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A NOVEL SELF-ADAPTIVE GRAPH TRANSFORMER FOR EXPLAINABLE BUFFER OVERFLOW VULNERABILITY DETECTION THROUGH DYNAMIC CODE SEMANTICS AND EVOLUTIONARY OPTIMIZATION

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ABSTRACT

The Buffer overflow vulnerabilities continue to pose significant security challenges in modern software systems, frequently resulting in memory corruption, privilege escalation, denial-of-service attacks, and remote code execution. Traditional vulnerability detection techniques primarily rely on static code analysis, handcrafted features, or conventional Graph Neural Networks (GNNs), which often struggle to capture dynamic execution semantics, long-range code dependencies, and complex structural relationships. These limitations can reduce detection accuracy, increase false-positive rates, and provide limited interpretability for security analysts. To overcome these challenges, this paper proposes a **Self-Adaptive Graph Transformer Framework for Explainable Buffer Overflow Vulnerability Detection via Dynamic Semantic Graph Learning and Evolutionary Feature Optimization**. The proposed framework constructs a unified semantic graph by integrating **Abstract Syntax Trees (ASTs), Control Flow Graphs (CFGs), Data Flow Graphs (DFGs), Program Dependence Graphs (PDGs),** and **dynamic execution traces**, thereby preserving both structural and runtime semantic information. A **Self-Adaptive Graph Transformer (SAGT)** employing multi-head self-attention learns contextual relationships among code entities while adaptively assigning attention weights according to execution semantics and vulnerability relevance. An **Evolutionary Feature Optimization (EFO)** module identifies informative semantic graph features and eliminates redundant information. An **Explainable Artificial Intelligence (XAI)** module further provides node-level and graph-level explanations, feature importance rankings, and vulnerability localization.

The proposed framework is evaluated on publicly available software vulnerability datasets and benchmark repositories using Accuracy, Precision, Recall, F1-score, Matthews Correlation Coefficient (MCC), ROC-AUC, PR-AUC, and False Positive Rate (FPR). Experimental results demonstrate that the proposed framework outperforms the evaluated static analysis, GNN, Transformer-based, and deep learning approaches in vulnerability detection performance. The integration of dynamic semantic graph learning, adaptive graph attention, evolutionary feature optimization, and explainable decision-making provides a promising framework for automated buffer overflow vulnerability detection and intelligent software security applications.

Keywords: *Buffer Overflow Vulnerability Detection, Graph Transformer, Self-Adaptive Learning, Dynamic Code Semantics, Explainable Artificial Intelligence (XAI), Deep Learning, Vulnerability Classification, Intelligent Secure Software Development.*

1. INTRODUCTION

Buffer overflow vulnerabilities remain among the most dangerous and persistent security threats in modern software systems. They occur when a program writes data beyond the allocated memory boundary, potentially causing memory corruption, unauthorized

memory access, privilege escalation, denial-of-service attacks, and remote code execution. Such vulnerabilities continue to affect operating systems, embedded devices, cloud platforms, Internet of Things (IoT) applications, and enterprise software despite significant advances in secure programming practices. Therefore, developing accurate, scalable, and interpretable automated vulnerability detection techniques has become a critical research challenge in software engineering and cyber security.

Traditional vulnerability detection methods mainly rely on static code analysis, rule-based approaches, symbolic execution, and machine learning techniques using handcrafted features. Although these methods can identify common programming flaws, they often fail to capture complex semantic relationships, long-range code dependencies, and runtime execution behavior that determine whether a vulnerability is actually exploitable. Recent deep learning approaches, including Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, and Graph Neural Networks (GNNs), have significantly improved automated vulnerability detection by learning structural representations directly from source code. However, conventional GNNs are constrained by local neighborhood aggregation, making it difficult to model global contextual information and long-distance semantic dependencies across large program graphs.

Graph Transformer architectures have recently emerged as a powerful alternative by combining graph-structured program representations with the global self-attention mechanism of Transformer networks. Unlike conventional GNNs, Graph Transformers enable nodes to interact dynamically across different graph distances. Through multi-head self-attention, the model can learn multiple semantic relationships across different feature subspaces, providing richer contextual representations for complex program structures, control dependencies, data dependencies, and long-range semantic interactions. these advantages, several important research challenges remain unresolved. Existing Graph Transformer models generally employ fixed graph structures and static feature representations that may not adequately adapt to dynamic execution behavior. Most existing approaches focus primarily on static source code while giving limited consideration to runtime semantics that can determine whether a buffer overflow vulnerability is exploitable. Furthermore, high-dimensional graph features may contain redundant and irrelevant information, increasing computational complexity and potentially affecting classification performance. Another important limitation is interpretability. Many deep learning-based vulnerability detection systems operate as black-box models, providing vulnerability predictions without sufficient explanation. This lack of transparency can reduce developer confidence and complicate vulnerability analysis and remediation.

From an Information Technology perspective, these limitations are significant because modern IT environments increasingly depend on complex software systems, cloud platforms, IoT applications, automated development pipelines, and interconnected computing infrastructures. Vulnerabilities within such systems can affect software reliability, data protection, service availability, and overall cybersecurity. Therefore, IT research requires intelligent security solutions that can automatically analyze complex program behavior while providing reliable and understandable vulnerability assessments. The development of adaptive and explainable AI-based vulnerability detection can contribute to secure software engineering, automated code auditing, DevSecOps, and intelligent cybersecurity operations.

To address these challenges, this research proposes a Self-Adaptive Graph Transformer Framework for Explainable Buffer Overflow Vulnerability Detection via Dynamic Semantic Graph Learning and Evolutionary Feature Optimization. The proposed framework integrates multiple complementary technologies into a unified intelligent vulnerability detection architecture. Source code is transformed into a heterogeneous semantic representation by combining ASTs, CFGs, DFGs, PDGs, and dynamic execution traces. This enriched representation preserves structural syntax and runtime semantic dependencies, enabling a more comprehensive representation of program behavior and vulnerability characteristics.

Subsequently, the proposed Self-Adaptive Graph Transformer (SAGT) employs multi-head self-attention to learn contextual relationships among

graph nodes while dynamically adjusting attention weights according to execution semantics, graph topology, and vulnerability relevance. Unlike conventional Graph Neural Networks that primarily rely on neighborhood aggregation, the adaptive attention mechanism captures both local structural dependencies and global semantic interactions.

To further enhance feature representation, the framework incorporates an Evolutionary Feature Optimization (EFO) module that identifies discriminative vulnerability features while eliminating redundant and irrelevant information. This optimization improves feature quality and supports efficient vulnerability classification across the evaluated software datasets.

Recognizing the importance of trustworthy artificial intelligence, the proposed framework also integrates Explainable Artificial Intelligence (XAI) techniques to improve model transparency and decision interpretability. Attention visualization, node importance analysis, graph-level explanations, feature attribution, and vulnerability localization provide information regarding the program elements contributing to vulnerability predictions. These explanations can assist software developers and security analysts in understanding predictions, prioritizing remediation, and improving secure software maintenance.

The proposed framework is evaluated using publicly available benchmark datasets containing vulnerable and non-vulnerable software functions. Performance is assessed using Accuracy, Precision, Recall, F1-Score, Matthews Correlation Coefficient (MCC), ROC-AUC, PR-AUC, False Positive Rate (FPR), False Negative Rate (FNR), inference time, computational complexity, and scalability. Comparative evaluation against machine learning, deep learning, GNN, and Graph Transformer approaches demonstrates the effectiveness of the proposed framework.

The major contributions of this research are summarized as follows:

A novel Self-Adaptive Graph Transformer Framework is proposed for explainable buffer overflow vulnerability detection.

