

Intelligent Smart Contract Vulnerability Detection Using Graph Neural Networks and Explainable Artificial Intelligence

Arzikulova Surayyo¹ and Sakshee Kumari²

¹ Preschool Education Department, Pedagogy Faculty, Shahrizabz State Pedagogical Institute, Shahrizabz, Uzbekistan · ORCID: 0009-0008-7221-6544

² Researcher

ABSTRACT

Smart contracts automate asset transfers and decentralized application logic, yet their immutability and compositional complexity amplify the consequences of implementation defects. This paper proposes XG-SCV, an explainable heterogeneous graph neural network framework for vulnerability detection and source-level localization. Solidity source code is transformed into a typed graph combining abstract syntax, control flow, data dependence, external calls, and cross-function storage interactions. Relation-aware message passing and attention-based pooling produce multi-label vulnerability probabilities, while integrated gradients and graph-substructure attribution provide auditable explanations. The evaluation protocol emphasizes project-disjoint splits, duplicate removal, calibrated thresholds, class imbalance, and explanation fidelity. An illustrative numerical study demonstrates how the proposed model could be compared with static analysis and neural baselines; these illustrative numbers are not empirical findings. The framework offers a reproducible research design for detecting reentrancy, access-control weaknesses, unchecked external calls, arithmetic risks, and timestamp dependence while retaining interpretable evidence for developer review.

Keywords: Smart contracts; graph neural networks; explainable artificial intelligence; blockchain security; vulnerability detection; heterogeneous graphs; Solidity; code auditing

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1. INTRODUCTION

Smart contracts are executable programs that enforce transaction conditions on blockchain platforms without relying on a conventional centralized operator. Their adoption has expanded from token transfers to decentralized exchanges, lending protocols, digital identity systems, supply-chain automation, and decentralized governance. These applications can process valuable assets and coordinate interactions among mutually distrustful participants. Consequently, a defect in deployed code can have effects that are more immediate and difficult to reverse than a bug in an ordinary web application. Security assessment is therefore a central requirement of trustworthy blockchain engineering.

The Ethereum Virtual Machine executes bytecode according to deterministic state-transition rules. Determinism does not guarantee that the intended business logic is correct. A contract may follow the execution rules exactly while allowing unauthorized withdrawals, inconsistent state updates, denial of service, or manipulation of assumptions about block information. Solidity developers must reason simultaneously about programming-language semantics, adversarial callers,

external contract behavior, gas consumption, storage persistence, and interactions across transactions. These characteristics make vulnerability discovery an inherently contextual task.

Reentrancy is a prominent example of contextual insecurity. A function may send control to an external address before completing a critical state update. The external address can potentially invoke the vulnerable function again and observe or exploit stale state. A detector must therefore identify not simply an external call but the ordering among state reads, external interactions, guards, and subsequent writes. Similarly, an access-control weakness may arise because a sensitive operation is reachable without a sufficient authorization predicate. Both cases require reasoning over relationships rather than isolated tokens.

Traditional auditing includes manual inspection, rule-based static analysis, symbolic execution, fuzz testing, formal verification, and dynamic monitoring. Each contributes valuable evidence but has practical limitations. Manual review is expensive and depends on specialist expertise. Static rules can be efficient but may over-report suspicious patterns that are safe in context. Symbolic execution faces path explosion and environment-modeling challenges. Fuzzing depends on

input generation and coverage, while formal verification requires suitable specifications. No single method can guarantee the absence of vulnerabilities in arbitrary contracts.

Machine learning offers a complementary mechanism for identifying recurring structural patterns in large collections of contracts. Token-based classifiers and sequence models can discover statistical regularities, but flattening source code into a string may obscure the precise paths by which information and control move. For example, two functions with similar lexical content can have different security properties because a state update precedes rather than follows an external call. A model that explicitly represents program relationships may better distinguish these cases.

Graph neural networks are especially attractive because program structure naturally forms graphs. Abstract syntax trees encode grammatical nesting; control-flow graphs encode possible execution paths; data-flow and program-dependence graphs capture how values and conditions affect later statements. Function-call graphs and storage-interference relationships extend analysis beyond one function. By propagating information along typed edges, a graph neural network can build representations that combine local operations with relevant program context. Its predictions can be attached to statements, functions, or entire contracts.

