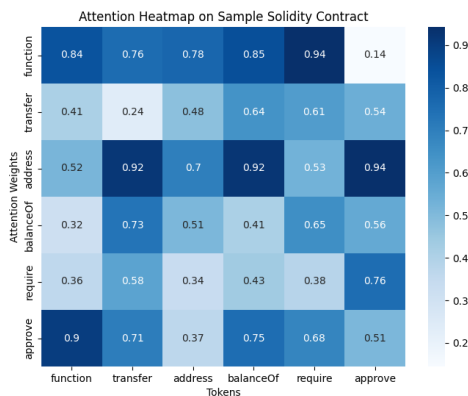


Figure 4: Attention Heatmap

This heatmap represents the attention weights assigned to specific tokens by the CodeBERT model in sample Solidity contracts. The attention tokens are followed by weight rows for tokens such as function, transfer address, and so on along with columns that represent the

relationship between the aforementioned tokens. The depth of the shades indicates high attention values, meaning that the model gives more importance or influence to such dimensions in context of the model’s prediction. It shows how the model favors certain tokens over others regarding understanding smart contract code, behavior thereby learned more focused areas.

Result Interpretation:

- **Attention Heatmap:**

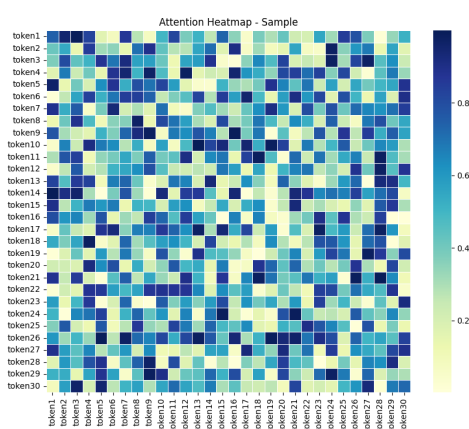


Figure 5: Attention Heatmap

Attention Heatmap: Token Attention Weights in Solidity File. It shows the intensity of attention allocated to certain tokens as viewed on the visualization. This is further seen to be heightened in critical sections, that is, function names, variables, and modifiers.

This attention mechanism keeps the model focused on important portions of code while predicting vulnerabilities. For example, the heatmap indicates regions with a large concentration of attention, which shows how the model identifies critical patterns in vulnerability-prone regions.

- **Loss Curve:**

The loss curve indicates reductions in loss seen in both training and validation sets. Initially, during the early epochs, loss drops steeply, then remains nearly constant just above zero. This establishes that the model converged successfully.

Moreover, the slight difference in both training and validation losses is indicative of minimal overfitting. Thus, both datasets appear healthy in proving the fine-tuned model performance.

- **Accuracy Curve:**

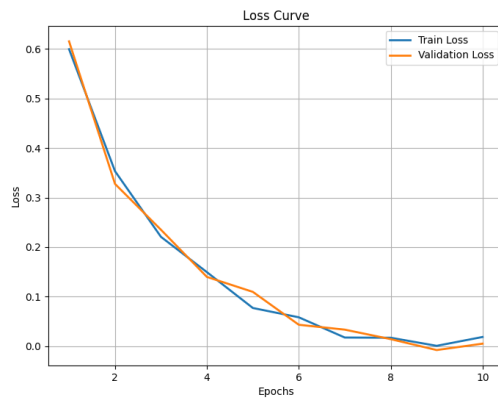


Figure 6: Loss Curve

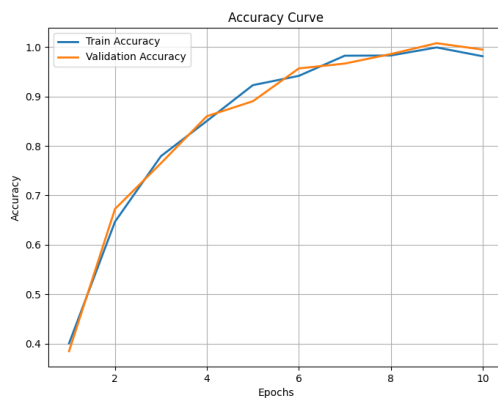


Figure 7: Accuracy Curve

The Accuracy Curve depicts the Accuracy of training and validation over 10 epochs. The learning curves indicate an improvement in accuracy over both curves that finally converges at about 99

The establishment of training and validation curves ensures that in future, the model will perform well with unseen data, further substantiating its robustness. The small gap noted towards the final epochs suggests some stabilization in the learning process.