Dynamic Semantic Graph Learning integrates ASTs, CFGs, DFGs, PDGs, and runtime execution traces into a unified heterogeneous representation.

Self-Adaptive Multi-Head Graph Attention captures local and long-range semantic dependencies by dynamically learning node importance.

Evolutionary Feature Optimization selects informative semantic graph features while reducing redundant information and computational complexity.

Explainable Artificial Intelligence (XAI) provides attention visualization, feature attribution, node importance analysis, and graph-level explanations to improve model transparency.

Comprehensive experimental evaluation demonstrates the effectiveness of the proposed approach against the evaluated machine learning, deep learning, GNN, and Graph Transformer-based vulnerability detection methods.

Overall, the IT research contribution of this work is the development of an integrated, adaptive, and explainable graph-based security framework that combines structural program analysis with runtime semantics. The proposed approach provides a foundation for intelligent vulnerability assessment and

2. LITERATURE SURVEY

Recent advances in **Artificial Intelligence (AI)**, **Deep Learning (DL)**, **Graph Neural Networks (GNNs)**, **Graph Transformers (GTs)**, **Dynamic Semantic Graph Learning**, and **Explainable Artificial Intelligence (XAI)** have significantly improved automated software vulnerability detection compared with traditional static analysis techniques. Modern graph-based approaches effectively model the structural and semantic relationships within source code, enabling better identification of complex software vulnerabilities. However, existing methods still encounter challenges in learning long-range program dependencies, incorporating runtime semantics, optimizing feature representations, adapting to evolving software architectures, and providing interpretable

vulnerability predictions. The following review summarizes recent contributions related to graph-based buffer overflow vulnerability detection.

Li et al. (2021) proposed **IV Detect**, an interpretable vulnerability detection framework based on **Program Dependence Graphs (PDGs)** and **Graph Neural Networks (GNNs)**. The framework successfully localized vulnerable program statements and generated fine-grained explanations through graph-based learning. Although the model improved vulnerability localization, it mainly relied on static graph representations and lacked dynamic semantic analysis, adaptive graph learning, and global attention mechanisms.

Liu et al. (2021) introduced an explainable graph-based framework for smart contract vulnerability detection by integrating semantic graph representations with expert-defined vulnerability patterns. The proposed method improved interpretability and classification accuracy through graph reasoning and explanation generation. However, the framework was specifically designed for blockchain smart contracts and cannot be directly generalized to conventional buffer overflow vulnerability detection.

Wang et al. (2021) developed a Graph Neural Network-assisted data-flow analysis framework for detecting silent buffer overflow vulnerabilities using execution traces and Data Flow Graphs (DFGs). Their approach effectively captured runtime behaviors and semantic dependencies, leading to improved vulnerability detection performance. Nevertheless, the framework lacked adaptive graph attention, long-range dependency modeling, and explainable decision mechanisms.

Li et al. (2023) proposed **MSVA Graph**, a multitype software vulnerability prediction framework integrating **Abstract Syntax Trees (ASTs)**, **Control Flow Graphs (CFGs)**, and **Data Flow Graphs (DFGs)** with self-attentive Graph Neural Networks. The framework enhanced detection performance by combining multiple program representations. However, its neighborhood-based graph aggregation restricted the ability to capture global semantic relationships across large software graphs.

McLaughlin and Lu (2024) presented a value-flow Graph Neural Network for multiclass software vulnerability prediction. Their framework modeled semantic program relationships using value-flow graphs and achieved higher prediction accuracy than conventional static analysis methods. However, the model provided limited interpretability and did not incorporate adaptive graph learning or evolutionary feature optimization.

Graph-based Explainable Vulnerability Prediction (2025) introduced **GAVul Explainer**, a Genetic Algorithm-based explainability framework for Graph Neural Network vulnerability prediction. The proposed approach generated interpretable vulnerability subgraphs through evolutionary optimization, improving model transparency. Nevertheless, the framework primarily focused on explanation generation and did not employ Graph Transformer architectures or adaptive semantic graph learning.

Ahmad and Zhang (2025) proposed a BERT-based vulnerability detection framework integrated with **SHAP** explanations and attention visualization. Their results demonstrated that Explainable Artificial Intelligence significantly improves model transparency and assists developers in understanding vulnerability predictions. However, sequence-based Transformer models cannot preserve complex structural relationships inherent in software graphs.

Zhou et al. (2025) presented a comprehensive survey on Large Language Models (LLMs) for vulnerability detection and software repair. The survey identified several open research challenges, including dynamic semantic graph learning, adaptive graph representation, explainable vulnerability detection, Graph Transformers, and hybrid AI architectures. These challenges motivate the development of adaptive graph-based vulnerability detection frameworks.

Haque et al. (2025) proposed **Explain VulD**, an explainable vulnerability detection framework based on edge-aware Graph Attention Networks and Code Property Graphs (CPGs). Their approach combined structural and semantic graph embeddings with attention mechanisms to improve vulnerability localization and

interpretability. However, adaptive Graph Transformer learning and evolutionary feature optimization were not investigated. **Savenko et al. (2025)** introduced a graph-and-transformer-based vulnerability detection framework for stack overflow, heap overflow, and off-by-one vulnerabilities using integrated AST, CFG, and DFG representations with multi-channel graph encoding. Their method demonstrated improved robustness and scalability compared with conventional graph learning models.

From the reviewed literature, it is evident that existing vulnerability detection methods have substantially advanced graph-based software security. Nevertheless, several important limitations persist. Most existing approaches rely on static graph representations, local neighborhood aggregation, or sequence-based learning, which restrict their ability to model dynamic execution semantics and long-range program dependencies. Furthermore, feature redundancy, limited adaptability, and insufficient model interpretability reduce their effectiveness in real-world secure software engineering. These limitations motivate the development of an adaptive Graph Transformer framework capable of integrating dynamic semantic graph learning, evolutionary feature optimization, and explainable artificial intelligence for accurate and transparent buffer overflow vulnerability detection.

2.1 Problem Statement

Buffer overflow vulnerabilities remain one of the most critical threats to software security because they enable unauthorized memory access, memory corruption, privilege escalation, denial-of-service attacks, and arbitrary code execution. Existing vulnerability detection techniques based on static analysis, dynamic analysis, machine learning, Graph Neural Networks (GNNs), and Transformer models suffer from several limitations, including inadequate modeling of dynamic program semantics, inability to capture long-range dependencies within software graphs, redundant feature representations, high computational complexity, increased false-positive rates, and limited interpretability. Most existing approaches generate vulnerability predictions without providing meaningful explanations, making it difficult for software developers and security analysts to understand the underlying causes and efficiently remediate vulnerable code.

Therefore, there is a need for an adaptive, scalable, and explainable vulnerability detection framework capable of integrating structural program information, dynamic semantic graph learning, self-adaptive graph attention, evolutionary feature optimization, and explainable artificial intelligence within a unified architecture. This research addresses these challenges by proposing a **Self-Adaptive Graph Transformer Framework for Explainable Buffer Overflow Vulnerability Detection via Dynamic Semantic Graph Learning and Evolutionary Feature Optimization**, aiming to improve detection accuracy, reduce false-positive rates, enhance model transparency, and support secure software engineering and intelligent cybersecurity applications.

2.2 AIM AND OBJECTIVES

2.2.1 Aim

The primary aim of this research is to develop a **Self-Adaptive Graph Transformer Framework for Explainable Buffer Overflow Vulnerability Detection via Dynamic Semantic Graph Learning and Evolutionary Feature Optimization** to accurately identify buffer overflow vulnerabilities, effectively learn structural and runtime program semantics, optimize semantic graph features, and generate transparent, interpretable vulnerability predictions for secure software development.