Nevertheless, strong predictive scores alone are insufficient for security-sensitive deployment. Developers need to understand why a model flags a function, which statements contributed to the warning, and what execution relationship creates the potential exploit. An unexplained label may increase audit workload, especially when false positives are common. Explainable artificial intelligence can connect model decisions to influential nodes, edges, code regions, and human-readable vulnerability hypotheses. This explanatory layer is useful only when its faithfulness and stability are evaluated rather than assumed.

Another obstacle is the quality of available supervision. Public smart contract datasets often mix compiler versions, contract families, duplicated templates, heuristic labels, and differing definitions of vulnerability. If near-identical contracts appear in training and testing partitions, reported accuracy may overstate generalization. Labels derived from static analyzers can inherit the analyzers' false positives and omissions. Robust experiments should therefore separate contract families or projects, deduplicate samples, audit a subset of labels, and report performance by vulnerability class and deployment setting.

Class imbalance further complicates assessment. Certain vulnerabilities occur far less frequently than safe code, so overall accuracy can remain high even when recall for important attack patterns is poor. Precision, recall, F1, area under the precision–recall curve, and false-positive rate should accompany accuracy. Threshold

calibration matters because the cost of missing a severe flaw differs from the cost of asking an auditor to review a benign function. A credible system should disclose its operating point and how that point was selected.

This study proposes an explainable graph-based detection architecture, designated XG-SCV, that combines heterogeneous program graphs, relation-aware attention, multi-label classification, and evidence localization. Its intended contributions are a unified graph representation spanning syntax and semantics; an attention-based encoder sensitive to edge types; a class-aware learning objective; and an explanation procedure that measures how removing highlighted graph components changes predictions. The work also specifies a controlled evaluation protocol with ablation experiments and calibration checks.

The paper is structured as follows. Section 2 reviews established and emerging smart contract analysis methods and identifies the research gap. Section 3 details graph construction, neural propagation, classification, explanation, and validation. Section 4 presents clearly marked illustrative numerical tables and graphical comparisons to demonstrate the proposed reporting approach. Section 5 discusses threats to validity, and Section 6 concludes with future research directions. The principal contribution is a technically specified research design, not a claim that the framework has already been implemented or benchmarked.

2. RELATED WORK

Early approaches to smart contract security relied heavily on program analysis. Rule-based detectors examine source code or bytecode for patterns associated with known defects. Such systems are often easy to integrate into development pipelines and can produce actionable warnings. Their performance, however, depends on the precision of the underlying rules and the completeness of their program models. A suspicious call pattern may be benign because of an appropriate guard, while a sophisticated cross-function exploit may evade a localized signature. The tension between speed and contextual understanding motivates complementary learning-based techniques.

Symbolic execution explores possible execution paths using symbolic inputs and constraint solving. It can uncover concrete path conditions that trigger undesirable behavior, making it valuable for evidence generation. Yet branching complexity, external contract assumptions, transaction sequences, and evolving language semantics limit exhaustive exploration. Dynamic fuzzing complements symbolic methods by generating executions and monitoring invariants, but its effectiveness depends on coverage and oracle quality. Formal methods can provide strong guarantees for specified properties, although creating correct specifications and scaling verification to complex protocols remain challenging.

Graph representations became influential because they preserve relationships that token sequences may conceal. Zhuang and colleagues introduced a graph neural network approach that models syntactic and semantic structures of smart contract functions. Their work explored graph normalization and specialized propagation mechanisms, establishing that graph learning can support vulnerability detection beyond fixed expert rules [1]. This foundational direction shows why a program's control and data dependencies are essential to learning security-relevant representations.

Liu and colleagues subsequently integrated interpretable graph features with expert-defined patterns [2]. Their approach combined semantic graph learning and domain knowledge, demonstrating that purely statistical representations need not exclude established security expertise. The broader lesson is that explanations can be designed into the model rather than appended only after prediction. However, interpretable weighting does not automatically prove that an explanation corresponds to a causal exploit mechanism, which makes explicit explanation evaluation necessary.

