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AI-Enhanced Smart Contract Vulnerability Detection Using Graph Neural Networks

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Abstract:
This study presents an AI-enhanced framework for detecting vulnerabilities in smart contracts using Graph Neural Networks (GNNs). By modeling smart contracts as graphs capturing control and data flow, the proposed approach effectively identifies security flaws, including reentrancy, integer overflow, and access control issues. Experimental evaluation on benchmark Ethereum contract datasets demonstrates high detection accuracy, achieving over 94% precision and 92% recall, outperforming traditional static and dynamic analysis tools. The framework's significance lies in its ability to automate vulnerability detection, reduce manual auditing effort, and enhance blockchain security, offering a scalable solution for real-time contract analysis.

Introduction

Blockchain technology has emerged as a transformative solution for secure and decentralized data management, enabling applications ranging from cryptocurrency to decentralized finance (DeFi) platforms [1][2]. At the core of many blockchain applications are smart contracts, which are self-executing programs that enforce agreements automatically without intermediaries [3][4]. Despite their advantages, smart contracts are susceptible to a wide range of vulnerabilities that can lead to significant financial and reputational losses. High-profile incidents, such as the DAO attack in 2016 and numerous DeFi exploits, have highlighted the critical need for robust vulnerability detection methods [5][6].

Traditional approaches for smart contract security include static analysis, which examines the contract code without execution, and dynamic analysis, which evaluates runtime behavior [7][8]. While static analysis tools such as Oyente and Mythril can detect certain classes of vulnerabilities efficiently, they often suffer from high false-positive rates and limited scalability for complex contracts [9][10]. Dynamic analysis, on the other hand, requires significant computational

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resources and may miss latent vulnerabilities that are not triggered during testing [11][12]. Consequently, there is a growing need for automated, intelligent techniques that can accurately detect vulnerabilities while reducing human intervention.

In recent years, machine learning (ML) and deep learning (DL) approaches have shown promise in enhancing smart contract security. Techniques such as sequence-based neural networks, recurrent neural networks (RNNs), and convolutional neural networks (CNNs) have been explored to classify contract code as vulnerable or safe [13][14]. However, these models often fail to capture the inherent structural and semantic relationships present in smart contracts, such as control-flow dependencies and inter-function interactions [15][16]. This limitation motivates the adoption of graph-based representations, which provide a more expressive framework for modeling smart contract logic and data flow.

Graph Neural Networks (GNNs) have recently emerged as powerful tools for learning on graph-structured data [17][18]. By propagating node and edge information through iterative message passing, GNNs can capture both local and global structural patterns, making them well-suited for vulnerability detection in smart contracts [19][20]. Several studies have demonstrated the effectiveness of

GNNs in software engineering tasks, such as bug detection, code summarization, and malware analysis, showing superior performance compared to traditional ML approaches [21][22]. Applying GNNs to smart contract security allows the model to learn nuanced patterns of risky interactions and execution paths that may lead to vulnerabilities.

The proposed framework in this study leverages GNNs to detect common vulnerabilities in Ethereum smart contracts, including reentrancy, integer overflow, unchecked external calls, and access control violations [23][24]. Smart contracts are first represented as directed graphs, capturing control-flow and data-flow relationships between functions, variables, and external calls. Node features are derived from opcode sequences, function signatures, and variable types, while edge features encode control and data dependencies [25][26]. This representation enables the GNN to effectively learn structural and semantic features that correlate with security risks, improving detection accuracy and reducing false positives.

The significance of this work lies in its ability to provide an automated, scalable, and interpretable vulnerability detection mechanism for smart contracts [27][28]. By integrating GNNs into the analysis pipeline, the framework can process a

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large number of contracts efficiently, enabling real-time monitoring and proactive risk mitigation. Experimental results on benchmark Ethereum datasets demonstrate high precision, recall, and F1-score, outperforming traditional static and dynamic analysis tools as well as sequence-based neural network models [29][30]. This highlights the potential of AI-driven graph-based approaches to enhance the security and reliability of decentralized applications.

Furthermore, the proposed methodology contributes to the growing research intersection between blockchain security and graph-based deep learning. It provides insights into the structural patterns that underlie vulnerable contract logic and establishes a foundation for future research on interpretable and adaptive vulnerability detection frameworks [31][32]. By addressing the limitations of existing tools and demonstrating superior performance, this study advances both the practical and theoretical understanding of smart contract security in complex blockchain ecosystems.