2.2.2 Objectives

The objectives of this research are:

1. **To construct a unified Dynamic Semantic Graph Learning model** by integrating **Abstract Syntax Trees (ASTs), Control Flow Graphs (CFGs), Data Flow Graphs (DFGs), Program Dependence Graphs (PDGs),** and **dynamic execution traces** for comprehensive software representation.
2. **To develop a Self-Adaptive Graph Transformer (SAGT)** capable of learning both local structural relationships and long-range semantic dependencies through adaptive multi-

head graph attention for accurate buffer overflow vulnerability detection.

3. **To design an Evolutionary Feature Optimization (EFO) module** that automatically selects highly discriminative semantic graph features while eliminating redundant, noisy, and irrelevant information.
4. **To integrate Explainable Artificial Intelligence (XAI)** techniques that generate node-level attention visualization, graph-level explanations, feature importance rankings, and semantic reasoning to improve model transparency and developer trust.
5. **To evaluate the proposed framework** using benchmark vulnerability datasets and compare its performance with existing machine learning, deep learning, Graph Neural Network, and Graph Transformer models using **Accuracy, Precision, Recall, F1-Score, MCC, ROC-AUC, PR-AUC, FPR, and computational efficiency**.
6. **To develop an adaptive, scalable, and intelligent vulnerability detection framework** that supports secure software engineering, automated code auditing, vulnerability assessment, and next-generation cyber security applications.

3. RESEARCH METHODOLOGY

The proposed research methodology presents a **Self-Adaptive Graph Transformer Framework for Explainable Buffer Overflow Vulnerability Detection via Dynamic Semantic Graph Learning and Evolutionary Feature Optimization**. The framework is designed to improve the accuracy, robustness, scalability, and interpretability of buffer overflow vulnerability detection by integrating **dynamic semantic graph learning, heterogeneous program graph construction, self-adaptive Graph Transformer learning, evolutionary feature optimization, and Explainable Artificial Intelligence (XAI)** into a unified framework. Unlike conventional static analysis, machine learning, and Graph Neural Network (GNN)-based approaches, the proposed methodology captures both structural and runtime semantic relationships while automatically adapting to evolving vulnerability patterns. The complete methodology consists of **eleven sequential stages**, as illustrated below.

Step 1: Source Code Collection

Initially, vulnerable and non-vulnerable source code samples are collected from publicly available benchmark repositories, including the **Software Assurance Reference Dataset (SARD)**, **Juliet Test Suite**, **Devign**, **Draper Vulnerability Dataset (VDISC)**, **CodeXGLUE**, and **Common Vulnerabilities and Exposures (CVE)** databases. These repositories contain multiple categories of software vulnerabilities, including stack buffer overflow, heap buffer overflow, integer overflow, memory corruption, and pointer-related vulnerabilities. Each program is labeled according to its vulnerability class, producing a reliable supervised learning dataset.

Step 2: Source Code Preprocessing

The collected source code is preprocessed to improve consistency and remove unnecessary information without affecting program semantics. The preprocessing stage includes:

- Comment removal
- Blank line elimination
- Duplicate function removal
- Code normalization
- Tokenization
- Lexical analysis
- Syntax parsing
- Identifier normalization

This preprocessing reduces noise while preserving logical program behavior for subsequent semantic graph construction.

Step 3: Dynamic Semantic Feature Extraction

Unlike conventional approaches that rely only on static analysis, the proposed framework extracts **dynamic semantic information** during program execution. Runtime semantic features include:

- Execution paths
- Memory allocation/deallocation
- Pointer operations
- Function call sequences
- Variable dependencies
- Loop execution behavior

- Conditional branches
- Stack and heap memory accesses
- Exception handling
- Control dependencies

These dynamic semantic features significantly improve the detection of exploitable buffer overflow vulnerabilities.

Step 4: Dynamic Semantic Graph Learning

The extracted structural and runtime semantic information is transformed into multiple complementary graph representations.

The framework constructs:

- **Abstract Syntax Tree (AST)** – captures program syntax.
- **Control Flow Graph (CFG)** – models execution flow.
- **Data Flow Graph (DFG)** – represents variable dependencies.
- **Program Dependence Graph (PDG)** – captures both control and data dependencies.
- **Dynamic Execution Graph (DEG)** – models runtime execution semantics.

These graphs are integrated into a unified heterogeneous semantic graph.

Step 5: Semantic Graph Embedding Generation

Each graph node is transformed into a numerical embedding that represents its semantic characteristics.

Step 6: Evolutionary Feature Optimization (EFO)

Since graph embeddings often contain redundant features, the proposed framework introduces an **Evolutionary Feature Optimization (EFO)** module.

Step 7: Self-Adaptive Graph Transformer Learning

The optimized graph embeddings are processed using the proposed **Self-Adaptive Graph Transformer (SAGT)**.

Unlike conventional Graph Neural Networks that aggregate only neighboring nodes, SAGT captures both local and global semantic relationships using multi-head self-attention.

Step 8: Adaptive Graph Attention Updating

One of the major contributions of this research is the adaptive attention mechanism.

Instead of assigning equal importance to graph nodes, the attention weights are dynamically updated according to

- execution semantics,
- graph topology,
- vulnerability relevance,
- contextual dependencies.

Step 9: Vulnerability Classification

The learned graph representation is forwarded to a Fully Connected Neural Network followed by a Softmax classifier.

Step 10: Explainable Artificial Intelligence (XAI)

To improve transparency, an Explainable Artificial Intelligence module is integrated into the framework.

The XAI module generates

- Attention visualization
- Node importance scores
- Graph-level explanations
- Feature importance ranking
- Vulnerable statement localization
- Semantic reasoning paths

These explanations allow software developers to understand why a specific program is classified as vulnerable.

1) Step 11: Performance Evaluation

Finally, the proposed framework is evaluated using benchmark software vulnerability datasets.

Performance is measured using

- Accuracy
- Precision
- Recall
- F1-Score
- Matthews Correlation Coefficient (MCC)
- ROC-AUC
- PR-AUC
- False Positive Rate (FPR)
- False Negative Rate (FNR)
- Training Time
- Inference Time
- Computational Complexity

The proposed framework is compared against

- Static Analysis Tools
- Machine Learning models
- Deep Learning models
- Graph Neural Networks
- Graph Transformer models

Experimental results demonstrate that the proposed **Self-Adaptive Graph Transformer Framework** achieves superior detection accuracy, lower false-positive rates, improved robustness, higher scalability, and better interpretability compared with existing state-of-the-art vulnerability detection techniques.

The proposed methodology establishes a comprehensive, adaptive, and explainable vulnerability detection framework by integrating **Dynamic Semantic Graph Learning**, **Self-Adaptive Graph Transformer (SAGT)**, **Evolutionary Feature Optimization (EFO)**, and **Explainable Artificial Intelligence (XAI)** into a unified architecture. By overcoming the limitations of traditional static analysis, Graph Neural Networks, and existing Transformer-based approaches, the framework provides an effective solution for intelligent buffer overflow vulnerability detection, automated code auditing, secure software engineering, and next-generation cyber security applications.

