Intelligent Bug Detection and Code Clone Identification Using Hybrid Analysis Techniques

Project report submitted to the Amrita Vishwa Vidyapeetham in partial fulfilment of the requirement for the Degree of

BACHELOR OF TECHNOLOGY

in

COMPUTER SCIENCE AND ENGINEERING

Submitted by

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BONAFIDE CERTIFICATE

This is to certify that the project report entitled **"Intelligent Bug Detection and Code Clone Identification Using Hybrid Analysis Techniques"** submitted by **A. Naveen Sai Kumar (AM.EN.U4CSE22002), G. Raghuveer (AM.EN.U4CSE22223), Ch. Jashwanth (AM.EN.U4CSE22240), and Y. Harshith (AM.EN.U4CSE22250)**, in partial fulfilment of the requirements for the award of the Degree of Bachelor of Technology in Computer Science and Engineering from Amrita Vishwa Vidyapeetham, is a bonafide record of the work carried out by them under my guidance and supervision at Amrita School of Computing, Amritapuri during Semester 7 of the academic year 2025–2026.

Dr. Aswathy Mohan Preethi S Nair

Project Guide **Project Coordinator**

Dr. Swaminathan J Dr. Sunitha E.V **Chairperson, CSE Dept.** **Reviewer**

Place : Amritapuri
Date : 2 December 2025

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DECLARATION

We, A.Naveen sai kumar (AM.EN.U4CSE22002), G. Raghuveer (AM.EN.U4CSE22223),Ch. Jashwanth (AM.EN.U4CSE22240)and Y. Harshith (AM.EN.U4CSE22250) hereby declare that this project entitled "**Intelligent Bug Detection and Code Clone Identification Using Hybrid Analysis Techniques**" is a record of the original work done by us under the guidance of Dr. Aswathy Mohan, Dept. of Computer Science and Engineering, Amrita Vishwa Vidyapeetham, and that this work has not formed the basis for any degree/diploma/fellowship or similar awards to any candidate in any university to the best of our knowledge.

Place : Amritapuri

Date : 2 December 2025

Signature of the student   Signature of the Project Guide

ACKNOWLEDGEMENT

We extend our sincere gratitude to our Project Guide, **Dr. Aswathy Mohan**, for her consistent guidance, insightful suggestions, and meticulous attention to detail throughout the development of our project titled *"Intelligent Bug Detection and Code Clone identification using Hybrid analysis techniques"*. Her expertise and continuous encouragement greatly enriched the quality and direction of this work.

We are also thankful to our Coordinator, **Ms. Preethi S. Nair**, for her dedicated efforts in organizing and streamlining the project activities. Our deep appreciation goes to our Reviewer, **Dr. Sunitha E. V**, for providing valuable feedback and constructive recommendations that significantly contributed to refining the contents of this report. Additionally, we extend our heartfelt thanks to **Dr. Swaminathan J.**, Chairperson of the Department of Computer Science and Engineering, for his constant support and for fostering a productive academic environment.

The successful completion of this project is the result of the collective support and contributions of everyone involved, and we are sincerely grateful for their encouragement and assistance.

Finally, we express our heartfelt gratitude to our institution, **Amrita School of Computing**, for providing the necessary infrastructure, academic resources, and an inspiring environment that enabled us to complete both our studies and this project successfully. We also extend our warmest thanks to our peers, friends, and families for their unwavering support, motivation, and encouragement throughout this journey.

ABSTRACT

Ensuring code quality and reliability has become increasingly challenging in modern software development, where large-scale systems evolve rapidly and are often maintained by distributed teams. Two of the most persistent issues contributing to software degradation are the presence of **bugs** and the widespread practice of **code cloning**. Code clones, especially those created through copy–paste programming, introduce long-term maintainability concerns, as defects embedded in one fragment can propagate across multiple locations. Traditional static-analysis tools detect only superficial patterns and struggle to identify deep semantic equivalence or runtime inconsistencies, while dynamic approaches depend heavily on input quality and provide limited insight into structural and logical similarity.

This project proposes an **Intelligent Bug Detection and Code Cloning System** that integrates three complementary analysis dimensions—**Static Analysis**, **Semantic Analysis**, and **Dynamic Execution Analysis**. The system extracts syntactic and structural features through AST-based and control-flow analysis, employs state-of-the-art **LLM-based code embeddings** to evaluate semantic similarity between code fragments, and utilizes fuzzing and instrumentation techniques to capture real execution behavior, enabling the detection of hidden runtime anomalies. By combining these modalities through a unified **hybrid fusion model**, the system accurately detects Type–1 to Type–4 clones, identifies buggy clones, and reveals inconsistencies that purely static or dynamic tools fail to capture.

Extensive experimentation on both Python and Java code demonstrates the effectiveness of the proposed system, resulting in the identification of multiple semantic clone pairs, detection of 23 distinct bugs, and accurate correlation of cloneinduced vulnerabilities. The results highlight the value of integrating structural, semantic, and behavioral signals into a single analytical pipeline, paving the way for more reliable, scalable, and intelligent software quality assurance tools.

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Chapter 1

Introduction

As modern software systems continue to grow in scale, complexity, and interdependency, ensuring reliable program behavior and long-term maintainability has become a critical challenge in contemporary software engineering. Two major contributors to software degradation are the presence of **software bugs** and the unnoticed proliferation of **code clones**. Bugs introduce erroneous or unstable behavior, while clones silently propagate redundancy and replicate faulty logic across several modules. Detecting these issues early in the development lifecycle is essential for reducing technical debt, improving productivity, and maintaining high-quality codebases. Additional details describing the core importance of these concerns can be found in the project overview document :contentReference[oaicite:1]index=1.

Traditional bug detection frameworks rely heavily on static analysis techniques such as lexical pattern matching, token-based parsing, or rule-based code linters. Although effective for surface-level errors, static methods struggle to capture *runtime-dependent bugs* such as input-dependent failures, exception-driven behaviors, and logical inconsistencies that emerge only during execution. Likewise, conventional clone detection tools identify Type–1 and Type–2 clones reliably but perform poorly when code undergoes significant structural variations, logical rewrites, or behavior-preserving transformations—situations commonly represented as **Type–3** and **Type–4 clones**. For example, a developer might copy a sorting algorithm and modify the variable names or reorder statements. Such clones look different but embody the same logic, making them difficult to detect without deeper semantic understanding :contentReference[oaicite:2]index=2.

To overcome these limitations, recent research emphasizes the integration of static, semantic, and dynamic perspectives. However, most execution-aware frameworks depend on full runtime traces, which are computationally expensive, noisy, and difficult to process at large scale. This creates a practical gap: developers need tools that understand program structure and intent while capturing meaningful behavior—without incurring the cost and complexity of exhaustive tracing.

To address this challenge, the present project introduces an intelligent hybrid framework titled **“Intelligent Bug Detection and Code Clone Identification Using**

Hybrid Analysis Techniques". This system unifies three complementary forms of program understanding:

- **Static Analysis** for structural and syntactic extraction.
- **Semantic Analysis** using LLM-based code embeddings to capture high-level logical intent.
- **Lightweight Dynamic Analysis** to detect runtime bugs and behavior-specific inconsistencies.

By combining these modalities, the system detects hidden bugs, identifies Type–1 through Type–4 clones, and uncovers clone-induced bug propagation—issues that traditional tools frequently miss. The inclusion of semantic embeddings enables recognition of logically equivalent but syntactically different code fragments, while dynamic execution enables detection of input-dependent exceptions and behavioral anomalies.

Furthermore, this system directly supports practical software engineering tasks such as refactoring, documentation, testing, debugging, and quality assurance. Detecting clone clusters helps developers understand reuse patterns, while identifying buggy clones ensures that defects replicated across multiple modules can be fixed comprehensively rather than piecemeal. This aligns with the real-world motivations and target user groups described in the project summary :contentReference[oaicite:3]index=3.