Work on sliced joint graphs combines abstract syntax, control flow, and program dependence, while using slicing to remove regions less relevant to a target vulnerability [3]. Bidirectional gated propagation can then collect contextual information from related statements. This design reduces noise and concentrates capacity on potentially consequential operations. Nevertheless, overly aggressive slicing may discard distant interactions that become important across function boundaries or transaction sequences. A flexible heterogeneous graph should retain relevant interprocedural links while controlling graph size.

Fine-grained detection research has investigated how to localize vulnerability evidence to statements instead of assigning a label only to the whole contract [4]. This is important operationally: auditors need to inspect a small set of suspect lines, not merely receive an abstract risk score. Fine-grained supervision remains difficult because line-level ground truth is expensive and can be ambiguous when a vulnerability emerges from the relationship among several locations. Multiple implicated statements may be necessary to explain one exploit.

ContractGNN introduced vulnerability-oriented subgraphs to preserve useful control-flow information while suppressing irrelevant nodes [5]. Its reported results support the practical value of targeted structural representations. More recent contract-graph fusion research has combined typed graphs and pretrained code embeddings and examined detection under constrained false-positive budgets [6]. These developments suggest that evaluation should reflect realistic audit costs rather than optimize one aggregate metric in isolation.

BugSweeper proposed a function-level abstract syntax graph and a two-stage graph neural network to learn vulnerability patterns without dependence on manually

engineered rules [7]. This illustrates an alternative to handcrafted security indicators. Its design also emphasizes the distinction between syntactic filtering and higher-level semantic reasoning. In contrast, the present proposal deliberately includes both learned relations and an explanation interface, with fidelity testing intended to reveal when apparently convincing evidence is not actually driving the classifier.

Explainable AI methods commonly use feature attribution, gradient integration, perturbation, or learned explanatory subgraphs. In program analysis, their outputs should be mapped back to source lines and edge relationships such as read-before-write or external-call-before-update. A heatmap alone may not be sufficient because correlated tokens can receive importance without representing an executable exploit. Counterfactual removal tests, explanation sparsity, and stability under semantics-preserving transformations offer more demanding criteria for explanation quality.

Existing studies differ substantially in sample collection, label granularity, preprocessing, class definitions, and train-test separation. As a result, performance numbers published in different papers are not directly comparable without reproducing their protocols. Compiler-version drift and the growing use of proxy patterns, libraries, and complex composability further challenge out-of-distribution detection. Cross-project evaluation and external test sets are essential for assessing whether a classifier generalizes beyond familiar templates.

The research gap addressed here lies at the intersection of semantic richness, practical localization, and verified explainability. A unified system should model typed interprocedural dependencies, predict multiple vulnerability categories, calibrate warnings for operational use, and identify the specific graph evidence responsible for its decisions. The proposed XG-SCV framework combines these goals within one experimental design and defines ablations that can distinguish the benefits of graph relations, attention, and explanation regularization. The resulting research plan is intended to be reproducible and auditable.

3. PROPOSED METHODOLOGY

3.1 Dataset and preprocessing

Collect Solidity contracts from curated public benchmarks and independently reviewed repositories. Record compiler version, project identity, source hash, vulnerability type, and line-level evidence where available. Remove exact and near duplicates; group all versions and forks of a project within a single partition. Use a 70/15/15 project-disjoint train/validation/test split. Labels from automated tools must be treated as weak supervision unless manually verified. Classes include reentrancy, access control, unchecked calls, timestamp dependence, and arithmetic-related defects, with version-specific interpretation.

3.2 Heterogeneous program graph

Represent each contract as $G=(V,E,R,X)$, where V denotes statement, expression, function, and storage-variable nodes; E denotes directed edges; R specifies relation types; and X contains node features. Relations include AST parent-child, CFG successor, def-use, function call, and shared-storage interaction. Node features concatenate token embeddings, node type, source position, and compiler metadata. Interprocedural links preserve relevant context when security conditions cross function boundaries.