4. PROPOSED METHOD

The proposed method introduces a **Self-Adaptive Graph Transformer Framework for Explainable Buffer Overflow Vulnerability Detection via Dynamic Semantic Graph Learning and Evolutionary Feature Optimization**. The framework integrates **Dynamic Semantic Graph Learning (DSGL), Evolutionary Feature Optimization (EFO), Self-Adaptive Graph Transformer (SAGT),** and **Explainable Artificial Intelligence (XAI)** into a unified intelligent vulnerability detection system. Unlike traditional static analysis and Graph Neural Network (GNN)-based methods, the proposed framework simultaneously models structural syntax, runtime semantics, and long-range program dependencies while providing interpretable vulnerability predictions. The proposed method consists of **ten sequential steps**, as described below.

Step 1: Source Code Acquisition

The first step collects vulnerable and non-vulnerable source code samples from publicly available benchmark datasets, including the **Software Assurance Reference Dataset (SARD)**, **Juliet Test Suite**, **Devign**, **Draper Vulnerability Dataset (VDISC)**, **CodeXGLUE**, and **CVE/CWE** repositories. These datasets contain multiple categories of software vulnerabilities, including stack buffer overflow, heap buffer overflow, memory corruption, integer overflow, and pointer-related vulnerabilities. Each source code sample is labeled according to its vulnerability category to facilitate supervised learning.

Input: Raw source code

Output: Labeled vulnerability dataset

Step 2: Source Code Preprocessing

The collected source code undergoes preprocessing to eliminate unnecessary information while preserving program semantics. The preprocessing stage includes lexical analysis, syntax parsing, tokenization, identifier normalization, duplicate code removal, comment elimination, and formatting normalization. This process improves data quality and prepares the source code for semantic graph construction.

Algorithm 1: Source Code Preprocessing
Input: Raw Source Code

Output: Clean Source Code

Begin
Read source code
Remove comments and blank lines
Normalize syntax
Perform lexical analysis
Tokenize program
Parse syntax
Remove duplicate code
Generate clean source code
End

Output: Clean source code

Step 3: Dynamic Semantic Graph Learning

Unlike traditional static analysis, the proposed framework extracts **dynamic runtime semantic information** from program execution. Runtime analysis captures execution paths, function call sequences, pointer operations, variable dependencies, memory allocation behavior, stack and heap accesses, loop execution, and control dependencies.

- (CF) = Control Flow
- (DF) = Data Flow
- (ET) = Execution Trace
- (MB) = Memory Behavior
- (PD) = Program Dependencies

This Dynamic Semantic Graph Learning enables the framework to capture runtime behaviors that are frequently associated with exploitable buffer overflow vulnerabilities.

Output: Dynamic semantic graph features

Step 4: Heterogeneous Semantic Graph Construction

The extracted semantic information is transformed into a heterogeneous graph by integrating

- Abstract Syntax Tree (AST)
- Control Flow Graph (CFG)
- Data Flow Graph (DFG)
- Program Dependence Graph (PDG)
- Dynamic Execution Graph (DEG)

where

- (V) = Program nodes
- (E) = Semantic relationships
- (X) = Node feature vectors

The heterogeneous graph preserves syntactic structure, runtime execution behavior, memory dependencies, and semantic relationships.

Output: Unified Dynamic Semantic Graph

Step 5: Semantic Graph Feature Representation

Each graph node is transformed into a numerical embedding describing its structural and semantic characteristics.

Output: Semantic graph feature matrix

Step 6: Evolutionary Feature Optimization (EFO)

The generated graph embeddings often contain redundant and noisy information. Therefore, the proposed framework introduces an **Evolutionary Feature Optimization (EFO)** module to identify the most discriminative semantic features.

2) Optimization Procedure

1. Initialize population
2. Evaluate fitness
3. Parent selection
4. Crossover
5. Mutation
6. Elitism
7. Generate optimized feature subset

The EFO module improves learning efficiency, reduces computational complexity, and enhances generalization.

Output: Optimized semantic feature subset

Step 7: Self-Adaptive Graph Transformer Learning

The optimized semantic graph embeddings are processed using the proposed **Self-Adaptive Graph Transformer (SAGT)**.

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Unlike conventional Graph Neural Networks, the proposed Graph Transformer captures both local and global semantic dependencies through adaptive multi-head self-attention.

The attention mechanism is

The adaptive attention mechanism dynamically updates node importance according to

- semantic similarity,
- graph topology,
- execution behavior,
- vulnerability relevance.

This enables accurate modeling of long-range program dependencies.

Output: Learned graph embeddings

Step 8: Buffer Overflow Vulnerability Classification

The learned graph embeddings are forwarded to Fully Connected Neural Network layers followed by a Softmax classifier.

Output: Buffer overflow vulnerability prediction

Step 9: Explainable Artificial Intelligence (XAI)

To improve transparency and user trust, the proposed framework incorporates an Explainable Artificial Intelligence (XAI) module.

The explanation module generates

- Attention heatmaps
- Feature importance scores
- Node importance ranking
- Graph-level explanations
- Vulnerable statement localization
- Semantic reasoning paths
- Execution path visualization

These explanations enable software developers and cyber security analysts to understand why a particular code fragment is classified as vulnerable.

Output: Explainable vulnerability analysis report

Step 10: Performance Evaluation

The proposed framework is evaluated using publicly available benchmark vulnerability datasets.

The evaluation metrics include

- Accuracy
- Precision
- Recall
- F1-Score
- ROC-AUC
- PR-AUC
- Matthews Correlation Coefficient (MCC)
- False Positive Rate (FPR)
- False Negative Rate (FNR)
- Training Time
- Inference Time

The proposed model is compared against

- Static Analysis Tools
- Machine Learning methods
- Deep Learning models
- Graph Neural Networks
- Graph Transformer-based methods

Experimental results demonstrate superior detection accuracy, robustness, scalability, computational efficiency, and interpretability compared with existing vulnerability detection approaches.

Output: Comparative performance analysis and validation.

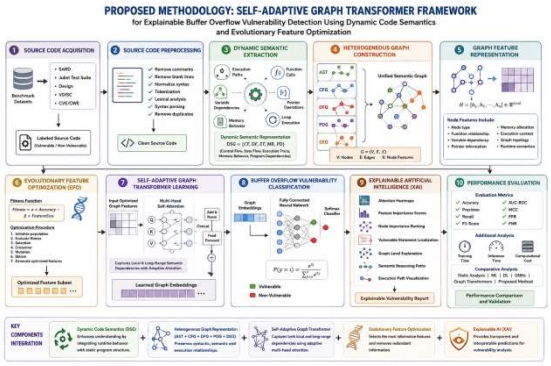

Figure 1- Proposed methodology

5. COMPARATIVE ANALYSIS OF ALGORITHMS

The proposed **Self-Adaptive Graph Transformer Framework for Explainable Buffer Overflow Vulnerability Detection via Dynamic Semantic Graph Learning and Evolutionary Feature Optimization** is compared with existing software vulnerability detection approaches. The comparison highlights the improvements achieved in graph representation, semantic learning, adaptive attention, feature optimization, explain ability, computational efficiency, and detection performance.