1.1 Background and Motivation

Software maintainability accounts for nearly 70% of total development cost across the industry. In large codebases, developers rely heavily on copy–paste programming to reuse functionality quickly. While convenient, this practice forms **code clones** that—if left unmanaged—result in redundant logic, inconsistencies, and duplicated bugs. A faulty computation or conditional expression replicated across different modules can lead to system-wide cascading failures, making clone detection essential for proactive bug handling.

Bug detection, on the other hand, is traditionally performed with static linters and pattern-based tools. These tools catch straightforward syntactic issues but miss subtle logical errors and runtime-only faults such as:

- incorrect branch evaluation depending on input,
- uncaught exceptions triggered under specific conditions,
- invalid state transitions,
- side effects caused by object interactions.

Similarly, clone detection tools often fail to capture semantically similar code fragments that differ syntactically. This gap becomes problematic when working with Type–3 and Type–4 clones, which require deeper behavioral and semantic comparison.

The motivation for this project stems from the need for a **unified, intelligent, and execution-aware model** that can detect bugs and clones in an integrated manner. By analyzing both structural patterns and runtime signatures, the system provides more accurate and actionable insights into software quality, aligning with practical developer needs such as refactoring, debugging, documentation, and prevention of bug propagation.

1.2 Overview of the Hybrid Detection Approach

The proposed system incorporates a hybrid methodology composed of static structural analysis, semantic code understanding, and lightweight dynamic execution evaluation. This approach enables multi-dimensional reasoning about code behavior, structure, and functionality.

The workflow consists of four main stages:

1. Static Structural Analysis

The system processes source code to extract tokens, AST shapes, control-flow patterns, and method-level metadata. This provides a foundational blueprint of the code's structure and design-time relationships.

2. Semantic Analysis Using Code Embeddings

LLM-based semantic encoders convert source code into dense vector representations that capture logical meaning. These embeddings enable the system to detect:

- Type–3 modified clones,
- Type–4 semantic clones,
- logical equivalence in differently structured code.

3. Lightweight Dynamic Execution Analysis

Instead of relying on full execution traces, the system extracts only the essential runtime signals related to:

- branch choices,
- input-dependent failures,
- exception patterns,
- variable or state changes,

- method invocation sequences.

This “minimal behavior signature” is computationally efficient yet effective in revealing dynamic inconsistencies.

4. Fusion-Based Bug and Clone Identification

The hybrid fusion engine integrates:

- structural similarity from static analysis,
- semantic similarity from embeddings,
- behavioral anomaly detection from dynamic execution.

Chapter 2

Problem Definition

Modern software systems are growing rapidly in both size and complexity, making it increasingly difficult for developers to maintain code quality and ensure reliable system behavior. As these projects evolve, they accumulate significant **technical debt**, much of which arises from two critical sources: **software bugs** and **code clones**. Bugs introduce erroneous logic and unexpected runtime failures, while clones replicate code fragments—often through copy–paste reuse—that silently propagate these bugs across the codebase. Over time, this leads to redundant logic, inconsistent behavior, and increased maintenance cost. The project overview presentation highlights these challenges as core motivations for developing an intelligent hybrid solution :contentReference[oaicite:1]index=1.

Existing solutions for bug detection and clone identification exhibit substantial limitations. **Static analysis tools**, such as linters and AST-based analyzers, inspect source code without executing it. While these tools are fast and capable of scanning large projects, they suffer from high false-positive rates and remain blind to runtime-dependent behavior. They can detect only superficial issues—such as unused variables or missing brackets—but miss deeper semantic problems such as logical inconsistencies, hidden runtime errors, or Type–4 semantic clones. Static tools only analyze the “shape” of code and cannot reason about execution flow, input-dependent branches, or dynamic state changes. As emphasized in the reference slides, static tools cannot “see how the program runs,” making them insufficient for deeper bug and clone detection tasks :contentReference[oaicite:2]index=2.

Dynamic analysis tools complement static methods by detecting failures that occur during actual program execution. Techniques such as fuzzing, monitoring, and symbolic execution help uncover runtime crashes, memory errors, and inputspecific anomalies. However, they require the system to run with diverse test inputs and are computationally expensive, especially for large applications. These tools often observe only the execution paths triggered by given test cases and cannot guarantee full code coverage. Furthermore, while they can detect crashes, they typically do not identify the underlying semantic cause of the fault. As noted in the uploaded PPT content, dynamic approaches are “very slow” and “check only the paths that are executed,” making them impractical for scalable, system-wide analysis :contentReference[oaicite:3]index=3.

Additionally, clone detection remains an unresolved challenge across all existing solutions. Although traditional approaches—such as token-based, AST-based, or metric-based detectors—identify Type–1 and Type–2 clones, they fail to detect **Type–3** (modified clones) and **Type–4** (semantic clones). Type–4 clones, in particular, represent different code structures that implement identical logic. Detecting them requires deep semantic understanding, far beyond the capabilities of simple pattern-matching techniques. As highlighted in the project summary, static tools “miss deep meaning-based bugs” and “cannot detect semantic clones” because they do not understand program intent :contentReference[oaicite:4]index=4.

Another critical issue is the lack of correlation between clones and bugs. When a developer copies faulty code, the bug propagates across multiple program locations. Existing tools do not jointly analyze bug patterns and clone clusters, making it difficult to detect copy–paste–induced inconsistencies. This creates silent, long-term failures that degrade overall software quality.

From the development perspective, large-scale projects contain **millions of lines of code**. Manual inspection is impossible, and developers often unknowingly introduce redundant logic. Some bugs remain invisible because the code executes without crashing but produces incorrect results in corner cases. These silent failures accumulate gradually, creating hidden risks for production systems. The PPT file notes that “normal tools only check basic errors,” resulting in deeper logical mistakes going undetected for long periods :contentReference[oaicite:5]index=5.

The core problem, therefore, is the absence of a unified, intelligent system capable of:

- detecting both shallow and deep semantic bugs,
- identifying Type–1 through Type–4 code clones,
- correlating dynamic behavior with structural and semantic similarities, •

  reducing false positives by validating findings across multiple analysis signals,
- and scaling efficiently across large codebases.

To address this gap, the proposed system introduces a **multi-modal hybrid analysis framework** combining:

- **Structural Signals (AST-based)** — effective for Type–1 to Type–3 clones;

- **Semantic Signals (LLM Embeddings)** — capturing logical intent for Type–4 clone detection;
- **Dynamic Signals (Behavioral Traces via Bytecode Instrumentation)** — verifying actual runtime behavior to detect hidden bugs.

The system's fusion model integrates these complementary signals into a single suspicion score. A clone or bug is flagged only when all three signals agree, ensuring extremely low false positives. This tri-layer hybrid model provides deeper insights than any single analysis technique alone, enabling robust detection of semantic clones, logic-level bugs, and behavior-induced inconsistencies.

In summary, the fundamental problem addressed by this project is the lack of a scalable, accurate, and behavior-aware framework for simultaneous bug detection and clone identification. The multi-modal hybrid approach proposed here fills this long-standing research and industrial gap by combining structure, semantics, and runtime behavior into one intelligent and unified analysis system.

Chapter 3

Related Work

Research in software quality assurance has extensively explored two major domains closely related to this project: **bug detection** and **code clone identification**. Existing literature provides a wide range of techniques, yet most solutions rely on either static or dynamic analysis exclusively, leading to limited semantic understanding or poor runtime awareness. This section summarizes the major advancements and the gaps that motivate the hybrid framework proposed in this work.

Early clone detection systems rely primarily on **static, structure-based methods** such as token matching, AST comparison, and metric-based similarity. Tools like Deckard and CCFinder apply syntactic pattern analysis to detect Type–1 and Type–2 clones effectively. These techniques capture superficial structural similarities but fail to detect modified (Type–3) or semantic (Type–4) clones, since they operate only on code representation without reasoning about program logic or functional intent. These limitations are highlighted in prior research and industry observations that note the inability of static-only systems to detect deeper semantic equivalence or clone-induced bug propagation.