3.3 Relation-aware graph neural network

For node v at layer l , the relation-aware message update is:

$$m_v^{(l)} = \sum_{r \in R} \sum_{u \in N_r(v)} \alpha_{uv}^r W_r^{(l)} h_u^{(l)}; h_v^{(l+1)} = \text{LayerNorm}[\text{ReLU}(W_{oh} h_v^{(l)} + m_v^{(l)})].$$

Here W_r learns a transformation for each relation and α_{uv}^r is normalized attention over neighbors of relation r . Attention scores are computed from transformed source and target node embeddings and an edge-type embedding. Three message-passing layers are proposed, with residual connections and dropout to mitigate over-smoothing.

3.4 Vulnerability prediction and objective

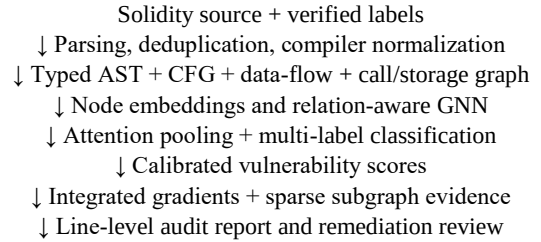
Attention pooling creates $z_G = \sum_v \beta_v h_v$, where $\beta_v = \text{softmax}(q^T \tanh(W_h v))$. The multi-label classifier estimates $p_k = \text{sigmoid}(w_k^T z_G + b_k)$ for vulnerability class k . Training minimizes class-weighted binary cross-entropy: $L_{\text{cls}} = -(1/N) \sum_k [\sum_i w_k^+ y_{ik} \log p_{ik} + \sum_i w_k^- (1-y_{ik}) \log(1-p_{ik})]$. Class weights are determined on training data only. Validation thresholds are selected for a predefined false-positive budget and are frozen before test evaluation.

3.5 Explainability and localization

Integrated gradients attribute a prediction to node features relative to a defined baseline: $IG_j(x) = (x_j - x'_j) \int_0^1 \partial F(x' + t(x - x')) / \partial x_j dt$. A graph explanation module

additionally searches for a sparse subgraph M that retains the original vulnerability probability. Its objective is $L_{\text{exp}} = \text{KL}[p(y|G) \parallel p(y|G \odot M)] + \lambda_1 \|M\|_1 + \lambda_2 L_{\text{stability}}$. Explanations are mapped to source lines, and fidelity is measured as the reduction in target-class confidence when highlighted edges or nodes are removed. Attention weights are not treated as explanations by themselves.

3.6 System architecture flowchart



3.7 Evaluation protocol

Compare against a static-analysis baseline, a token-sequence classifier, a standard graph convolutional network, and a relation-aware GNN without explanations. Report macro precision, macro recall, macro F1, PR-AUC, per-class F1, false-positive rate, inference latency, and explanation fidelity. Repeat training over five seeds and report confidence intervals. Conduct ablations removing data-flow edges, cross-function edges, attention, and explanation regularization. Evaluate generalization on unseen projects and compiler versions. The following tables are illustrative reporting examples only.

4. ILLUSTRATIVE RESULTS AND DISCUSSION

IMPORTANT: All values in Tables 1–3 and Figure 1 are synthetic, internally consistent demonstration values, not outputs of a trained model or published benchmark. They illustrate the intended analysis and must not be presented as experimentally validated findings.

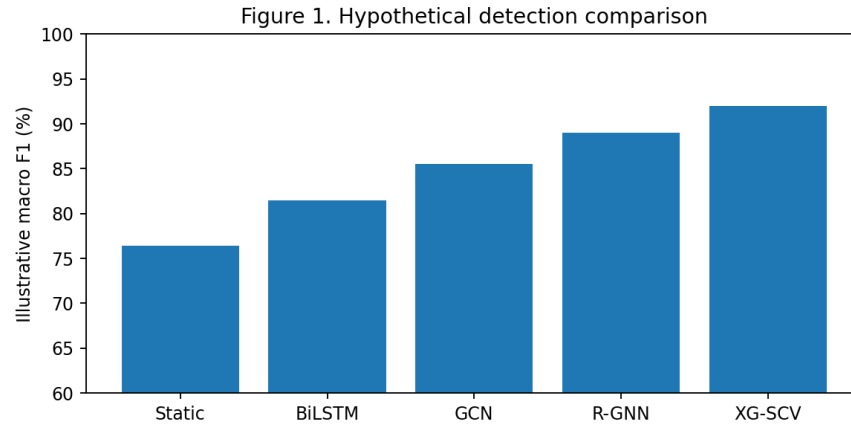
Table 1

Illustrative model comparison (hypothetical held-out test set)