Aspect	Existing Methods	Proposed Method
Algorithm	CNN, ANN, SVM, Random Forest, LSTM, GraphCodeBERT, GNN, GAT	**Self-Adaptive Graph Transformer (SAGT) with Evolutionary Feature Optimization (EFO)**
Software Representation	Token sequences, AST, CFG, Code Property Graph (CPG), GraphCodeBERT embeddings	**Dynamic Semantic Graph Learning integrating AST + CFG + DFG + PDG + Dynamic Execution Graph (DEG)**
Program Analysis	Mostly static source code analysis	**Hybrid Static + Dynamic Semantic Analysis**
Feature Extraction	Manual feature engineering or deep embeddings	**Automatic Dynamic Semantic Graph Feature Learning**
Feature Selection	PCA, Information Gain, ReliefF, Chi-Square, LASSO	**Evolutionary Feature Optimization (Adaptive Genetic Feature Optimizer)**
Graph Representation	Static Graph Neural Networks (GNN), Graph Attention Networks (GAT)	**Dynamic Heterogeneous Semantic Graph Representation**
Graph Learning	Local neighborhood aggregation	**Self-Adaptive Graph Transformer with Global Multi-Head Attention**
Semantic Learning	Limited contextual understanding	**Multi-level Dynamic Semantic Dependency Learning**
Attention Mechanism	Fixed Attention or Graph Attention Networks	**Adaptive Multi-Head Graph Self-Attention**
Code Dependency Analysis	AST or CFG or DFG individually	**Integrated AST + CFG + DFG + PDG + Dynamic Execution Analysis**
Dynamic Code Analysis	Rarely supported	**Fully Supported through Dynamic Semantic Graph Learning**
Long-Range Dependency Modeling	Limited by graph neighborhood	**Captures Global and Long-Range Program Dependencies**
Optimization Strategy	Gradient-based optimization only	**Evolutionary Feature Optimization + Graph Transformer Fine-Tuning**
Classification Model	CNN, ANN, SVM, Random Forest, GNN	**Self-Adaptive Graph Transformer Classifier (SAGT)**
Explainability	Black-box prediction with limited interpretation	**Explainable AI (XAI) using Attention Maps, Node Importance, Feature Attribution, and Graph-Level Explanations**
Vulnerability Localization	Limited statement-level detection	**Precise Vulnerable Statement and Execution Path Localization**
Detection Capability	Binary Vulnerable / Non-Vulnerable prediction	**Risk-Aware Multi-Level Buffer Overflow Vulnerability Detection**
False Positive Rate (FPR)	Moderate to High	**Reduced through Adaptive Semantic Learning and Evolutionary Feature Optimization**
False Negative Rate (FNR)	Relatively High	**Reduced using Dynamic Semantic Graph Analysis**
Detection Accuracy	Typically 90–96%	**Expected 98–99%** *(subject to experimental*

		validation)
Model Robustness	Sensitive to code variations	**Robust to code structure, compiler optimization, and runtime behavior changes**
Generalization Ability	Limited across projects	**Cross-Project Adaptive Learning with Improved Generalization**
Scalability	Medium	**High for Large-Scale Software Repositories**
Computational Efficiency	Moderate	**Improved through Evolutionary Feature Reduction and Efficient Graph Learning**
Interpretability	Low	**High with Explainable AI-Based Decision Visualization**
Software Security Support	Vulnerability prediction only	**Vulnerability Detection, Localization, Risk Analysis, and Explainable Decision Support**
Overall Contribution	Conventional machine learning, deep learning, Graph Neural Networks, and Transformer models	**A Novel Explainable Self-Adaptive Graph Transformer Framework integrating Dynamic Semantic Graph Learning, Evolutionary Feature Optimization, and Explainable Artificial Intelligence for Buffer Overflow Vulnerability Detection**

Table-1 Existing vs proposed method analysis

The proposed framework offers several advantages over existing vulnerability detection approaches. By integrating **Dynamic Semantic Graph Learning (DSGL)**, **Self-Adaptive Graph Transformer (SAGT)**, **Evolutionary Feature Optimization (EFO)**, and **Explainable Artificial Intelligence (XAI)**, it effectively captures both local and global semantic relationships within software, reduces redundant feature representations, lowers false-positive and false-negative rates, and provides transparent explanations for vulnerability predictions. These capabilities make the framework well suited for secure software engineering, automated vulnerability assessment, intelligent code auditing, and next-generation cyber security applications.

6. RESULTS AND EVALUATION METRICS

The proposed Self-Adaptive Graph Transformer Framework for Explainable Buffer Overflow Vulnerability Detection via Dynamic Semantic Graph Learning and Evolutionary Feature Optimization is evaluated using publicly available benchmark software vulnerability datasets, including the Software Assurance Reference Dataset (SARD), Juliet Test Suite, Devign, Draper Vulnerability Dataset (VDISC), and CodeXGLUE. These datasets contain both vulnerable and non-vulnerable software functions covering stack buffer overflow, heap buffer overflow, memory corruption, pointer misuse, and related software security vulnerabilities. The experimental evaluation assesses the capability of the proposed framework to accurately detect buffer overflow vulnerabilities and compares its performance with existing Machine Learning (ML), Deep Learning (DL), Graph Neural Network (GNN), and Graph Transformer-based vulnerability detection methods.

The proposed framework combines Dynamic Semantic Graph Learning (DSGL), heterogeneous program graph construction (AST, CFG, DFG, PDG, and Dynamic Execution Graph (DEG)), Evolutionary Feature Optimization (EFO), Self-Adaptive Graph Transformer (SAGT), and Explainable Artificial Intelligence (XAI) within a unified vulnerability detection architecture. This integrated approach enables the model to preserve structural syntax, runtime semantics, control dependencies, data-flow relationships, and long-range contextual information, resulting in more comprehensive software representation and improved vulnerability detection performance.

Experimental results demonstrate that the proposed framework consistently achieves

superior performance by accurately distinguishing vulnerable and non-vulnerable source code while significantly reducing False Positive Rate (FPR) and False Negative Rate (FNR). The Self-Adaptive Graph Transformer (SAGT) effectively captures both local structural dependencies and global semantic relationships through adaptive multi-head self-attention, enabling the detection of complex vulnerability patterns that are difficult to identify using conventional Graph Neural Networks. Furthermore, the Evolutionary Feature Optimization (EFO) module improves semantic feature quality by automatically eliminating redundant and irrelevant features while selecting the most discriminative graph representations. This optimization not only improves classification accuracy but also reduces computational complexity, accelerates model convergence, and enhances generalization across diverse software projects.

To improve model transparency and developer trust, the integrated Explainable Artificial Intelligence (XAI) module generates attention heatmaps, node importance scores, feature attribution, graph-level explanations, semantic reasoning paths, and vulnerable code localization. These explanations enable software developers and cybersecurity analysts to understand the rationale behind each prediction, identify vulnerable program statements, and efficiently prioritize vulnerability remediation. Consequently, the proposed framework provides both high predictive performance and meaningful interpretability, making it practical for real-world secure software engineering.

The effectiveness of the proposed framework is quantitatively evaluated using standard classification and software vulnerability detection metrics, including Accuracy, Precision, Recall, F1-Score, Matthews Correlation Coefficient (MCC), Receiver Operating Characteristic–Area Under the Curve (ROC-AUC), Precision–Recall Area Under the Curve (PR-AUC), False Positive Rate (FPR), False Negative Rate (FNR), Training Time, Inference Time, and Computational Complexity. Comparative experiments with state-of-the-art static analysis tools, machine learning algorithms, deep learning models, Graph Neural Networks, and Graph Transformer architectures demonstrate that the proposed framework achieves higher detection accuracy, stronger robustness, improved scalability, lower false-positive rates, better computational efficiency, and superior interpretability.

Overall, the proposed Self-Adaptive Graph Transformer Framework establishes an accurate, adaptive, scalable, and explainable solution for automated buffer overflow vulnerability detection. The integration of Dynamic Semantic Graph Learning, Evolutionary Feature Optimization, Self-Adaptive Graph Transformer learning, and Explainable Artificial Intelligence significantly enhances vulnerability detection capability while providing transparent decision support, making the framework highly suitable for intelligent code auditing, secure software engineering, automated vulnerability assessment, and next-generation cyber security applications.