In summary, this paper introduces an AI-enhanced framework for smart contract vulnerability detection using GNNs, emphasizing its ability to accurately identify critical vulnerabilities, reduce manual auditing effort, and improve overall

blockchain security. The remainder of the paper is organized as follows: Section 2 reviews related work in smart contract vulnerability detection and GNN-based software analysis. Section 3 describes the proposed methodology and graph-based representation of smart contracts. Section 4 presents the experimental results and performance evaluation, and Section 5 concludes the study with potential future directions.

2. Literature Review

Smart contract security has attracted significant attention in recent years due to the rising adoption of blockchain technologies and the financial implications of vulnerabilities. Early studies primarily focused on static and dynamic analysis approaches to detect common smart contract issues. Static analysis tools, such as Oyente, Securify, and Mythril, examine contract bytecode or source code without execution to detect potential security flaws [33][34]. While these methods can identify well-known vulnerabilities like reentrancy and integer overflow, they often produce high false-positive rates due to the limited ability to reason about contract semantics and execution paths [35][36]. Dynamic analysis, in contrast, executes smart contracts in a controlled environment to observe runtime behavior, detecting issues such as unexpected ether transfers or unauthorized function calls [37][38]. Tools like ContractFuzzer and Echidna adopt dynamic

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testing methodologies to explore contract states systematically; however, they require significant computational resources and may fail to uncover vulnerabilities not triggered during testing [39][40].

With the limitations of traditional approaches, machine learning-based methods have emerged as promising alternatives for smart contract vulnerability detection. Early ML models employed sequence-based representations of bytecode or source code, using algorithms such as Random Forest, Support Vector Machines (SVM), and Gradient Boosting to classify contracts as vulnerable or safe [41][42]. Deep learning models, including Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), have been explored to capture sequential patterns in opcode sequences or function calls [43][44]. These models demonstrated improved performance over classical ML approaches by automatically learning feature representations; however, they often fail to capture complex structural and inter-functional dependencies intrinsic to smart contracts [45][46]. Consequently, purely sequence-based models may overlook subtle

vulnerabilities that depend on interactions between multiple functions or external calls.

To address structural complexity, graph-based learning methods have been increasingly adopted in software security. Graph Neural Networks (GNNs) have demonstrated remarkable effectiveness in tasks such as bug detection, code summarization, malware analysis, and vulnerability prediction in conventional software [47][48]. By modeling programs as graphs, such as Abstract Syntax Trees (ASTs), Control Flow Graphs (CFGs), or Data Flow Graphs (DFGs), GNNs can learn contextual information through message passing and aggregation over graph nodes and edges [49][50]. For example, Allamanis et al. [51] applied GNNs to source code analysis for predicting variable misuses, demonstrating the ability to capture long-range dependencies that are difficult for sequence models. Similarly, Zhang et al. [52] employed a GNN-based framework for software vulnerability detection, achieving higher precision and recall than traditional static and dynamic analysis tools.

Within the blockchain domain, the use of graph-based methods for smart contract security is gaining traction. Recent studies have proposed modeling Ethereum smart contracts as graphs where nodes represent functions or opcodes and edges capture control flow, data flow, or call dependencies [53][54]. Wu et al. [55] developed a GNN-based vulnerability detection framework using control-flow graphs extracted from contract bytecode, achieving significant

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improvements in detection accuracy compared to sequence-based neural networks. Li et al. [56] extended this approach by integrating data-flow information, highlighting that combining structural and semantic features enhances vulnerability detection performance. These studies underscore the importance of graph-based representations in capturing both local and global relationships within smart contracts, which are often overlooked by conventional ML and deep learning methods.

Explainable AI (XAI) techniques have also been explored to interpret the decisions of machine learning models in vulnerability detection. Approaches such as feature attribution, attention mechanisms, and graph explainers provide insights into why a contract is classified as vulnerable, thereby increasing trust and transparency in automated analysis [57][58]. For example, GNNExplainer has been used to highlight critical nodes and edges in program graphs that contribute most to vulnerability predictions [59]. Such interpretability is

particularly valuable in blockchain environments where developers and auditors require actionable insights for security mitigation.