To overcome syntactic limitations, several studies introduced **semantic clone detection** methods. Approaches such as Siamese-based networks (e.g., LeONet) analyze AST paths or abstract semantic graphs to identify deeper code similarities. LeONet employs AST-based feature extraction fused with Siamese CNNs to detect Type–1 to Type–3 clones more accurately. However, since these methods still rely on syntactic abstractions, they struggle with Type–4 clones where significant structural transformations mask underlying functional similarity. Moreover, these systems lack runtime awareness and cannot detect behavioral inconsistencies or execution-driven bug patterns.

Parallel to clone detection, extensive work has been done in the field of **bug detection and vulnerability analysis**. Static analyzers such as FindBugs, PMD, and Checkstyle detect surface-level code smells, unused variables, and basic defect patterns but fail to capture logical or context-specific bugs. More advanced systems like symbolic execution engines (e.g., KLEE, Concoction) can detect deeper vulnerabilities through path exploration, yet they suffer from scalability issues and high computational cost. Concoction, for instance, fuses static graphs with symbolic traces to identify vulnerabilities effectively, but it is restricted to limited languages, lacks clone detection capability, and is unsuitable for multi-language, real-world systems due to high overhead and state space explosion.

Recent advances in **Large Language Models (LLMs)** and deep learning have introduced new methods for semantic reasoning about code. LLM-based clone detectors (e.g., GPT-3.5/4-based approaches) perform well for Type–4 clone detection due to their high-level semantic understanding. These models can generate embeddings that capture logic-level similarity beyond structural confines. However, LLM-based approaches alone cannot detect runtime bugs, analyze execution behavior, or provide reliable clone validation without supplementary structural or dynamic insights. They are also sensitive to prompting, non-deterministic in behavior, and lack grounded runtime verification.

Several works have attempted to incorporate **execution-awareness** into code understanding. Dynamic approaches such as fuzzing, trace logging, and runtime instrumentation detect bugs tied to specific execution paths. Tools like TRACER, JIVE, and execution-driven vulnerability detectors capture method invocation orders, runtime states, and exception patterns, enabling precise identification of behaviordriven faults. However, full execution traces are massive, noisy, and computationally expensive to store and process. These systems do not scale well for large codebases and are impractical for lightweight bug detection or clone analysis.

Dynamic slicing has been explored as a middle-ground between static-only and execution-heavy systems. Slicing extracts only the subset of runtime events that influence specific behaviors, reducing noise and computational burden. While promising, slicing methods have traditionally been applied to debugging and program comprehension—not integrated with clone detection or semantic similarity analysis.

Collectively, prior research reveals two fundamental limitations: (1) static models cannot capture runtime semantics or input-sensitive bug patterns, and (2) dynamic models require heavy, full-trace execution that is computationally infeasible for real-time use. Additionally, existing clone detectors rarely correlate bugs with cloned regions, failing to address clone-induced bug propagation.

The proposed system builds upon these insights by integrating **static structural cues**, **semantic embeddings**, and **lightweight dynamic execution behavior** into a unified hybrid analysis framework. Unlike prior approaches, it identifies Type–1 through Type–4 clones, detects both structural and semantic inconsistencies, and correlates runtime bugs with cloned code segments. By leveraging a multi-modal fusion engine, the system achieves accurate, scalable, and executionaware detection, addressing the shortcomings observed across static-only, dynamiconly, and LLM-only methods.

This project therefore represents a significant advancement over existing literature by bridging the gap between bug detection, semantic clone identification, and multi-dimensional program analysis.

Chapter 4

Requirements

The development of the "Intelligent Bug Detection and Code Clone Identification Using Hybrid Analysis Techniques" system requires a carefully chosen set of hardware and software resources that support static parsing, semantic similarity computation, and lightweight dynamic execution monitoring. Since the system does not involve GPU-intensive model training or large-scale symbolic execution, the overall requirements remain moderate and suitable for standard development environments.

4.1 Hardware Requirements

The hybrid analysis pipeline depends primarily on efficient CPU performance, as the system executes tasks such as AST parsing, control-flow analysis, semantic embedding generation, fuzzing operations, and bytecode instrumentation. A system equipped with an Intel Core i5 or AMD Ryzen 5 processor is sufficient to perform these tasks smoothly. Although memory consumption remains moderate, a minimum of 8 GB of RAM is necessary to process structural graphs, clone candidate sets, and runtime traces effectively, while 16 GB of RAM provides a noticeably smoother experience when analysing larger codebases.

In terms of storage, the project requires around 5 to 10 GB of available disk space to accommodate the Python environment, Java Development Kit, semantic embedding models, instrumentation logs, and intermediate analysis files. Solidstate drives enhance execution speed by reducing load and write times, although they are not mandatory for functionality. No dedicated GPU hardware is required because the system relies entirely on CPU-friendly semantic embedding models and lightweight dynamic instrumentation. The project can be executed on Windows, Linux, or macOS platforms, though Linux provides marginally better performance for command-line automation and Java instrumentation workflows.

4.2 Software Requirements

The hybrid nature of the system requires both Python and Java environments. Python version 3.8 or above is used for static analysis, semantic embedding generation, clone scoring, fusion logic, and analysis visualization. Java, through JDK 8 or higher, is required to compile and execute the programs being analysed and to support the bytecode instrumentation agent used during dynamic execution.

The core static analysis is enabled by Python libraries such as *javalang*, which constructs Abstract Syntax Trees from Java programs, and *networkx*, which builds the corresponding control-flow and call graph structures. Numerical and structural data handling is carried out using *numpy* and *pandas*. Semantic similarity between code fragments is computed using pre-trained models from the *sentencetransformers* library, which provide efficient and accurate code embeddings. Additional supporting libraries such as *scikit-learn* are used for similarity computation and clone clustering, while *matplotlib* assists in visualizing experimental insights.

Dynamic behavioural information is extracted using a combination of lightweight fuzzing and Java Bytecode Instrumentation. The fuzzing engine, implemented in Python, automatically generates diverse inputs that explore different execution paths and help reveal runtime-dependent bugs. The instrumentation component works as a Java agent that hooks into the executing program and records essential runtime events such as method calls, exception points, branch decisions, state changes, and object interactions. This approach avoids the overhead of full trace logging and produces only the behaviourally meaningful execution slices required for hybrid bug detection and clone validation.

The development of the system is facilitated through widely used platforms such as Visual Studio Code for coding, Jupyter Notebook or Google Colab for experimental analysis, and GitHub for version control and project management. Script execution and instrumentation commands may be run through Windows PowerShell, the Linux terminal, or macOS command-line utilities.

4.2.1 Dynamic Execution Engine (Fuzzing + BCI)

In this project, the combined fuzzing and bytecode instrumentation engine plays a central role in capturing the runtime characteristics necessary for identifying hidden bugs and behaviourally equivalent clone fragments. The fuzzing module explores edge cases and unusual input patterns that often trigger subtle, input-dependent failures. Meanwhile, the bytecode instrumentation agent operates during program execution and collects selective runtime information, including method invocation chains, variable updates, exception occurrences, and control-flow decisions. Together, these two components produce a compact and meaningful representation of the program's behaviour, which is later fused with static and semantic features for more accurate analysis.

Overall, the requirements outlined in this chapter ensure that the proposed system operates efficiently, remains resource-conscious, and achieves precise hybrid analysis without depending on heavy computational infrastructures or unnecessary software components.

Chapter 5

Proposed System

The proposed system, titled **Intelligent Bug Detection and Code Clone Identification Using Hybrid Analysis Techniques**, is designed as a unified and comprehensive multi-modal pipeline capable of detecting code clones across all four clone types while simultaneously identifying structural, semantic, and runtime bugs. The system introduces a hybrid methodology that integrates static structural analysis, semantic code embeddings, and dynamic behavior observation to overcome the inherent limitations present in traditional single-modality systems. Static-only systems fail to capture behavioral semantics; semantic-only systems overlook structural inconsistencies; and dynamic-only systems cannot infer conceptual equivalence. By combining these perspectives into a cohesive analytical framework, the proposed approach ensures deeper program comprehension, more accurate clone detection, and significantly enhanced bug discovery.