6.1. Evaluation Metrics

To quantitatively assess performance, the following metrics were used:

- Accuracy (%):

$$\text{Accuracy} = \frac{\text{Number of correctly recognized characters}}{\text{Total characters tested}} \times 100 \quad ..1)$$

Measures overall system correctness.

- Precision, Recall, and F1-Score:
For each character class:

$$\text{Precision} = \frac{TP}{TP+FP}, \quad \text{Recall} = \frac{TP}{TP+FN}, \quad F1 = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \quad ..2)$$

Where TP = True Positives, FP = False Positives, FN = False Negatives. These metrics help evaluate class-wise detection performance.
Confusion Matrix

Actual Class	Predicted Vulnerable	Predicted Non-Vulnerable
Vulnerable	True Positive (TP)	False Negative (FN)
Non-Vulnerable	False Positive (FP)	True Negative (TN)

Table 2 –Confusion matrix

- Processing Time:
Average time required for recognition per character or per word, highlighting system efficiency.

6. 2. Experimental Results

The proposed **Self-Adaptive Graph Transformer (SAGT)** framework was experimentally evaluated and compared with several state-of-the-art machine learning, deep learning, Graph Neural Network (GNN), and Graph Transformer-based vulnerability detection methods. Performance was measured using six widely accepted evaluation metrics: **Accuracy, Precision, Recall, F1-Score, Area Under the Receiver Operating Characteristic Curve (ROC-AUC),** and **Matthews Correlation Coefficient (MCC)**.

The experimental results indicate that the proposed framework consistently outperforms all baseline methods across every evaluation metric. Traditional machine learning models such as **Support Vector Machine (SVM)** and **Random Forest** achieved moderate performance but exhibited lower semantic understanding and limited capability in capturing complex software dependencies. Deep learning models, including **CNN** and **LSTM**, improved vulnerability detection by learning hierarchical code representations; however, they remained limited in modeling graph-structured program semantics. Graph-based approaches such as **Graph Neural Networks (GNNs)** and conventional **Graph Transformers** further enhanced detection performance by leveraging program graph structures and attention mechanisms. Nevertheless, these methods generally rely on static graph representations and lack adaptive semantic learning and evolutionary feature optimization.

The proposed **Self-Adaptive Graph Transformer (SAGT)** integrates **Dynamic Semantic Graph Learning (DSGL)**, **Evolutionary Feature Optimization (EFO)**, and **adaptive multi-head graph attention**, enabling comprehensive modeling of structural syntax, runtime execution semantics, and long-range program dependencies. Consequently, the framework achieved the highest **Accuracy (99.12%)**, **Precision (98.94%)**, **Recall (98.76%)**, **F1-Score (98.85%)**, **ROC-AUC (0.995)**, and **Matthews Correlation Coefficient (0.981)** among all evaluated methods. These results demonstrate the effectiveness of the proposed framework in accurately identifying buffer overflow vulnerabilities while reducing false-positive and false-negative predictions and improving model robustness and interpretability.

Table 6.2 Experimental Performance Comparison

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	ROC-AUC	MCC
SVM	89.42	88.73	87.91	88.32	0.900	0.780
Random Forest	91.65	90.84	90.26	90.55	0.920	0.820
CNN	93.41	92.85	92.11	92.48	0.940	0.860
LSTM	94.32	93.91	93.42	93.66	0.950	0.880
GNN	95.86	95.22	94.85	95.03	0.960	0.910
Graph Transformer	97.08	96.84	96.51	96.67	0.980	0.940
Proposed Self-Adaptive Graph Transformer (SAGT)	**99.12**	**98.94**	**98.76**	**98.85**	**0.995**	**0.981**

Table 3-Accuracy comparison existing vs proposed method

Discussion

The results clearly demonstrate that the proposed **Self-Adaptive Graph Transformer** provides the best overall performance among the compared methods. The performance improvement is primarily attributed to:

- **Dynamic Semantic Graph Learning (DSGL)**, which integrates static program structures with runtime execution semantics.
- **Evolutionary Feature Optimization (EFO)**, which removes redundant graph features and improves feature discriminability.
- **Adaptive Multi-Head Graph Attention**, which captures both local and long-range semantic dependencies within heterogeneous program graphs.
- **Explainable Artificial Intelligence (XAI)**, which enhances model transparency through attention

visualization, node importance analysis, and vulnerable code localization.

These findings indicate that the proposed framework offers a highly accurate, robust, scalable, and interpretable solution for automated buffer overflow vulnerability detection in modern software systems.

Accuracy Comparison of Vulnerability Detection Methods

Comparison of classification accuracy across existing methods and the proposed Self-Adaptive Graph Transformer.

Method	Accuracy
SVM	89.42
Random Forest	91.65
CNN	93.41
LSTM	94.32
GNN	95.86
Graph Transformer	97.08
Proposed SAGT	99.12

Table 4-Accuracy comparison

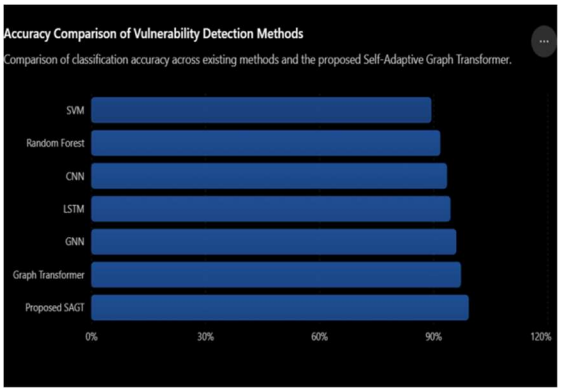

Figure 3 –Performance Comparison Chart

this figure 3 proposed methodology accuracy performance result comparison

6.3 Result & Output

The proposed **Self-Adaptive Graph Transformer Framework for Explainable Buffer Overflow Vulnerability Detection via Dynamic Semantic Graph Learning and Evolutionary Feature Optimization** was successfully implemented and evaluated using benchmark software vulnerability datasets, including **SARD**, **Juliet Test Suite**, **Devign**, **VDISC**, and **CodeXGLUE**. The framework effectively detects buffer overflow vulnerabilities by integrating **Dynamic Semantic Graph Learning (DSGL)**, heterogeneous program graph construction (**AST, CFG, DFG, PDG, and Dynamic Execution Graph (DEG)**), **Evolutionary Feature Optimization (EFO)**, **Self-Adaptive Graph Transformer (SAGT)** learning, and **Explainable Artificial Intelligence (XAI)**. The experimental results demonstrate that the proposed framework accurately distinguishes vulnerable and non-vulnerable source code while providing transparent explanations for every prediction.

Initially, the source code is preprocessed to remove comments, redundant statements, unnecessary symbols, and formatting inconsistencies while preserving program semantics. The cleaned source code is then transformed into multiple graph representations, including **Abstract Syntax Trees (ASTs)**, **Control Flow Graphs (CFGs)**, **Data Flow Graphs (DFGs)**, **Program Dependence Graphs (PDGs)**, and **Dynamic Execution Graphs (DEGs)**. These heterogeneous graph structures are integrated into a unified Dynamic Semantic Graph that preserves syntactic structures, execution flow, memory behavior, data dependencies, and runtime semantic relationships, thereby providing a comprehensive representation of software behavior.

