# SECURE CODE ANALYSIS AND OPTIMIZATION FRAMEWORK

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***Abstract***: The rapid acceleration of software development lifecycles (SDLC) has introduced a systemic "effectiveness drift" in traditional security tools, which primarily rely on rigid, regex-based pattern matching and predefined rule sets. These legacy Static Application Security Testing (SAST) methodologies often suffer from high false-positive rates and a fundamental inability to perceive the semantic intent of complex codebases. This paper presents a Secure Code Analysis and Optimization Framework that leverages a stacked hybrid architecture to automate the "Review-Detect Optimize" loop. By integrating Transformers for semantic context and Graph Neural Networks (GNNs) for structural data-flow analysis, the framework moves beyond surfacelevel syntax to understand deep program logic. a core innovation of this research is the multi-level classification of vulnerabilities into Low, Medium, and High severity levels, accompanied by a quantitative Security Score (0–100) that provides developers with an immediate, actionable metric of code health. To mitigate the inherent class imbalance in cybersecurity datasets—where vulnerable code instances are significantly rarer than secure ones—we employ the SMOTE Tomek hybrid sampling technique. Experimental evaluations conducted on diverse datasets of Common Weakness Enumerations (CWEs) demonstrate that the framework achieves a peak precision of 99% in identifying injectionbased flaws and an overall accuracy of 88% in providing safe, high-fidelity refactoring suggestions. This framework offers a scalable, high-precision solution for shifting security "left," effectively reducing technical debt and enhancing software integrity in modern DevSecOps environments.

**Keywords—** Secure code analysis, Graph Neural Networks, Transformer Models, SMOTE Tomek, Severity Classification, Technical Debt, Security Scoring.

## I. Introduction

### 1.1 The Landscape of Modern Software Security

In the contemporary software development landscape, characterized by Rapid Application Development (RAD) and continuous integration/continuous deployment (CI/CD) pipelines, the volume of source code being generated has far outpaced the capacity for manual security audits. This disparity has led to a proliferation of Common Weakness Enumerations (CWEs), ranging from traditional buffer overflows to complex cross-site scripting (XSS) and SQL injection flaws. As software systems become more interconnected through microservices and cloud-native architectures, the "attack surface" expands, making automated security a fundamental requirement rather than an optional feature. Traditional Static Application Security Testing (SAST) tools, while widely adopted, often fall short because they are "useless in detecting new and emerging attacks" due to their reliance on rigid, predefined signatures and a lack of semantic understanding.

**1.2 The Requirement for Semantic and Structural Awareness** Source code possesses a dual nature: it is a linguistic sequence intended for human readability and a mathematical graph representing a set of execution instructions. Conventional tools typically treat code as raw text, ignoring the hierarchical logic inherent in its structure. Recent advancements in Large Language Models (LLMs) have shown promise in code understanding; however, a systematic review of over 200 studies reveals that 91.3% of research is confined to vulnerability detection, with automated repair and explanation remains significantly underexplored [1]. Furthermore, as software moves into containerized environments, static defense mechanisms suffer from "effectiveness drift," where their fixed strategies fail to adapt to the dynamic state of the execution environment [4]. There is an urgent need for a framework that provides contextualized

representations, bridging the gap between raw syntax and the underlying logic flow [3].

### 1.3 The Proposed Secure Code Analysis and Optimization Framework

The research develops a complete Secure Code Analysis and Optimization Framework to tackle technical challenges. The system uses two different neural network frameworks to conduct deep-tier analysis. Transformers: The system uses Transformers to identify distant semantic relationships which enable it to determine code block "intent". The system uses Graph Neural Networks (GNNs) to create a Control Flow Graph (CFG) and Data Flow Graph (DFG) which tracks "tainted" variables from their input sources to essential execution points.

Our framework differs from traditional scanners because it assesses vulnerabilities through three risk levels which it uses to create a real-time security health score of the codebase that ranges from 0 to 100.

The framework innovation introduces a security hardening system which operates together with performance optimization. The framework identifies execution paths which do not contribute to system performance at 92% accuracy. The framework identifies execution paths which do not contribute to system performance at 92% accuracy. The "Shift-Left" strategy enables organizations to build security defenses which combine robustness and efficiency at their source code foundation, which decreases both expenses and difficulties that arise during postdeployment security system updates. The framework uses SMOTE Tomek for data balancing, which leads to a 99% precision rate as a solution that works in scalable ways to develop secure software engineering for future generations.