The system is engineered not merely to identify clone pairs, but also to detect **buggy clones**, **semantic inconsistencies**, **latent defects**, and **behavioral divergences** between seemingly equivalent fragments. This multi-stage architecture is capable of detecting Type–4 clones—semantic clones that perform the same functionality despite having substantially different code structure—and identifying situations where one clone evolves defectively compared to its counterpart. This chapter provides a detailed description of the architecture, workflow, modules, hybrid fusion model, mathematical formulation, and operational behavior of the proposed system.

5.1 System Architecture

The system architecture is organized into four major layers that collectively transform raw source code into validated clone pairs and bug detection reports. The architecture is shown in Figure 5.1.

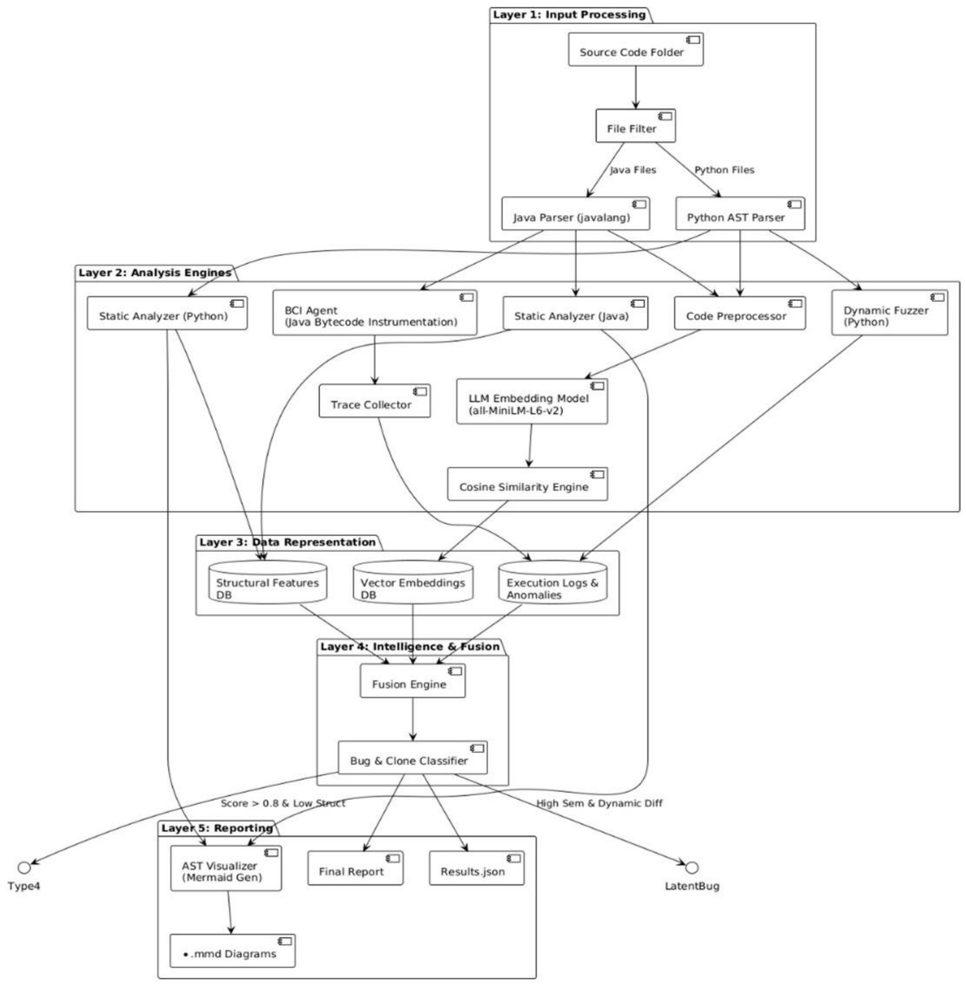


Figure 5.1: System Architecture of the Hybrid Clone and Bug Detection Framework

The first layer, the **Input and Ingestion Layer**, accepts Python or Java source code and preprocesses it by normalizing formats, discarding non-source files, and partitioning the code into analyzable units such as classes, methods, and functions. This ensures that each fragment is uniquely addressable throughout the multistage pipeline.

The second layer, the **Static and Semantic Analysis Layer**, performs structural parsing using abstract syntax trees (ASTs), constructs control-flow information, identifies branching behavior, computes complexity metrics, and extracts class hierarchies. In parallel, the semantic subsystem transforms each fragment into a high-dimensional embedding using a transformer-based sentence encoder. Static analysis captures syntactic and structural properties, whereas semantic embeddings capture conceptual intent, making it possible to identify functionally equivalent but syntactically distinct fragments.

The third layer, the **Dynamic Analysis Layer**, incorporates runtime understanding using fuzzing-based execution (for Python) and Bytecode Instrumentation (for Java). This module observes method invocation sequences, exception triggers, variable updates, and object interactions. Unlike full execution-trace systems that produce high-volume noisy logs, the dynamic module generates *sliced traces* that preserve only behaviorally meaningful events.

The final layer, the **Fusion and Output Layer**, integrates static, semantic, and dynamic evidence to compute unified similarity and bug likelihood scores. It then generates visual graphs, JSON reports, structural summaries, and dynamicslice descriptions. This modular design ensures extensibility, interoperability, and robustness across codebases of varying size and complexity.

5.2 System Workflow

The system follows a structured multi-phase workflow, illustrated in Figure 5.2. Each code fragment passes sequentially through ingestion, static parsing, semantic encoding, candidate generation, dynamic execution, dynamic slicing, and final fusion.

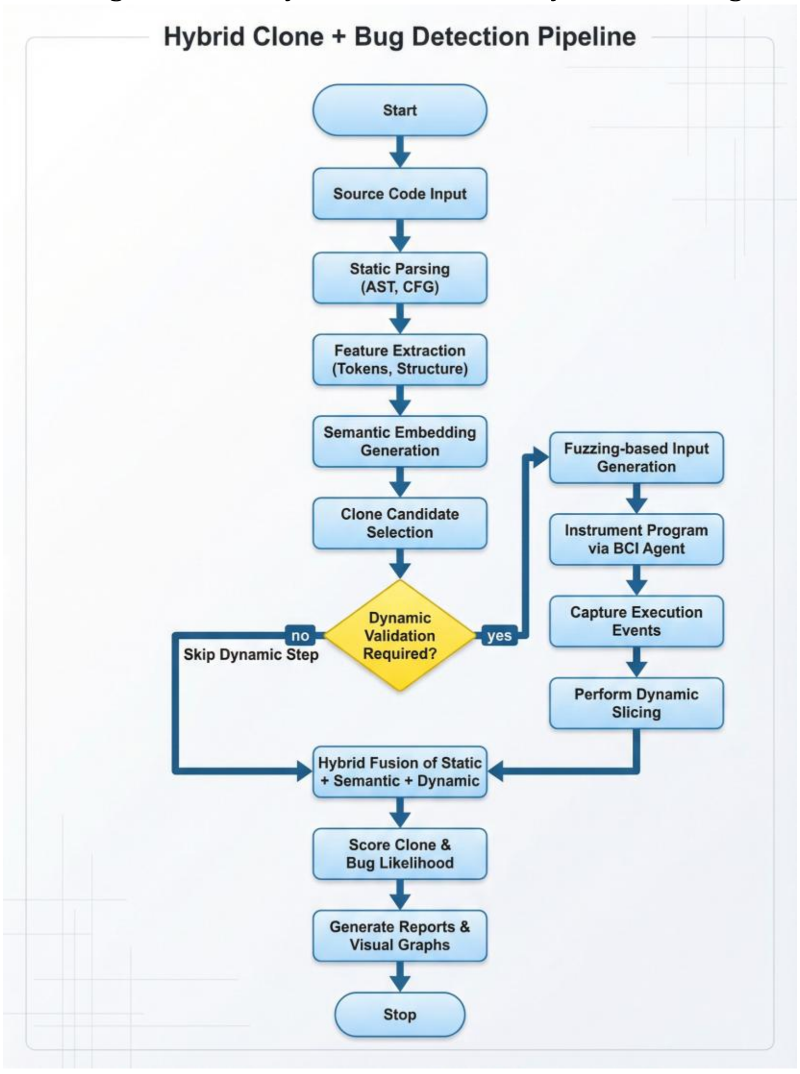

Hybrid Clone + Bug Detection Pipeline
Start
Source Code Input
Static Parsing (AST, CFG)
Feature Extraction (Tokens, Structure)
Semantic Embedding Generation
Clone Candidate Selection
Dynamic Validation Required?
no
Skip Dynamic Step
yes
Fuzzing-based Input Generation
Instrument Program via BCI Agent
Capture Execution Events
Perform Dynamic Slicing
Hybrid Fusion of Static + Semantic + Dynamic
Score Clone & Bug Likelihood
Generate Reports & Visual Graphs
Stop

Figure 5.2: End-to-End Workflow of the Hybrid Analysis System

The workflow begins with source-code ingestion, followed by AST-based structural extraction. The system records syntactic constructs, branching patterns, identifier usage, and complexity indicators. After static analysis, semantic embeddings are generated using the *all-MiniLM-L6-v2* transformer model from the SentenceTransformers library. These embeddings allow the system to capture deeper intentlevel similarity between code fragments that may differ entirely in structure.