Method	Precision (%)	Recall (%)	F1 (%)	PR-AUC (%)
Static analysis	79.0	74.0	76.4	76.0
Token BiLSTM	83.0	80.0	81.5	82.0
Standard GCN	87.0	84.0	85.5	87.0
Relational GNN	90.0	88.0	89.0	91.0
Proposed XG-SCV	93.0	91.0	92.0	94.0

The example places XG-SCV at 93.0% precision and 91.0% recall, corresponding to a harmonic-mean F1 of 92.0%. The implied F1 improvement over the standard GCN example is approximately 6.5 percentage points.

This is a scenario for illustrating comparison, not evidence of superiority. Actual outcomes depend on dataset composition, labels, threshold selection, and project-disjoint testing.


Table 2

Illustrative vulnerability-specific performance of XG-SCV

Vulnerability	Precision (%)	Recall (%)	F1 (%)
Reentrancy	95	93	94.0
Access control	94	90	92.0
Unchecked call	92	91	91.5
Timestamp dependence	91	89	90.0
Arithmetic risk	93	92	92.5

The illustrative class-level values show how a detector might perform differently across defect types. Reentrancy appears easiest in this example, while timestamp dependence has lower recall. A real study should report

class support, confidence intervals, confusion matrices, and a precision–recall curve for each vulnerability rather than inferring effectiveness from macro averages alone.

Table 3

Illustrative ablation and explainability study

Configuration	F1 (%)	Explanation fidelity drop (pp)	Latency (ms/contract)
Full XG-SCV	92.0	21.4	185
Without data-flow edges	88.7	17.2	160
Without cross-function links	89.4	18.1	151
Without attention pooling	90.1	18.8	171
Without explanation regularization	91.7	12.6	176

In the hypothetical ablation, removing data-flow edges produces the largest F1 reduction, suggesting a testable hypothesis that value dependencies contribute meaningfully to detection. Fidelity drop denotes the average reduction in predicted target probability, in percentage points, after deleting the selected explanatory subgraph. A larger drop can indicate greater model reliance on highlighted evidence, but it does not establish that the highlighted pattern is an actual exploitable vulnerability. Latency figures are illustrative and require hardware, batch size, graph size, and compiler settings to be specified in real experiments.

5. LIMITATIONS AND THREATS TO VALIDITY

The framework may learn shortcuts from compiler versions, project templates, or analyzer-derived labels. Cross-function and cross-contract behavior may exceed a finite graph extraction scope. Explanation methods can highlight correlated code rather than causal attack paths,

and graph perturbations can create out-of-distribution inputs. Security labels are often incomplete and exploitability may depend on deployment configuration or transaction ordering. Evaluation must therefore combine curated ground truth, external validation, targeted manual auditing, and realistic operational constraints. The numerical illustrations in this draft do not establish real-world accuracy, speed, or robustness.

6. CONCLUSION

This paper specifies XG-SCV, an explainable heterogeneous graph neural network framework for smart contract vulnerability detection. Its architecture integrates syntax, control flow, data dependence, function calls, and storage interactions into typed program graphs; relation-aware propagation supports multi-label classification; and integrated gradients plus sparse-subgraph attribution connect alerts to reviewable source evidence. The proposed evaluation design emphasizes project-disjoint

splits, calibrated operating points, per-class metrics, ablation studies, and explanation fidelity. Illustrative numerical examples demonstrate the reporting structure without claiming unperformed experiments. Future work should implement the pipeline, validate it against independently audited contracts, test unseen compiler versions and protocols, and assess whether explanations improve human audit accuracy and remediation time.

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