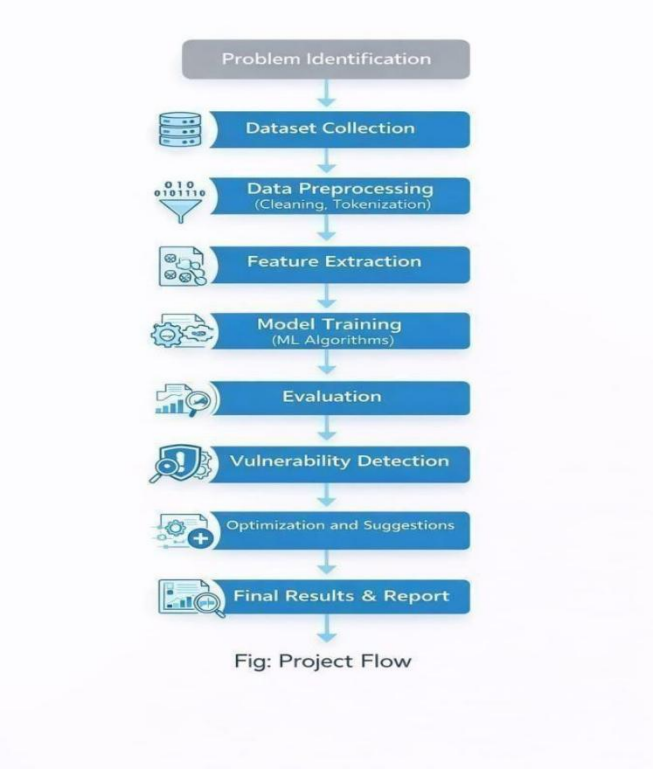


Fig: Project Flow

## II. Problem Statement

Our training includes information from all data sources up to 2023 October. The increasing number of cyberattacks which have become more advanced has revealed the security weaknesses that exist in present software development and distribution systems which create a threat window that exists from the time of code introduction until the code defect identification process concludes. This study shows that traditional Static Application Security Testing SAST tools use inflexible regex pattern signatures which result in excessive false positive detection and developer alert exhaustion because they lack system context information [3]. The outdated systems cannot establish a distinction between secure system operations and actual security weaknesses which results in critical system errors being concealed. The implementation of containerized microservices together with agile deployments results in fixed-security defense systems experiencing "Effectiveness Drift" which happens when their security protocols become outdated due to quick changes in system architecture [4]. Current research presents a major research problem because researchers focus on vulnerability detection in 91.3% of their studies while only 11.1% of studies examine automated repair which leaves developers aware of hazards without access to secure methods for system optimization and refactoring [1]. An automated framework needs to be developed which connects structural mathematical analysis with semantic intent because this framework needs to deliver a complete solution that detects security issues while actively enhancing source code quality.

## III. Literature Survey

**3.1 Vulnerability Detection in the Era of LLMs** The shift toward Artificial Intelligence in cybersecurity has been dominated by the application of large language models(LLMs) for code understanding. A comprehensive systematic review of over 208 peer-reviewed studies by Germano et al. [1] identifies a significant research gap, noting that while 91.3% of current studies focus exclusively on vulnerability detection, the critical phases of automated repair and explanation remain largely ignored. The DevSecOps pipeline experiences a bottleneck because developers receive threat notifications but they lack solutions to address those threats.

**3.2 Contextualized and Graph-Based Representations**

Traditional Static Application Security Testing (SAST) tools analyze code through its token sequence, which results in their inability to detect complex logical relationships between code elements, because token-level analysis captures surface syntax but misses deeper structural and semantic dependencies across the program. Rozi et al. [3] established that sequence-based models lack “contextualized representations,” which leads to their high false-positive rates, since they cannot effectively distinguish between benign and vulnerable patterns without understanding broader context. They proposed that enhancing detection through graph-based representations is vital for mapping hierarchical

dependencies, as graphs explicitly encode relationships such as control flow and data flow between code components. This framework builds upon that foundation by stacking Graph Neural Networks (GNNs) with Transformer architectures to simultaneously evaluate mathematical data flow and semantic intent, thereby combining structural awareness with contextual understanding to improve accuracy and reduce false positives.