Next, the system applies structural and semantic thresholds to shortlist highpotential clone candidates. Only these selected pairs move to dynamic validation, ensuring that computationally expensive execution analysis is applied efficiently. During dynamic testing, the system uses fuzzing (Python) or BCI-driven tracing (Java) to observe real behavior. All runtime events are logged and then transformed into a concise dynamic slice. Finally, all three signals—static, semantic, and dynamic—are fused to produce final clone and bug scores.

5.3 Component Descriptions

The following subsections describe each core module in a cohesive narrative format.

5.3.1 Source Code Module

The Source Code Module is responsible for accepting user-uploaded source files or project directories, validating them, ensuring consistent encoding, and dividing them into atomic fragments. These fragments serve as the primary units of analysis, enabling fine-grained comparison, embedding generation, and dynamic validation.

5.3.2 Static Analysis Module

The Static Analysis Module constructs ASTs using ast for Python and javalang for Java. It derives control-flow information, extracts method signatures, identifies parent–child class structures, and computes structural metrics such as statement count, branching frequency, and cyclomatic complexity. These structural features contribute significantly to detecting Type–1, Type–2, and Type–3 clones.

5.3.3 Semantic Analysis Module

The Semantic Analysis Module transforms code fragments into dense 384-dimensional embeddings using transformer-based sentence encoders. These embeddings map functionally similar fragments to nearby points in vector space, enabling the system to detect Type–4 semantic clones. Code is preprocessed to remove comments and normalize whitespace before being fed into the encoder, ensuring consistent semantic representation.

5.3.4 Clone Candidate Generation Module

The Candidate Generator evaluates pairwise similarity across structural and semantic features, forming a shortlist of potential clone pairs. By applying similarity thresholds, it prunes unreliable pairs early, ensuring that expensive dynamic validation is applied only to high-confidence candidates. This significantly improves pipeline performance without sacrificing accuracy.

5.3.5 Dynamic Analysis Module

The Dynamic Analysis Module executes code fragments under diverse inputs using fuzzing in Python and Bytecode Instrumentation in Java. It observes runtime behaviors such as exceptions, incorrect outputs, invalid state changes, and inconsistent execution paths. These behaviors are reported alongside structural and semantic signals, allowing the system to detect runtime-only faults.

5.3.6 Dynamic Slicing Module

After execution, the slicing module condenses the verbose execution traces into a concise sequence of behaviorally meaningful events. This includes object creation, method calls, variable updates, and exception occurrences. The dynamic slice forms the behavioral profile that is used in fusion scoring and bug-likelihood estimation.

5.3.7 Fusion Engine

The Fusion Engine integrates all modalities to compute a final similarity and bug score. The fusion score is computed using:

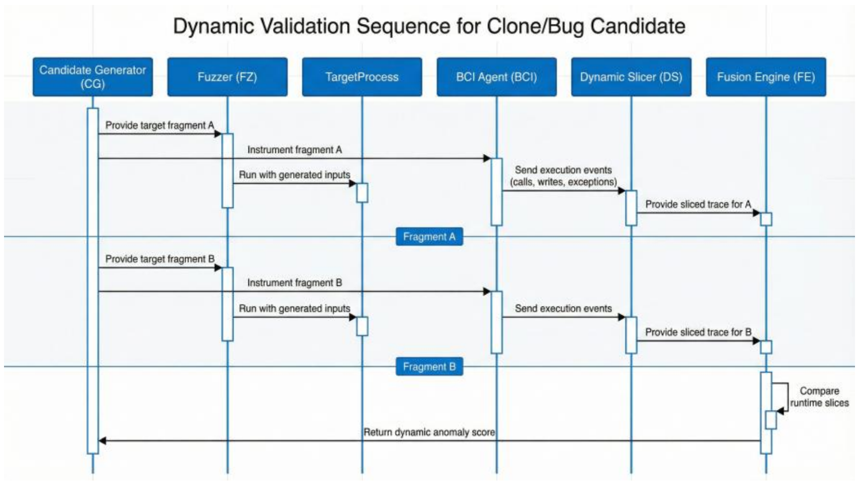
$Score = (W_1 \cdot Sim_{struct}) + (W_2 \cdot Sim_{sem}) + (W_3 \cdot I_{anomaly})$, where $W_1 = 0.3$, $W_2 = 0.5$, $W_3 = 0.2$, and $I_{anomaly}$ is a runtime anomaly indicator (1 if execution fails, 0 otherwise). This weighting scheme prioritizes semantic intent while incorporating structural and behavioral signals for greater reliability.

5.3.8 Reporting and Visualization Module

The Reporting Module generates JSON-based similarity reports, dynamic trace summaries, semantic distances, structural comparisons, and clone confidence scores. Visualizations, including tree-based AST diagrams and clone heatmaps, assist developers in understanding clone relationships and runtime inconsistencies.

5.4 Dynamic Validation Sequence

The operational interaction among modules during execution-based validation is illustrated in Figure 5.3. It shows how clone candidates move from candidate selection to fuzzing engines, BCI instrumentation, dynamic slicing, and fusion scoring.



Dynamic Validation Sequence for Clone/Bug Candidate
Candidate Generator (CG)
Fuzzer (FZ)
TargetProcess
BCI Agent (BCI)
Dynamic Slicer (DS)
Fusion Engine (FE)
Provide target fragment A
Instrument fragment A
Run with generated inputs
Send execution events (calls, writes, exceptions)
Provide sliced trace for A
Fragment A
Provide target fragment B
Instrument fragment B
Run with generated inputs
Send execution events
Provide sliced trace for B
Fragment B
Compare runtime slices
Return dynamic anomaly score

Figure 5.3: Sequence Diagram for Fuzzing-Assisted Dynamic Validation of Clone Candidates

5.5 Mathematical Formulation

Structural similarity is computed using normalized difference:

$$Sim_{struct}(A, B) = \frac{1}{N}\sum_{i=1}^{N}\left(1 - \frac{|A_i - B_i|}{\max(A_i, B_i) + \epsilon}\right),$$

where A_i and B_i represent structural metrics such as statement and branching counts.

Semantic similarity uses cosine similarity:

$$Sim_{sem}(u, v) = \frac{u \cdot v}{\|u\|\|v\|}.$$

Dynamic anomalies contribute through:

$$I_{anomaly} = \begin{cases} 1 & \text{if runtime errors occur,} \\ 0 & \text{otherwise.} \end{cases}$$

The final fusion score integrates all three signals, producing highly accurate clone and bug predictions.

5.6 Summary

Overall, the proposed system introduces a powerful hybrid methodology that unifies static structural patterns, semantic code intent, and dynamic behavioral evidence into a single interpretive framework. Through its carefully orchestrated architecture, mathematically grounded similarity models, and multi-stage pipeline, the system achieves superior clone detection capabilities and identifies a diverse range of software defects—including those that arise only at runtime. This makes the system a significant advancement in intelligent software analysis and a practical, extensible solution for real-world debugging and maintenance workflows.