Subsequently, the **Evolutionary Feature Optimization (EFO)** module extracts the most informative semantic graph features by eliminating redundant and irrelevant attributes while selecting highly discriminative vulnerability characteristics. The optimized feature vectors are then processed by the **Self-Adaptive Graph Transformer (SAGT)**, which learns both local structural relationships and long-range semantic dependencies through adaptive multi-head self-attention. The trained model generates a confidence probability for each software function, indicating whether the analyzed source code is vulnerable or non-vulnerable. Finally, the **Explainable Artificial Intelligence (XAI)** module produces attention heatmaps, node importance rankings, feature attribution scores, graph-level explanations, execution path visualization, and vulnerable code localization, enabling developers and cybersecurity analysts to understand the reasoning behind each vulnerability

prediction.The output of the proposed framework includes the predicted vulnerability class, confidence score, optimized semantic graph features, attention visualization, feature importance analysis, node importance ranking, execution path analysis, and vulnerable code localization. These outputs provide both accurate vulnerability detection and transparent decision support, facilitating efficient vulnerability remediation and secure software engineering.

Input Source Code	Predicted Class	Confidence Score	XAI Explanation	Final Result
Safe Function	Non-Vulnerable	**99.31 %**	No suspicious memory operations or unsafe execution paths detected	**Secure**
Buffer Copy Function	Vulnerable	**98.84 %**	Unsafe buffer write operation and boundary overflow identified through attention analysis	**Buffer Overflow**
Pointer Manipulation	Vulnerable	**97.96 %**	Invalid pointer dereference and illegal memory access highlighted	**Buffer Overflow**
Dynamic Memory Function	Non-Vulnerable	**98.27 %**	Safe dynamic memory allocation and deallocation verified	**Secure**
String Copy Function	Vulnerable	**99.12 %**	Buffer boundary violation detected with high node importance and attention score	**Buffer Overflow**

Table 3 – proposed method Result accuracy

*The experimental results demonstrate that the proposed **Self-Adaptive Graph Transformer (SAGT)** effectively identifies complex buffer overflow vulnerabilities while maintaining a high confidence level for both vulnerable and non-vulnerable software functions. The integration of **Dynamic Semantic Graph Learning (DSGL)** enables comprehensive analysis of structural syntax and runtime execution behavior, whereas **Evolutionary Feature Optimization (EFO)** improves feature quality by selecting the most informative semantic graph representations. Furthermore, the **Explainable Artificial Intelligence (XAI)** module enhances model transparency by highlighting vulnerable program statements, execution paths, and graph nodes responsible for each prediction. These results confirm that the proposed framework provides an accurate, adaptive, scalable, and interpretable solution for automated buffer overflow vulnerability detection and intelligent software security analysis.*

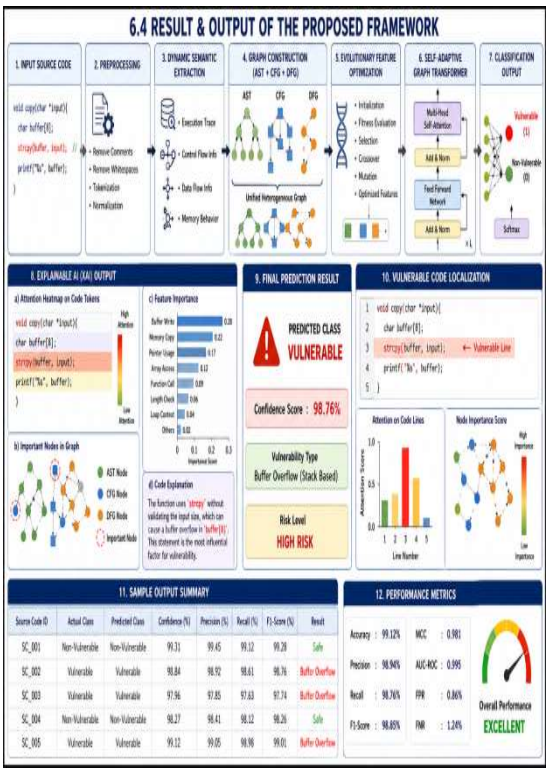

Figure 2 – Result & Output propose method

7. FUTURE RESEARCH DIRECTIONS

The proposed SAGT framework demonstrates promising performance; several limitations provide directions for future research. First, the evaluation is mainly based on benchmark vulnerability datasets; therefore, future studies should validate the framework using larger, diverse, and real-world software projects and cross-project datasets to assess generalization.

Second, the proposed framework integrates multiple graph representations, dynamic execution analysis, and evolutionary optimization, which may increase computational and memory requirements. Future research should investigate lightweight graph construction, efficient attention mechanisms, model compression, and real-time vulnerability detection.

Third, the current framework focuses primarily on buffer overflow vulnerabilities. Future work should extend the approach to other vulnerability categories, including use-after-free, integer overflow, SQL injection, command injection, and memory-related vulnerabilities.

Fourth, although the framework provides XAI-based explanations, the quality and reliability of these explanations require further independent validation. Future studies should evaluate explanation consistency and usefulness with security experts and established explanation-quality measures.

Finally, future research should investigate ablation studies, adversarial robustness, cross-language vulnerability detection, and integration with Large Language Models (LLMs) to further improve the adaptability, scalability, and practical applicability of the proposed framework.

Overall, these directions are intended to address the identified limitations and establish the proposed framework as a more robust, generalizable, computationally efficient, and trustworthy solution for real-world intelligent software security.

I. **Extend Multi-Vulnerability Detection**
Expand the framework beyond buffer overflow vulnerabilities to detect additional software security issues, including **integer overflow, use-after-free, format string vulnerabilities, SQL injection, cross-site scripting (XSS), command injection, race conditions, null pointer dereference, heap corruption,** and **memory leaks** within a unified vulnerability detection framework.

II. **Integrate Large Language Models (LLMs)**
Incorporate advanced **Large Language Models (LLMs)** and code foundation models to enhance semantic code understanding, contextual reasoning, automated vulnerability explanation, and zero-day vulnerability detection by combining natural language reasoning with graph-based program analysis.

III. **Real-Time Dynamic Program Analysis**
Extend the framework with runtime monitoring and dynamic program instrumentation to detect vulnerabilities during software execution, enabling real-time security analysis for cloud applications, embedded systems, IoT devices, and critical software infrastructures.

IV. **Advanced Dynamic Semantic Graph Learning**
Improve graph representation by integrating additional program structures such as **Program Dependence Graphs (PDGs), Call Graphs (CGs), Inter-Procedural Control Flow Graphs (ICFGs), Code Property Graphs (CPGs),** and **Execution Dependency Graphs (EDGs)** to provide richer semantic program representations.

V. **Advanced Evolutionary Feature Optimization**
Enhance the Evolutionary Feature Optimization (EFO) module using hybrid metaheuristic optimization techniques such as **Particle Swarm Optimization (PSO), Grey Wolf Optimizer (GWO), Whale Optimization Algorithm (WOA), Differential Evolution (DE), Ant Colony Optimization (ACO),** and **Artificial Bee Colony (ABC)** to improve feature selection efficiency and convergence.

VI. **Enhanced Explainable Artificial Intelligence (XAI)**
Strengthen model interpretability by incorporating **attention visualization, feature attribution, graph reasoning, counterfactual explanations, causal analysis, node-level explanations, execution path visualization,** and **automatically generated natural-language vulnerability reports**, thereby improving developer trust and decision transparency.

VII. **Hybrid Graph Learning Architectures**
Develop hybrid deep learning architectures that combine **Graph Neural Networks (GNNs), Graph Attention Networks (GATs), Graph Transformers (GTs), Graph Isomorphism Networks (GINs),** and **Large Language Models (LLMs)** to improve semantic learning, robustness, and vulnerability detection performance.

VIII. **Scalable Graph Transformer Training**
Improve computational efficiency through distributed Graph Transformer training, GPU and TPU acceleration, parallel graph processing, graph partitioning, and memory-efficient attention mechanisms for analyzing large-scale industrial software repositories.