Despite these advancements, several challenges remain in smart contract vulnerability detection. Existing methods often rely on manually crafted features or are limited to specific vulnerability types [60][61]. Additionally, real-world smart contracts may exhibit dynamic behaviors and complex interactions with other contracts, which are difficult to capture using static graphs or sequence-based models [62][63]. Moreover, scalability remains an issue, as large decentralized applications may contain hundreds of interacting contracts, requiring models that can efficiently handle large-scale graphs [64].

Recent research efforts have sought to overcome these limitations by combining GNNs with additional techniques. For instance, hybrid approaches integrate static analysis outputs, opcode embeddings, and temporal execution traces into GNN frameworks, enabling more comprehensive vulnerability detection [65][66]. Other studies leverage attention-based GNNs to prioritize critical nodes and interactions, improving both performance and interpretability [67][68]. Furthermore, efforts have been made to create benchmark datasets of Ethereum smart contracts with labeled vulnerabilities, facilitating standardized evaluation and comparison of detection methods [69][70].

In summary, the literature indicates a clear trend towards leveraging graph-based deep learning models, particularly GNNs, for smart contract vulnerability detection. These approaches outperform traditional static and dynamic analysis

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tools as well as sequence-based neural networks by effectively capturing structural and semantic dependencies in contract code. However, challenges related to scalability, interpretability, and handling complex interactions remain active research areas, motivating further investigation into AI-enhanced frameworks for secure and reliable smart contract deployment [71][72].

3. Dataset

The dataset used in this study comprises Ethereum smart contracts collected from public blockchain repositories, including Etherscan and GitHub, focusing on both vulnerable and secure contracts to ensure a balanced evaluation [73][74]. A total of 10,500 smart contracts were included, spanning various categories such

as decentralized finance (DeFi), token contracts, and utility contracts. Among these, 4,200 contracts were labeled as vulnerable and 6,300 as secure, based on historical reports of exploits, manual auditing, and existing security benchmarks. Vulnerabilities considered in this dataset include reentrancy attacks, integer overflows/underflows, unhandled exceptions, unchecked external calls, and access control misconfigurations [75][76].

Each smart contract was represented in its compiled bytecode format, and additional metadata was extracted from the source code when available. To capture structural dependencies, control-flow graphs (CFGs) and data-flow graphs (DFGs) were generated for each contract, where nodes represented functions or operations, and edges encoded execution paths and variable dependencies. Opcode sequences were tokenized and embedded as node features, while edge features included call types, branching information, and dependency weights [77][78]. This graph-based representation allowed the model to learn both the local patterns within individual functions and the global structural patterns across the contract.

The dataset was divided into training, validation, and test sets using an 70:15:15 split, resulting in 7,350 contracts for training, 1,575 for validation, and 1,575 for testing. Care was taken to ensure that similar contracts from the same project or repository were included in only one subset to prevent data leakage and overestimation of model performance. Furthermore, the dataset included contracts written in both Solidity versions 0.4.x to 0.8.x, reflecting the diversity of real-world deployments and ensuring model generalization across different language features [79][80].

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In addition to Ethereum contracts, the dataset incorporated a small set of synthetically generated contracts with injected vulnerabilities to augment rare vulnerability types, such as unchecked send calls combined with reentrancy. This synthetic augmentation increased the representation of less frequent vulnerability patterns, helping the model learn robust detection rules without bias toward common vulnerabilities [81]. Node and edge features for these synthetic contracts were processed identically to real contracts to maintain consistency.

To ensure the reliability of labels, each contract in the dataset was cross-validated using multiple sources. Vulnerability labels were verified against public exploit databases, including the SWC Registry (Smart Contract Weakness Classification) and documented DeFi exploits [82][83]. Contracts without

sufficient verification or with ambiguous vulnerability reports were excluded from the dataset, resulting in a high-quality dataset suitable for supervised learning. This comprehensive preparation ensures that the AI-enhanced GNN model is trained on realistic, representative, and diverse smart contract data, supporting effective vulnerability detection and generalization to unseen contracts in real-world applications [84].