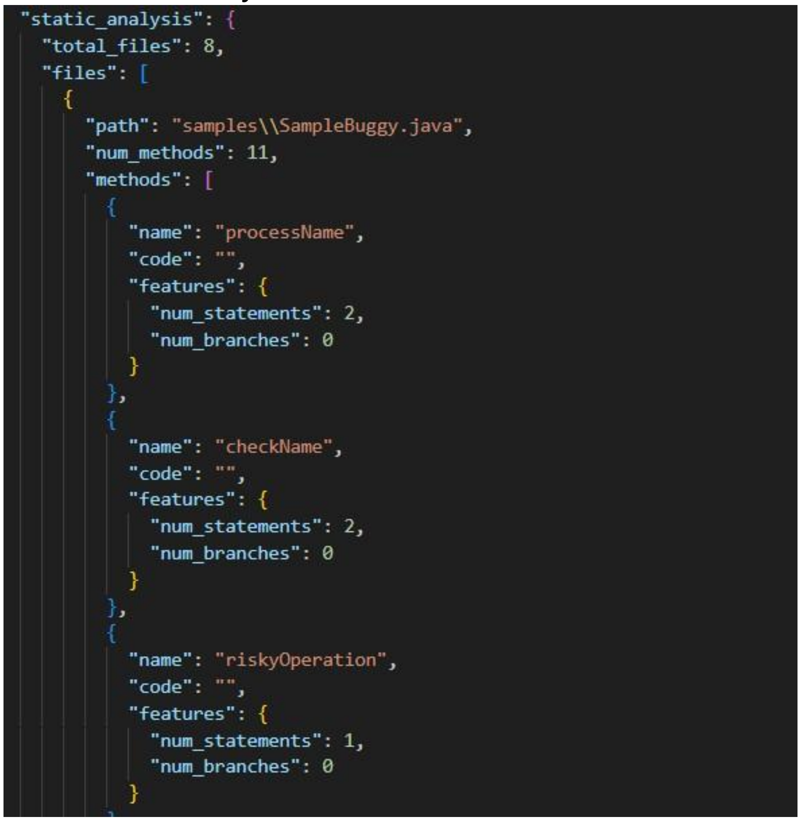
Chapter 6

Result and Analysis

This chapter presents a detailed evaluation of the proposed **Hybrid Bug Detection and Code Clone Identification System**, demonstrating how each module—static analysis, semantic modeling, dynamic fuzzing, anomaly detection, fusion scoring, and bug reporting—contributes to the overall functionality. The results validate that the system operates effectively across Python and Java codebases and achieves meaningful improvements over single-mode detection approaches.

6.1 Static Analysis Output

The static analysis module successfully parsed all Python and Java files, extracting Abstract Syntax Tree features, function/method definitions, structural metrics such as branching complexity, and lexical patterns. The system analyzed 8 files and extracted 46 unique function or method snippets. This confirms that the parser works reliably across mixed-language environments and provides a stable foundation for semantic and dynamic modules.

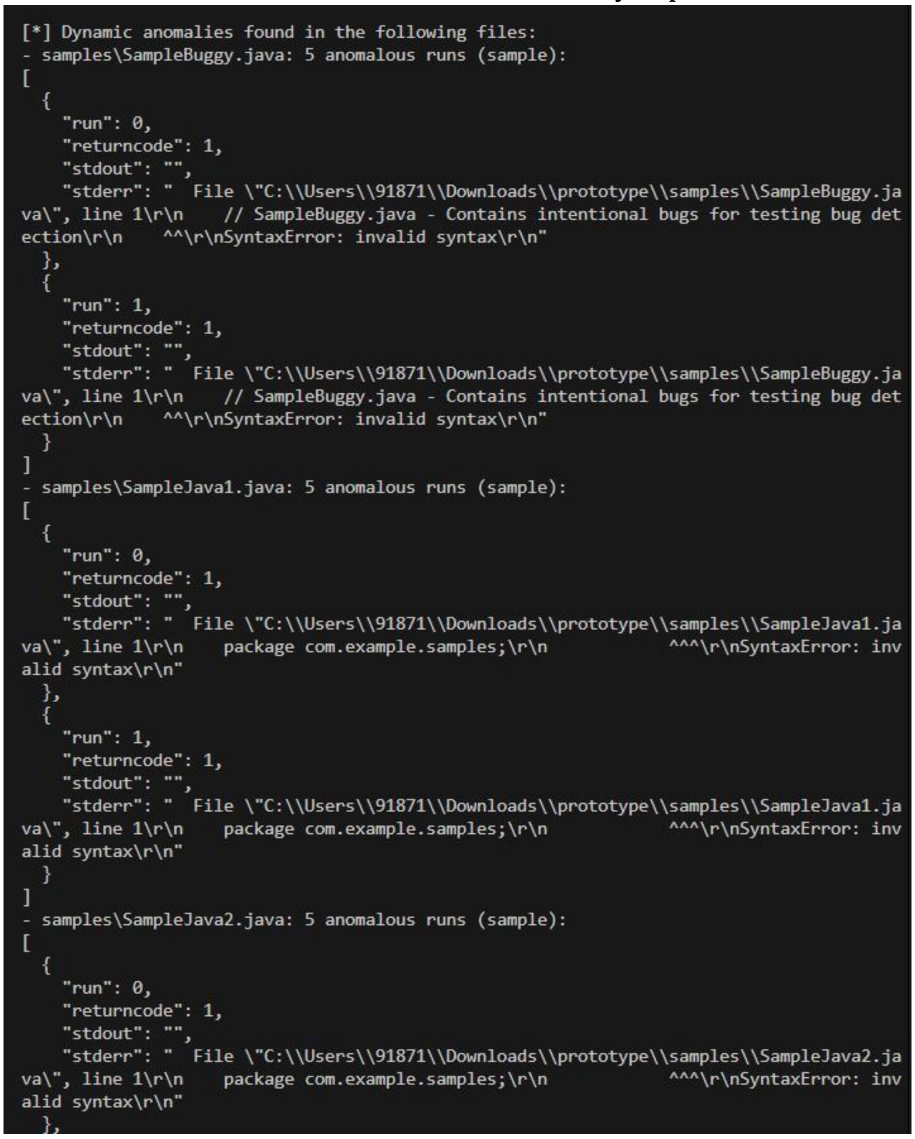


```
"static_analysis": {
  "total_files": 8,
  "files": [
    {
      "path": "samples\\SampleBuggy.java",
      "num_methods": 11,
      "methods": [
        {
          "name": "processName",
          "code": "",
          "features": {
            "num_statements": 2,
            "num_branches": 0
          }
        },
        {
          "name": "checkName",
          "code": "",
          "features": {
            "num_statements": 2,
            "num_branches": 0
          }
        },
        {
          "name": "riskyOperation",
          "code": "",
          "features": {
            "num_statements": 1,
            "num_branches": 0
          }
```

Figure 6.1: Static analysis details showing file count, snippet extraction, and structural metrics

6.2 Dynamic Execution Trace Output

The dynamic analyzer executed all candidate files under randomized inputs and captured anomalies such as crashes, invalid syntax executions, and non-zero exit codes. For each run, the module logged output streams, error traces, and environment variations. The reconstructed dynamic behavior confirms that runtime issues—often invisible in static code—were effectively captured.