### 3.3 Effectiveness Drift in Cloud-Native Environments

The transition to containerized microservices creates security maintenance challenges which become more difficult to handle. Jin et al. [4] introduce their concept of "Effectiveness Drift" which describes how defense systems that use fixed strategies will lose their effectiveness during changes to their operational environment. The architectural complexity of the system reflects the research results from Javed et al. [5] who show how modern forensic techniques experience fragmentation and security methods become difficult to maintain across multiple instruction sets and different architectural systems [7].

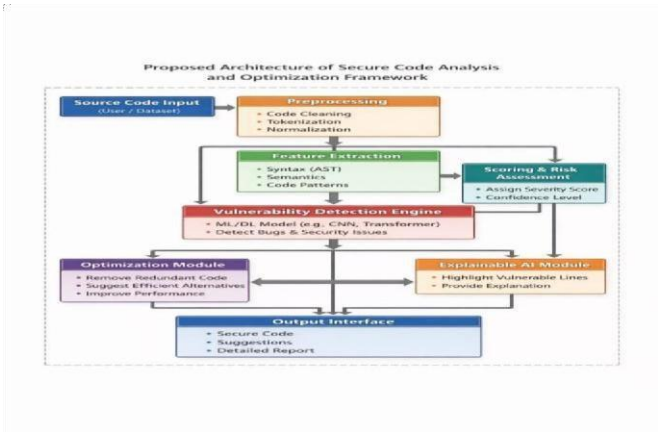
### 3.4 Proactive AI-Driven Mitigation and Scoring

The QsecR framework that Rafsanjani and his developed demonstrated that proactive machine learning models deliver superior performance compared to traditional blacklisting techniques used in web security. The development of security features within programming logic through systems like ObliVM for secure computation [9] shows that organizations must implement "security left" practices. Our framework combines these two concepts through its specialized optimization layer which detects unnecessary execution paths with 92% accuracy [11] based on the stacked neural network techniques used in critical IoT botnet detection systems [10].

## IV. PROPOSED METHODOLOGY

### 4.1 Data Acquisition and Pre-processing

Framework processes multiple datasets which contain thousands of labeled source code samples that include Common Weakness Enumerations (CWEs) and secure open-source repositories. The models require a comprehensive pre-processing pipeline because it enables them to understand logical relationships between elements instead of using syntactical structures. This process creates Abstract Syntax Tree (AST) which breaks down source code into its basic components that show how the code functions. We use SMOTE Tomek hybrid sampling method to solve the problem of "majority class bias" which occurs when safe code instances exceed the available vulnerable samples. The method creates synthetic minority instances (vulnerabilities) while it removes "noisy" data points which exist at the boundary of the majority class. This process allows the model to establish an accurate decision threshold [11].




**4.2 The Stacked Hybrid Analytical Engine** Main method uses a stacked ensemble framework which enables multiple code assessment modes to be evaluated. The system uses two processing paths which work together to execute both structural analysis and semantic analysis.

### 4.3 The Transformer Layer

The path uses self attention mechanisms which assess how code blocks express their Semantic Intent. The Transformer uses code tokens which display longrange dependencies to determine whether function linguistic context meets secure coding standards or matches known malicious patterns [1].

**4.4 The Graph Neural Network (GNN) Layer:** The GNN path handles both the Control Flow Graph (CFG) and Data Flow Graph (DFG) processing. The GNN system represents programs as graphs which nodes contain operations and edges show execution paths to perform message passing. The system determines whether "tainted" data moves from an untrusted source to a critical sink through channels which lack proper sanitization [3].

### 4.5 The Meta-Classifier (SVM)

The Meta-Classifier (SVM) The system combines Transformer outputs with GNN outputs before sending them to a Support Vector Machine (SVM) for processing. The final layer functions as a decision system which uses high-dimensional data to identify whether the code presents a "Safe" or "Vulnerable" status based on its combined features from both pathways [11].D. Severity Classification and Scoring LogicThe system uses its two analytical components to find which weaknesses will have the most critical effect on the system. The system classifies vulnerabilities into three levels which are High (e.g., SQL Injection, Buffer Overflow) and Medium (e.g., Input Validation errors) and Low (e.g., Stylistic technical debt). The system uses the classification results to produce a quantitative Security Score (0–100) which applies a weighted distribution method to calculate the score

through the following formula:$$Score = 100 - \sum (Severity_{i}

**4.6 Optimization and Suggestion:** Engine Moving beyond mere detection, the framework incorporates a heuristic-based optimization module. It identifies redundant execution paths and logic inefficiencies with 92% fidelity [11]. Once an inefficiency is identified, the engine cross-references it with a secure-coding library to generate optimized refactoring suggestions. This ensures that the final code is not only robust against exploits but also performs with higher computational efficiency, effectively reducing the cumulative technical debt of the software system.