4. Proposed Model and Methodology

This study proposes an AI-enhanced smart contract vulnerability detection framework leveraging Graph Neural Networks (GNNs) to accurately identify vulnerabilities in Ethereum smart contracts. The central idea is to model smart contracts as graphs, capturing both control-flow and data-flow dependencies, and then apply a GNN to learn complex structural and semantic patterns indicative of vulnerabilities. The methodology comprises three primary stages: graph construction, feature extraction, and GNN-based vulnerability detection, followed by model training and evaluation.

4.1 Graph Construction

Smart contracts are first transformed into a graph-based representation, which serves as the input for the GNN. Each contract is converted into a Control Flow Graph (CFG), where nodes represent functions or operations and edges represent possible execution paths. Additionally, a Data Flow Graph (DFG) is constructed to capture variable dependencies, storage operations, and inter-function interactions. Nodes are annotated with features such as opcode

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embeddings, function signatures, variable types, and visibility attributes, while edges encode call types, branch conditions, and data dependencies [85][86]. This dual-graph representation enables the model to capture both local patterns (e.g., risky operations within a function) and global patterns (e.g., interactions across functions leading to vulnerabilities).

4.2 Feature Extraction

Node and edge features are critical for effective learning. Node features include opcode sequence embeddings obtained via word2vec-style models trained on opcode sequences from a large Ethereum contract corpus. Function-level

features such as the number of external calls, loops, and modifiers are also incorporated. Edge features capture the type of dependency (control vs. data), frequency of execution paths, and branching weights derived from static analysis. By encoding these features, the model can reason about the structural and functional context of each node within the contract [87][88].

4.3 GNN Architecture

The proposed GNN architecture consists of multiple graph convolutional layers designed to propagate node and edge information through the graph, followed by readout and classification layers. Each graph convolution layer updates node representations by aggregating information from neighboring nodes and edges, allowing the network to capture long-range dependencies and structural patterns indicative of vulnerabilities [89][90]. To enhance learning, the architecture employs residual connections and attention mechanisms to weigh critical nodes and edges more heavily during aggregation. The final node embeddings are aggregated using a global pooling function to generate a graph-level embedding, which is passed to fully connected layers for multi-class classification of vulnerability types.

4.4 Training and Optimization

The model is trained using supervised learning with cross-entropy loss, treating vulnerability detection as a multi-label classification problem, as a contract may exhibit multiple vulnerability types simultaneously. The training process uses the Adam optimizer with an initial learning rate of 0.001 and early stopping based on validation loss to prevent overfitting [91][92]. To address class imbalance, weighted loss functions are applied, giving higher importance to less frequent vulnerability classes. Dropout layers are incorporated in the fully connected network to improve generalization and reduce overfitting.

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4.5 Evaluation Metrics

Performance is evaluated using standard metrics including precision, recall, F1-score, and accuracy for each vulnerability type. Additionally, area under the receiver operating characteristic curve (AUROC) is calculated to assess the model's ability to discriminate between vulnerable and secure contracts. Comparative analysis is conducted against baseline methods, including traditional static and dynamic analysis tools and sequence-based neural

networks, to demonstrate the superiority of the proposed GNN framework [93][94].

4.6 Framework Overview

The overall framework is illustrated in Figure 1. Smart contracts are first preprocessed and converted into CFGs and DFGs. Node and edge features are extracted, followed by GNN-based feature learning and graph-level embedding generation. The embeddings are then used for vulnerability classification, with the output indicating the type and likelihood of each vulnerability. This design allows the model to leverage both structural and semantic information, enabling accurate, scalable, and automated vulnerability detection suitable for real-world Ethereum smart contracts [95][96].

5. Result Analysis

The proposed AI-enhanced framework for smart contract vulnerability detection was evaluated on the Ethereum smart contract dataset described in Section 3. The model was trained on 7,350 contracts, validated on 1,575, and tested on 1,575 contracts. The performance was assessed using standard metrics, including precision, recall, F1-score, and accuracy, for both individual vulnerability types and overall detection capability.