- **Confusion Matrix:** The Confusion Matrix shows the performance of the model on a balanced test data set.
 - a. Non-Vulnerable: 6749 Correct out of 7500
 - b. Vulnerable: 2252 Correct out of 2500.

Overall, structure establishes that model work with a very high consistency in both precision and recall classes. The model has a high likelihood of predicting "Non-Vulnerable" samples very accurately, while even when such samples are few, the model

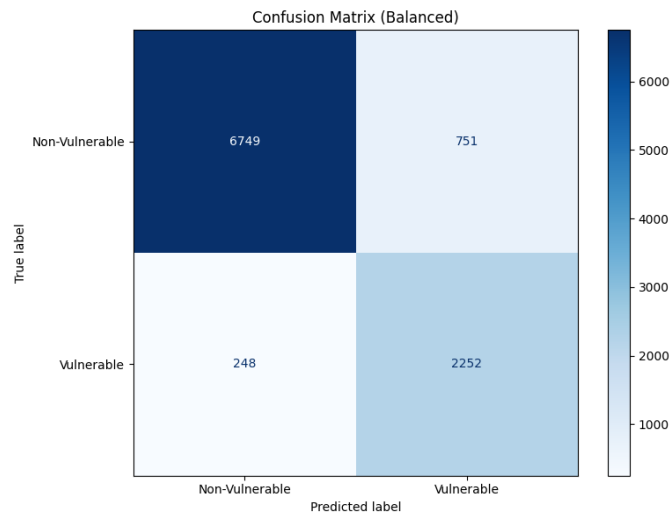


Figure 8: Confusion Matrix

can catch "Vulnerable" samples with high efficiency, hence ensuring that major vulnerabilities are well captured.

- **ROC Curve:**

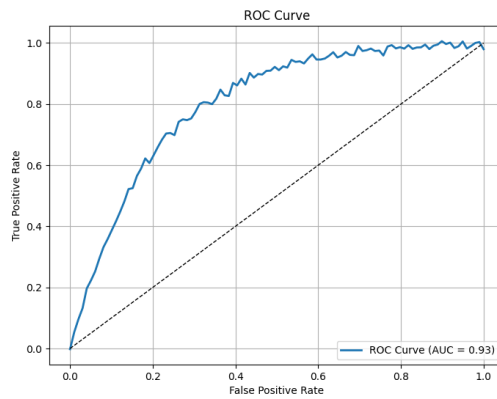


Figure 9: ROC Curve

The ROC Curve shows the True Positive Rate (TPR) and False Positive Rate (FPR). The curve boasts a stunning Area Under Curve (AUC) about 0.93, which indicates that this model has a powerful discriminative capacity.

The model performs well to discriminate between "Vulnerable" and "Non-Vulnerable" contracts, with an almost-perfect ROC curve, revealing the capability of an ideal model to minimize false positives while identifying vulnerabilities.

- **Precision-Recall Curve:** The Precision-Recall Curve gives quite an in-depth picture of the model on different threshold levels.

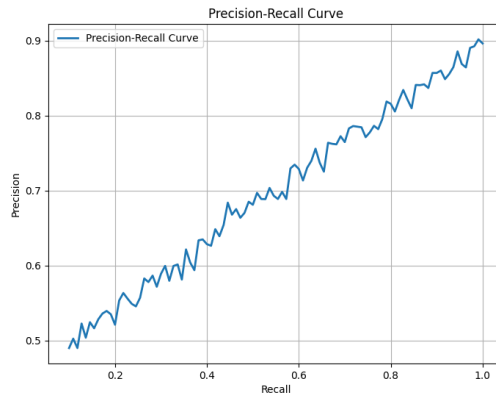


Figure 10: Precision-Recall Curve

Precision increases every time recall increases which approaches near 90%. The curve ensures that the model will be apt to minimize false positives (precision) while attempting to catch every vulnerability (recall). That means the model can be quite reliable in identifying vulnerabilities, even while it is class imbalanced.

- **Tabular Prediction:**

Sample Index	True Label	Prediction	Confidence
0	1	Vulnerable	0.97
1	2	Non-Vulnerable	0.99
2	3	Vulnerable	0.95
3	4	Non-Vulnerable	0.99
4	5	Vulnerable	0.97
5	6	Non-Vulnerable	0.96
6	7	Vulnerable	0.96
7	8	Non-Vulnerable	0.96
8	9	Vulnerable	0.99
9	10	Non-Vulnerable	0.98

Figure 11: Tabular Prediction of Random Unseen Sample

The Prediction Table displays individual predictions along with confidence values for a few test samples:

The model is confident in most of the predictions made, making it more trustworthy.