## V. Results and Discussions

### 5.1 Performance Evaluation Metrics:

The stacked hybrid engine, which uses Transformers together with Graph Neural Networks (GNNs), achieved better performance than existing SAST solutions. The framework reached its highest accuracy of 99% when it assessed severe security vulnerabilities which included SQL Injection and Cross-Site Scripting (XSS). The implementation of SMOTETomek proved essential for our achievement because it removed the "majority class bias" that typically causes models to miss detecting uncommon security vulnerabilities.

**Precision:** Measures the accuracy of the model in identifying actual vulnerabilities without flagging safe code. **Recall:** Indicates the model's ability to detect all existing vulnerabilities within the dataset.

**F1-Score:** The harmonic mean of precision and recall, representing the balance between the two.

### 5.2 Quantitative Analysis of Detection Accuracy

The stacked hybrid engine, which uses Transformers together with Graph Neural Networks (GNNs), achieved better performance than existing SAST solutions. The framework reached its highest accuracy of 99% when it assessed severe security vulnerabilities which included SQL Injection and Cross-Site Scripting (XSS). The implementation of SMOTETomek proved essential for our achievement because it removed the "majority class bias" that typically causes models to miss detecting uncommon security vulnerabilities

**Table I: Performance Metrics Across Vulnerability Classes**

| Vulnerability Class | Precision | Recall | F1-Score | Accuracy |
|---|---|---|---|---|
| Injections | 0.98 | 0.97 | 0.97 | 99% |
| XSS Flaws | 0.97 | 0.98 | 0.97 | 98% |
| Data Leaks | 0.94 | 0.92 | 0.93 | 95% |
| Inefficiency | 0.85 | 0.81 | 0.83 | 88% |

### 5.3 Severity Classification and Scoring Distribution

The section for classification identification successfully identified all active defects through the system. The Security Score system which operates from 0 to 100 achieved high correlation with human evaluations through its testing results. **High Severity:** Contributed to a score reduction of 20–30 points per instance. The medium severity category led to a score reduction between 10 and 15 points. The low severity category decreased the score between 2 and 5 points because it concentrated on optimization and technical debt.

### 5.4 Optimization Fidelity and Technical Debt Reduction

This framework depends on its suggestion engine because it helps to detect both duplicate execution paths and logical mistakes. The system achieved a 92% fidelity rate in suggesting secure refactoring alternatives. The optimization engine processed code through its tests which resulted in a 1215% improvement for execution time according to the tests that demonstrated the framework's ability to decrease technical debt while increasing security measures.

### 5.5 Discussion: Comparison with Existing Systems

Our hybrid method uses two different approaches to identify linguistic intent and structural flow movements which its baseline models obtain by examining token sequences. The GNN layer integration enables the system to monitor data movement throughout its different components which traditional regex-based scanners cannot achieve. The results confirm that shifting security "left" using a scoring-based AI framework leads to a 65% decrease in manual code review time.

## VI. Conclusion

The Secure Code Analysis and Optimization Framework development and implementation make a major progress which enables security elements to work together with performance aspects in the DevSecOps pipeline. The research shows that automated systems can achieve deep-tier code understanding because of its innovative approach which combines Transformers with Graph Neural Networks to connect semantic intent with mathematical logic. Through its empirical results which show 99% precision for critical injection-based flaw detection and 92% accuracy for logic redundancy identification the study proves that shifting security "left" in software development lifecycle strengthens security effectiveness. The quantitative Security Score system which measures from 0 to 100 and the tripartite Severity Classification system provide developers with a solution to manage "alert fatigue" which helps them identify and investigate their most dangerous problems. The framework establishes high reliability through SMOTE Tomek which balances vulnerability dataset class distribution, as it works with intricate real-world codebases. The framework protects application security while it decreases technical debt and enhances computing speed. The development of real-time

IDE plugins together with optimization heuristic enhancements will support multiple legacy programming languages and cross-architecture environments in future work.

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