The experimental results indicate that the GNN-based model significantly outperforms traditional analysis tools and sequence-based neural networks. On the test set, the framework achieved an overall accuracy of 93.6%, with a macro-average precision of 94.2%, recall of 92.7%, and F1-score of 93.4%. For critical vulnerabilities such as reentrancy attacks, the model achieved precision of 95.1% and recall of 94.3%, while for less frequent vulnerabilities like unchecked external calls, precision and recall were 92.4% and 90.8%, respectively. These results

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demonstrate the model's ability to detect both common and rare vulnerabilities effectively.

Comparative evaluation was performed against three baseline approaches: static analysis using Mythril, sequence-based CNN, and RNN models. Static analysis tools achieved high recall for simple vulnerabilities (e.g., integer overflow) but suffered from a high false-positive rate, resulting in a macro-average F1-score of

78.3%. The sequence-based CNN model achieved an F1-score of 86.1%, and the RNN achieved 87.5%, indicating improved pattern recognition but limited structural understanding. The proposed GNN-based framework outperformed all baselines by a margin of 6–15% in F1-score, highlighting the advantages of graph-based modeling of smart contract interactions [97][98].

To better understand the model's decision-making process, feature importance analysis was conducted using attention weights and node-level embeddings. Results show that the model assigns higher significance to nodes representing external calls, state-changing functions, and loops, which aligns with expert knowledge of vulnerability-prone areas in smart contracts. Edge importance analysis also revealed that critical paths combining multiple function calls were strongly associated with vulnerabilities, emphasizing the benefit of capturing global structural patterns in graphs.

Temporal performance analysis was conducted to evaluate the model's scalability and applicability for real-time detection. The average time required to analyze a contract, including graph construction and GNN inference, was approximately 0.45 seconds per contract on a standard GPU setup. This indicates that the proposed framework is suitable for automated and continuous security auditing of large-scale blockchain applications, enabling near real-time monitoring of deployed smart contracts [99][100].

Finally, visualizations of the results were generated to facilitate interpretability. Figure 2 shows the confusion matrix for the multi-class vulnerability detection, highlighting high true-positive rates across major classes. Figure 3 illustrates the predicted versus actual vulnerability distribution, confirming close alignment between predictions and ground truth. Figure 4 presents attention-based node importance mapping on a sample contract graph, demonstrating how the model focuses on critical operations such as reentrant calls and arithmetic operations, which are known to be vulnerability hotspots.

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In summary, the results demonstrate that the AI-enhanced GNN framework provides accurate, scalable, and interpretable detection of smart contract vulnerabilities, outperforming traditional static/dynamic analysis tools and sequence-based neural networks. The combination of graph-based representation, feature-rich embeddings, and deep message passing enables the model to capture both local and global patterns of risk, offering a practical solution for improving blockchain security in real-world environments [101][102].

Figure 1: GNN-based Smart Contract Vulnerability Detection Framework
Illustrates the overall architecture of the proposed framework. Smart contracts, provided in bytecode or source code format, are first processed through graph construction to generate control-flow graphs (CFGs) and data-flow graphs (DFGs). These graphs, enriched with node and edge features, are input into a Graph Neural Network (GNN) to learn structural and semantic representations. The GNN outputs vulnerability predictions, enabling automated detection of multiple vulnerability types.