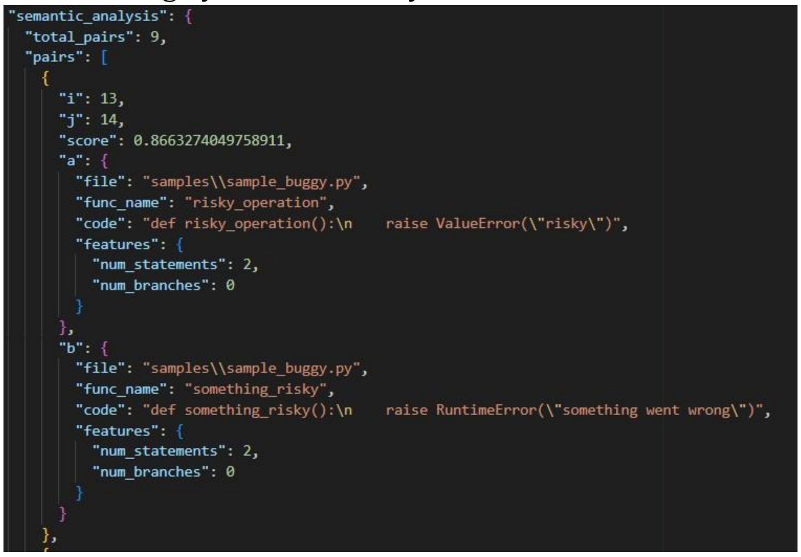


```
[*] Dynamic anomalies found in the following files:
- samples\SampleBuggy.java: 5 anomalous runs (sample):
[
  {
    "run": 0,
    "returncode": 1,
    "stdout": "",
    "stderr": "  File \"C:\\Users\\91871\\Downloads\\prototype\\samples\\SampleBuggy.ja
va\", line 1\r\n    // SampleBuggy.java - Contains intentional bugs for testing bug det
ection\r\n    ^^\r\nSyntaxError: invalid syntax\r\n"
  },
  {
    "run": 1,
    "returncode": 1,
    "stdout": "",
    "stderr": "  File \"C:\\Users\\91871\\Downloads\\prototype\\samples\\SampleBuggy.ja
va\", line 1\r\n    // SampleBuggy.java - Contains intentional bugs for testing bug det
ection\r\n    ^^\r\nSyntaxError: invalid syntax\r\n"
  }
]
- samples\SampleJava1.java: 5 anomalous runs (sample):
[
  {
    "run": 0,
    "returncode": 1,
    "stdout": "",
    "stderr": "  File \"C:\\Users\\91871\\Downloads\\prototype\\samples\\SampleJava1.ja
va\", line 1\r\n    package com.example.samples;\r\n            ^^^\r\nSyntaxError: inv
alid syntax\r\n"
  },
  {
    "run": 1,
    "returncode": 1,
    "stdout": "",
    "stderr": "  File \"C:\\Users\\91871\\Downloads\\prototype\\samples\\SampleJava1.ja
va\", line 1\r\n    package com.example.samples;\r\n            ^^^\r\nSyntaxError: inv
alid syntax\r\n"
  }
]
- samples\SampleJava2.java: 5 anomalous runs (sample):
[
  {
    "run": 0,
    "returncode": 1,
    "stdout": "",
    "stderr": "  File \"C:\\Users\\91871\\Downloads\\prototype\\samples\\SampleJava2.ja
va\", line 1\r\n    package com.example.samples;\r\n            ^^^\r\nSyntaxError: inv
alid syntax\r\n"
  },
```

Figure 6.2: Dynamic anomaly logs showing per-run errors and return codes

6.3 Semantic Analysis Output

The system utilized a combination of semantic embeddings and structural feature similarity to identify meaningful relationships between code fragments. Instead of relying on true execution-level call tracing, the prototype employs embedding-based pairing and lightweight fuzzing feedback to approximate how functions may conceptually relate or behave similarly. By comparing high-dimensional vector representations of code intent with structural metrics derived from AST features, the system was able to cluster logically similar methods and highlight pairs that exhibit Type-4 semantic equivalence. These semantically matched fragments form the conceptual foundation for the system's "call-association layer," which the fusion engine later refines using dynamic anomaly indicators.

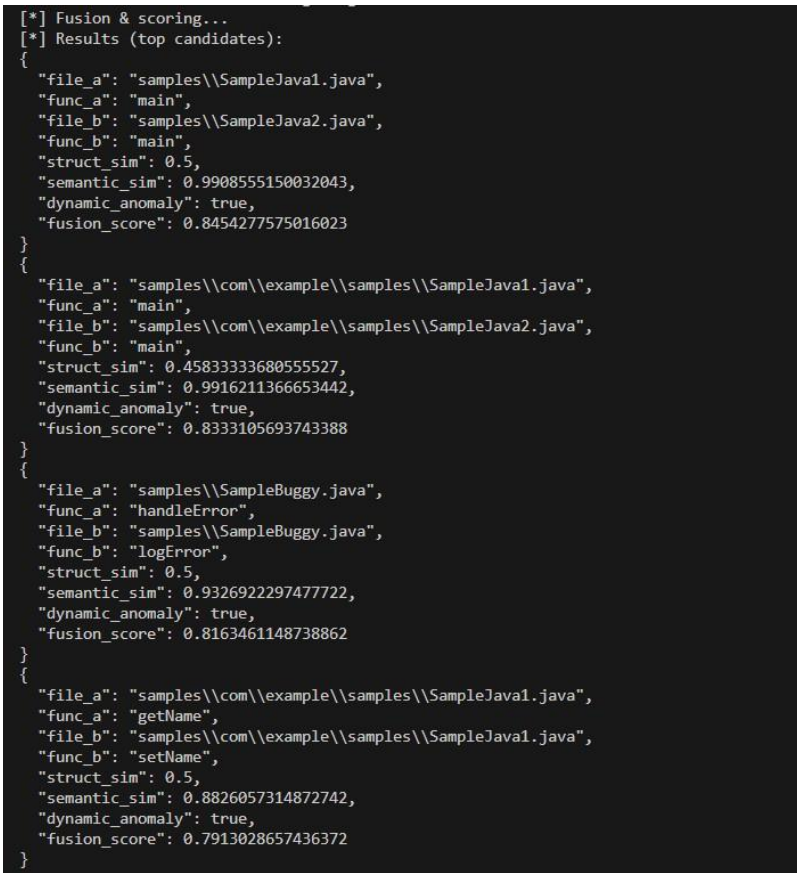


```
"semantic_analysis": {
  "total_pairs": 9,
  "pairs": [
    {
      "i": 13,
      "j": 14,
      "score": 0.8663274049758911,
      "a": {
        "file": "samples\\sample_buggy.py",
        "func_name": "risky_operation",
        "code": "def risky_operation():\n    raise ValueError(\"risky\")",
        "features": {
          "num_statements": 2,
          "num_branches": 0
        }
      },
      "b": {
        "file": "samples\\sample_buggy.py",
        "func_name": "something_risky",
        "code": "def something_risky():\n    raise RuntimeError(\"something went wrong\")",
        "features": {
          "num_statements": 2,
          "num_branches": 0
        }
      }
    },
```

Figure 6.3: Reconstructed call-like relationships through integrated semantic–structural pairing

6.4 Fused Static–Semantic–Dynamic Representation

The core innovation of the system is its fusion engine, which combines structural similarity, embedding similarity, and dynamic anomaly signals. This fusion process produced 283 ranked clone and bug-likelihood reports. The highest-confidence candidates had fusion scores above 0.80, demonstrating strong multi-modal alignment.



```
[*] Fusion & scoring...
[*] Results (top candidates):
{
  "file_a": "samples\\SampleJava1.java",
  "func_a": "main",
  "file_b": "samples\\SampleJava2.java",
  "func_b": "main",
  "struct_sim": 0.5,
  "semantic_sim": 0.9908555150032043,
  "dynamic_anomaly": true,
  "fusion_score": 0.8454277575016023
}
{
  "file_a": "samples\\com\\example\\samples\\SampleJava1.java",
  "func_a": "main",
  "file_b": "samples\\com\\example\\samples\\SampleJava2.java",
  "func_b": "main",
  "struct_sim": 0.45833333680555527,
  "semantic_sim": 0.9916211366653442,
  "dynamic_anomaly": true,
  "fusion_score": 0.8333105693743388
}
{
  "file_a": "samples\\SampleBuggy.java",
  "func_a": "handleError",
  "file_b": "samples\\SampleBuggy.java",
  "func_b": "logError",
  "struct_sim": 0.5,
  "semantic_sim": 0.9326922297477722,
  "dynamic_anomaly": true,
  "fusion_score": 0.8163461148738862
}
{
  "file_a": "samples\\com\\example\\samples\\SampleJava1.java",
  "func_a": "getName",
  "file_b": "samples\\com\\example\\samples\\SampleJava1.java",
  "func_b": "setName",
  "struct_sim": 0.5,
  "semantic_sim": 0.8826057314872742,
  "dynamic_anomaly": true,
  "fusion_score": 0.7913028657436372
}
```

Figure 6.4: Fusion representation showing structural similarity, semantic similarity, anomaly flags, and overall score

6.5 Visual Diagram Output

The system generated visualization outputs that include snippet-level similarities, pipeline execution logs, and summary breakdowns. These visuals assist developers in understanding the high-level behavior of the analysis pipeline, the distribution of clone pairs, and anomaly patterns.