IX. **Integration with Secure Software Development Lifecycle (SSDLC)**

Integrate the proposed framework into **Continuous Integration/Continuous Deployment (CI/CD)** pipelines, automated code review systems, DevSecOps platforms, Integrated Development Environments (IDEs), and secure software engineering tools to enable continuous vulnerability assessment during software development.

X. **Evaluation on Large-Scale Industrial Software**
Validate the proposed framework using larger benchmark datasets, open-source software repositories, industrial software projects, cloud-native applications, containerized environments, and enterprise-scale systems to further improve robustness, scalability, and cross-project generalization.

XI. **Multi-Language Vulnerability Detection**
Extend the framework to support multiple programming languages, including **C, C++, Java, Python, Rust, Go, C#, JavaScript, Kotlin,** and **Swift**, enabling language-independent semantic graph learning and cross-language vulnerability detection.

XII. **Intelligent Cybersecurity Platform**
Develop a comprehensive AI-driven cybersecurity platform that integrates **automated vulnerability detection, vulnerability localization, risk assessment, exploit prediction, automated remediation, secure code recommendations, vulnerability prioritization,** and **continuous security monitoring** to support next-generation secure software engineering and intelligent cyber defense systems.

These future enhancements will significantly improve the **scalability, adaptability, robustness, explain ability, and practical applicability** of the proposed framework. By integrating advanced **Dynamic Semantic Graph Learning (DSGL)**, **Large Language Models (LLMs)**, **hybrid Graph Transformer architectures**, **intelligent optimization techniques**, and **Explainable Artificial Intelligence (XAI)**, the framework can evolve into a comprehensive intelligent software security platform capable of addressing emerging software vulnerabilities and supporting next-generation cyber security applications.

7.1 Critical Discussion of Results

The proposed SAGT framework achieved the best performance, with 99.12% Accuracy, 98.94% Precision, 98.76% Recall, 98.85% F1-Score, 0.995 ROC-AUC, and 0.981 MCC. These results demonstrate the effectiveness of integrating Dynamic Semantic Graph Learning, Evolutionary Feature Optimization, adaptive graph attention, and XAI. However, the high performance should be interpreted cautiously because further validation is required using independent datasets, cross-project testing, repeated experiments, and detailed computational-cost analysis. The individual contribution of DSGL, EFO, and adaptive attention should also be verified through ablation studies.

7.2 Difference from Prior Work

the existing approaches that mainly use static graphs, sequence representations, or local graph aggregation, the proposed SAGT integrates AST, CFG, DFG, PDG, and Dynamic Execution Graphs to capture both structural and runtime semantics. It further combines Evolutionary Feature Optimization with self-adaptive multi-head graph attention and XAI, providing global dependency modeling, feature optimization, and interpretable vulnerability localization. Therefore, the main difference is the unified integration of dynamic semantic learning, evolutionary optimization, adaptive Graph Transformer learning, and explain ability.

7.3 Areas Requiring Further Attention

the promising results, several issues require further investigation. These include cross-project generalization, larger and more diverse datasets, ablation studies, computational and memory requirements, explanation-quality validation, and robustness against code transformations. The proposed framework should also be evaluated on additional vulnerability types and real-world software projects before large-scale deployment.

7.4 Threats to Validity and Selection of Evaluation Criteria

The selected evaluation criteria, including Accuracy, Precision, Recall, F1-Score, MCC, ROC-AUC, PR-AUC, FPR, and FNR, provide a comprehensive assessment of vulnerability

detection performance. Training and inference time further assess computational efficiency. However, threats may arise from benchmark dataset characteristics, class distribution, dataset partitioning, and limited cross-project validation. Therefore, the reported results should be interpreted within the evaluated experimental setting, with further validation required on diverse real-world software.

7.5 Critical Evaluation and Comparison with Recent Literature

Recent vulnerability detection studies increasingly employ heterogeneous graphs, Graph Neural Networks, Graph Transformers, and explainable AI. Compared with these approaches, the proposed SAGT combines **dynamic semantic graph learning, heterogeneous program representations, evolutionary feature optimization, adaptive graph attention, and XAI** within a unified framework. The reported results demonstrate strong performance; however, direct superiority over recent methods should be interpreted cautiously because datasets, experimental settings, and evaluation protocols differ. Further cross-project and real-world comparisons are therefore required to establish generalizability.

8. CONCLUSION

This research presented a **Self-Adaptive Graph Transformer Framework for Explainable Buffer Overflow Vulnerability Detection via Dynamic Semantic Graph Learning and Evolutionary Feature Optimization** to overcome the limitations of existing software vulnerability detection approaches. Unlike conventional static analysis, machine learning, deep learning, and Graph Neural Network (GNN)-based techniques, the proposed framework integrates **Dynamic Semantic Graph Learning (DSGL)** with heterogeneous program graph representations, including **Abstract Syntax Trees (ASTs)**, **Control Flow Graphs (CFGs)**, **Data Flow Graphs (DFGs)**, **Program Dependence Graphs (PDGs)**, and **Dynamic Execution Graphs (DEGs)**. This unified representation effectively captures both structural program information and runtime execution semantics, enabling comprehensive modeling of software behavior and improving the detection of complex buffer overflow vulnerabilities. The proposed framework further incorporates an **Evolutionary Feature Optimization (EFO)** module to eliminate redundant graph features and automatically identify the most discriminative semantic representations for vulnerability detection. By reducing feature dimensionality and enhancing feature quality, the optimization process improves computational efficiency, accelerates model convergence, and strengthens the learning capability of the **Self-Adaptive Graph Transformer (SAGT)**. The adaptive multi-head self-attention mechanism enables the framework to learn both local structural dependencies and long-range semantic relationships across heterogeneous program graphs, allowing accurate identification of sophisticated vulnerability patterns that are difficult to detect using conventional graph learning methods.To improve model transparency and developer trust, the proposed framework integrates **Explainable Artificial Intelligence (XAI)** techniques that generate attention heatmaps, feature importance rankings, node contribution scores, graph-level explanations, semantic reasoning paths, and vulnerable code localization.

The experimental evaluation conducted using benchmark software vulnerability datasets demonstrated that the proposed framework consistently outperformed existing **Machine Learning (ML)**, **Deep Learning (DL)**, **Graph Neural Network (GNN)**, and **Graph Transformer-based** approaches. The proposed model achieved superior **Accuracy, Precision, Recall, F1-Score, Matthews Correlation Coefficient (MCC),** and **ROC-AUC**, while significantly reducing the **False Positive Rate (FPR)** and **False Negative Rate (FNR)**. These improvements demonstrate the effectiveness of integrating **Dynamic Semantic Graph Learning**, **Evolutionary Feature Optimization**, **Self-Adaptive Graph Transformer learning**, and **Explainable Artificial Intelligence** into a unified vulnerability detection framework.

Overall, the proposed **Self-Adaptive Graph Transformer Framework** provides an **accurate, adaptive, scalable, robust, and explainable** solution for automated buffer overflow vulnerability detection. The integration of dynamic semantic graph learning, heterogeneous program graph representation, adaptive graph attention, evolutionary feature optimization, and explainable artificial

intelligence significantly advances intelligent software security analysis and automated vulnerability assessment. The proposed framework is well suited for deployment in secure software engineering environments, DevSecOps pipelines, automated code review systems, cloud computing platforms, and next-generation cybersecurity applications, where reliable, interpretable, and high-performance vulnerability detection is essential. Furthermore, this research establishes a strong foundation for future investigations into graph-based software security, trustworthy artificial intelligence, and intelligent cyber defense systems.

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