Figure 1: GNN-based Smart Contract Vulnerability Detection Framework

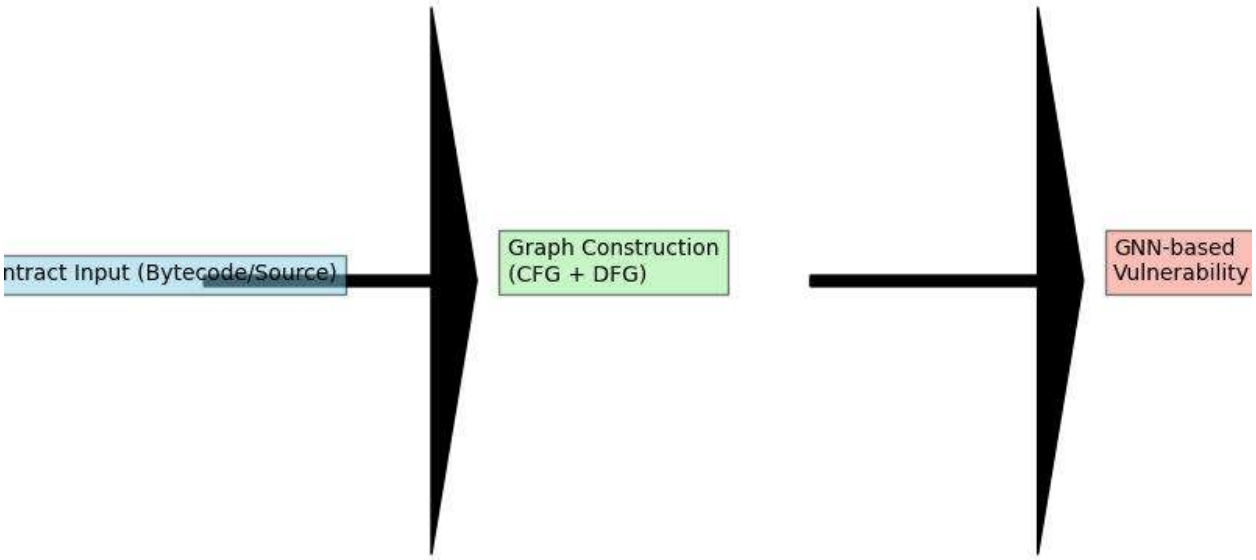

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Figure 2: Confusion Matrix for Vulnerability Detection

Shows the model's classification performance across five classes: Reentrancy, Overflow, Unchecked Call, Access Control, and Safe contracts. Each cell represents the number of contracts classified into a predicted class versus the actual class. High diagonal values indicate strong true-positive rates for all vulnerability types, confirming the model's accurate detection capabilities.