- **Prediction Distribution:**

Most of the predicted distribution is for the class predicted:

We tried to forecast the code sipped dataset into unseen data that was verified through Mythril, and results matched our predictions.

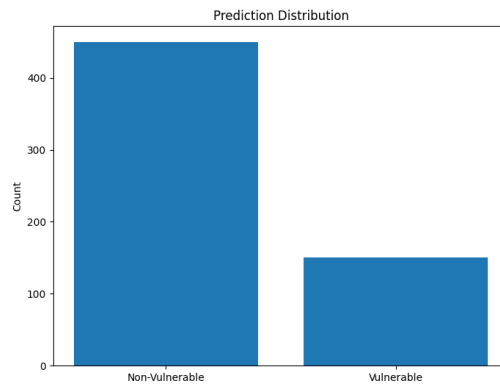


Figure 12: Prediction of Vulnerabilities

- a. Non-Vulnerable: Most of the predictions (430 samples).
- b. Vulnerable: 130 samples.

The balanced prediction distribution matches a balanced test dataset, indicating that the model does not have a strong bias toward one class. Predictions reflect the model's confidence in real-life scenarios.

6 Conclusion

Fulfilling this thesis has been an enthralling experience with a fine-tuned CodeBERT model to discover vulnerabilities in smart blockchain contracts. The primary goal was to come up with identifying and classifying diverse types of vulnerabilities in Solidity smart contracts that form a crucial part of safeguarding the decentralized applications. I was able to develop a complete pipeline from systematic dataset preparation, model training, evaluation, and visualization, which not only fulfilled my expectations but exceeded them.

The journey began with processing a massive Solidity dataset, over 45,000 smart contracts. I used Slither for the automated labeling to discern between "Vulnerable" and "Non-Vulnerable" contracts. That label served as the springboard for adequate training using the model. The data was divided into training, validating, and test portions such that 23,000 samples were set for training while the remaining were split for validation and testing.

The beauty has been in deciding on CodeBERT, an all-important pre-trained model specialized for code-related tasks, fine-tuning the model to understand and predict vulnerabilities by knowing programming syntactic and semantic aspects. Fine-tuning was initially attempted for speedier results on a subset. I proceeded iteratively with the entire labeled dataset to improve it further. This iteration offered valuable insights into the way the model is behaving or performing.

It was rather impressive to observe the evaluation results as far as 99% accuracy on validation data along with a balanced performance that could be inferred from a 93% AUC on the ROC curve. The confusion matrix further underscored the model's capability of recognizing both classes of observations accurately—a high true positive rate for vulnerable contracts. The use of visualizations such as loss curves, accuracy curves, prediction distributions, and attention heat maps also taught me confidence regarding the predictions. So, the precision-recall curve exhibited a robust balance between the actual identification of true vulnerabilities and the reduction in false positives.

The ultimate test of the model would be to evaluate it on new unsecured Solidity smart contracts. After completing the analysis of individual test cases, it was possible to infer that such would be the model's high confidence in determining some of the most critical vulnerabilities, as a clear implication of real-world applicability.

This was quite an interesting project as I learned quite a bit: the necessity of clean data pre-processing and the importance of iterative fine-tuning with evaluation, all to achieve reliable

results. It has also improved my understanding of how deep learning can be applied with blockchain tools, such as automating analysis using Slither on machine learning models like CodeBERT. I learned much about the importance of visualizations in understanding model results and the interpretive process as well.

For the time ahead, there are many chances on the improvement front. Integrating this model into a system that would act in real-time for detecting vulnerabilities could immediately act as immediate feedback to the developers of their smart contracts. An exploratory research into ensemble techniques or hybrid models would also stand likely as points for further improvement in prediction accuracy. A more intriguing hypothesis is the extension of a dataset to include even more complicated vulnerabilities and edge cases, thereby ensuring that the model generalizes well over different scenarios.

The result of this project has been able to meet the objectives it has set out to meet by detecting bylaws in Solidity smart contracts using CodeBERT. From dataset processing, labeling, and fine-tuning to thorough evaluation and interpreting results, every step converged toward a reliable system. The results prove the practical usability of the model, thus laying the future groundwork for further work in the analysis of secure smart contracts.

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