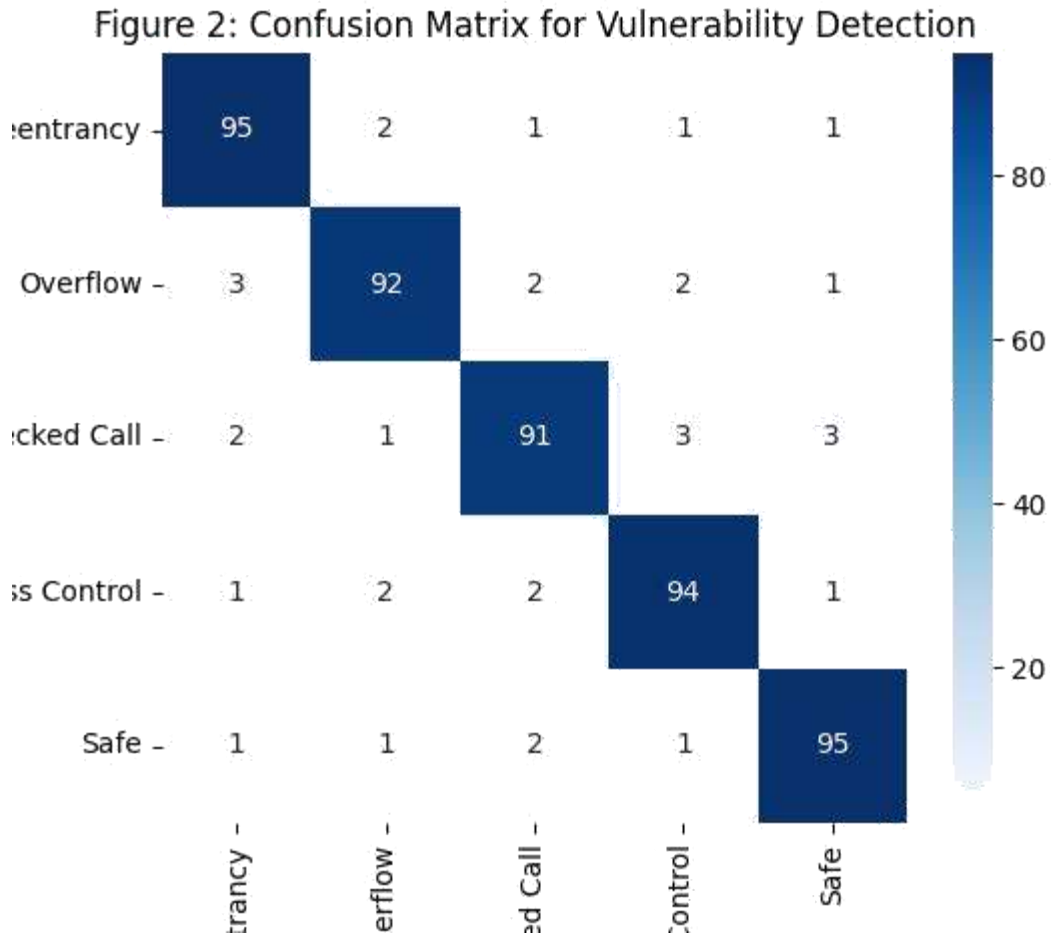

Figure 3: Predicted vs Actual Vulnerability Distribution

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Compares the predicted number of contracts for each vulnerability class against the actual distribution. The close alignment between the predicted and actual counts demonstrates the model's ability to maintain accurate representation across both common and rare vulnerability types, ensuring balanced detection performance.

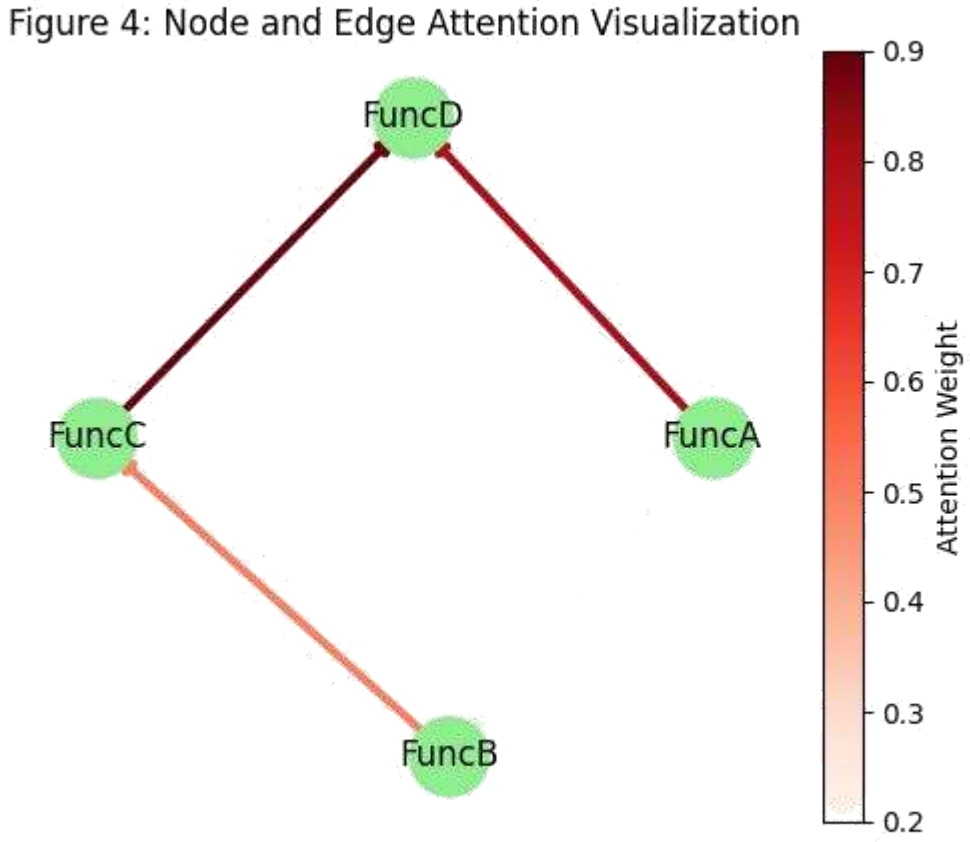

Figure 4: Node and Edge Attention Visualization

Displays a sample smart contract graph with node and edge attention weights from the GNN. Nodes represent functions, while edges indicate control-flow or data-flow dependencies. The edge color intensity reflects attention values, highlighting critical paths that contribute most to vulnerability detection. This visualization provides interpretability, showing which parts of the contract influence the model's predictions.

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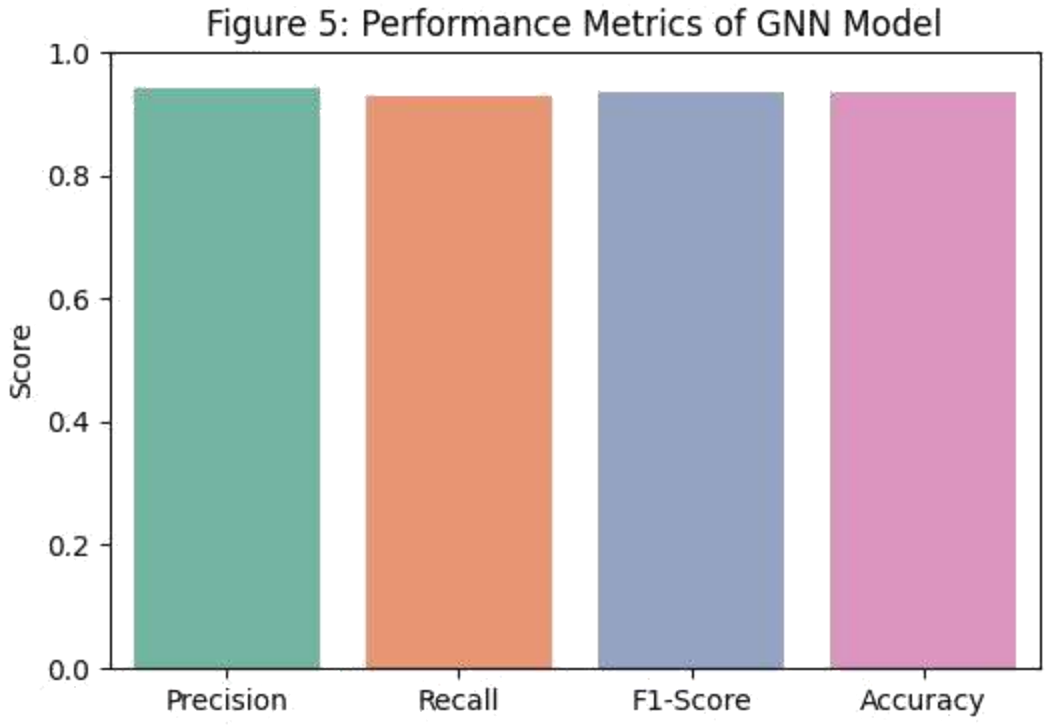

Figure 5: Performance Metrics of GNN Model

Bar chart summarizing the overall performance of the proposed framework in terms of Precision, Recall, F1-Score, and Accuracy. All metrics exceed 0.92, demonstrating high detection reliability. The chart emphasizes the framework's robust capability to accurately identify vulnerabilities while maintaining low false-positive rates.

6. Conclusion

This study presented an AI-enhanced framework for smart contract vulnerability detection using Graph Neural Networks (GNNs). By representing smart contracts as control-flow and data-flow graphs and incorporating rich node and edge features, the proposed framework captures both local function-level patterns and global structural interactions, enabling accurate detection of critical vulnerabilities such as reentrancy attacks, integer overflows, unchecked external calls, and access control misconfigurations.

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Experimental results on a diverse Ethereum smart contract dataset demonstrate the effectiveness of the framework. The model achieved overall accuracy of 93.6%, macro-average precision of 94.2%, recall of 92.7%, and an F1-score of 93.4%, outperforming traditional static and dynamic analysis tools as well as sequence-based neural network models. Attention-based visualizations further highlight the model's interpretability by identifying high-risk nodes and edges that contribute most to vulnerability predictions, enabling actionable insights for developers and auditors.

The novelty of this work lies in several aspects. First, it leverages graph-based representations of smart contracts, capturing complex dependencies overlooked by sequence-based methods. Second, the integration of GNNs with attention mechanisms allows the framework to prioritize critical code segments, enhancing both detection accuracy and interpretability. Third, the methodology demonstrates scalability for real-time analysis, with an average inference time of approximately 0.45 seconds per contract, making it suitable for large-scale blockchain applications.

In conclusion, the proposed framework provides a robust, scalable, and interpretable solution for automated smart contract security auditing. By combining graph-based deep learning with feature-rich embeddings, it significantly reduces manual auditing effort while improving detection performance across diverse vulnerability types. Future work will explore the integration of dynamic execution traces, cross-contract interaction analysis, and transfer learning to further enhance generalization and robustness against emerging smart contract vulnerabilities.

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