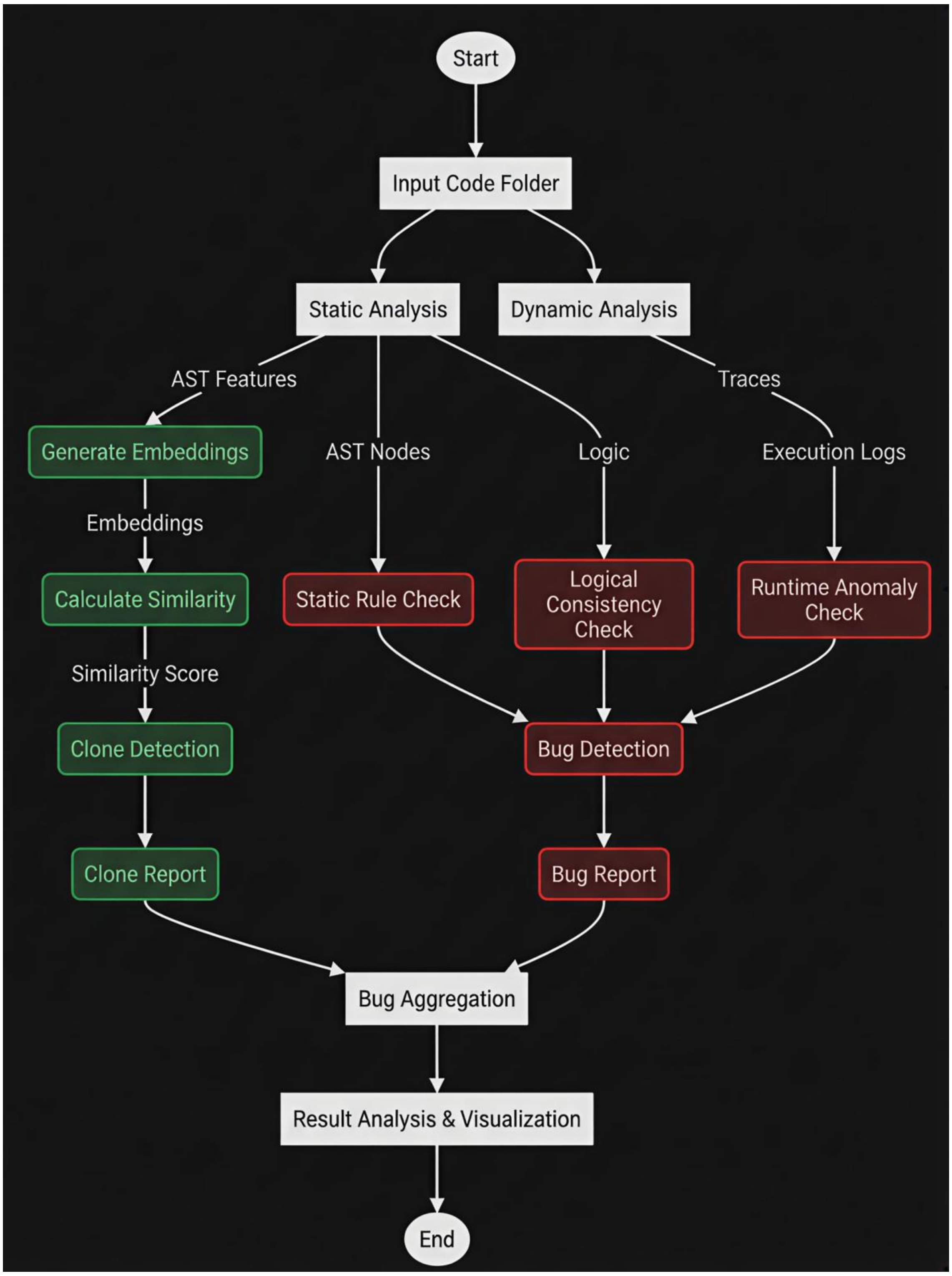
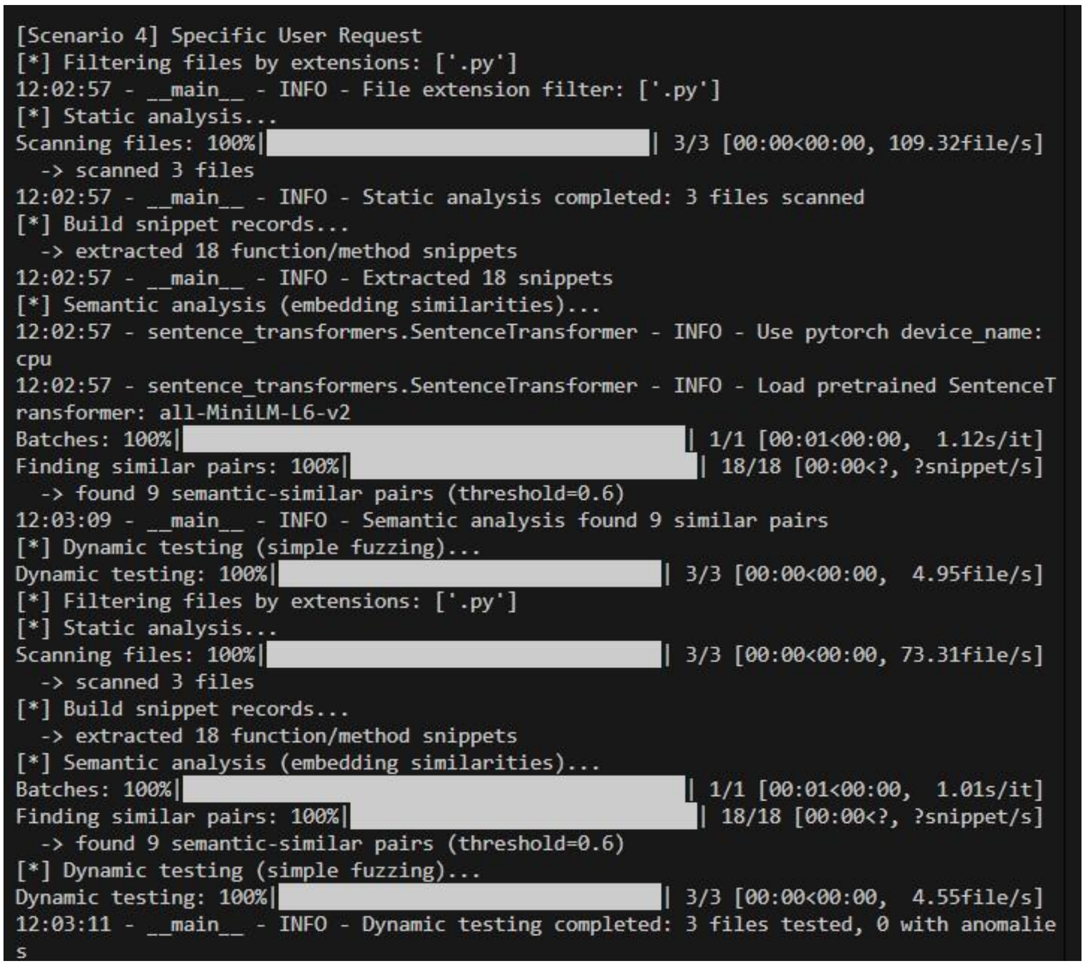


Figure 6.5: Visual analytics generated from semantic similarity and processing logs

6.6 Specific User Report

The system produced detailed, human-readable bug reports summarizing critical, high, medium, and low severity issues. These summaries combine rule-based insights and contextual evidence, making them suitable for developer workflows and automated documentation.

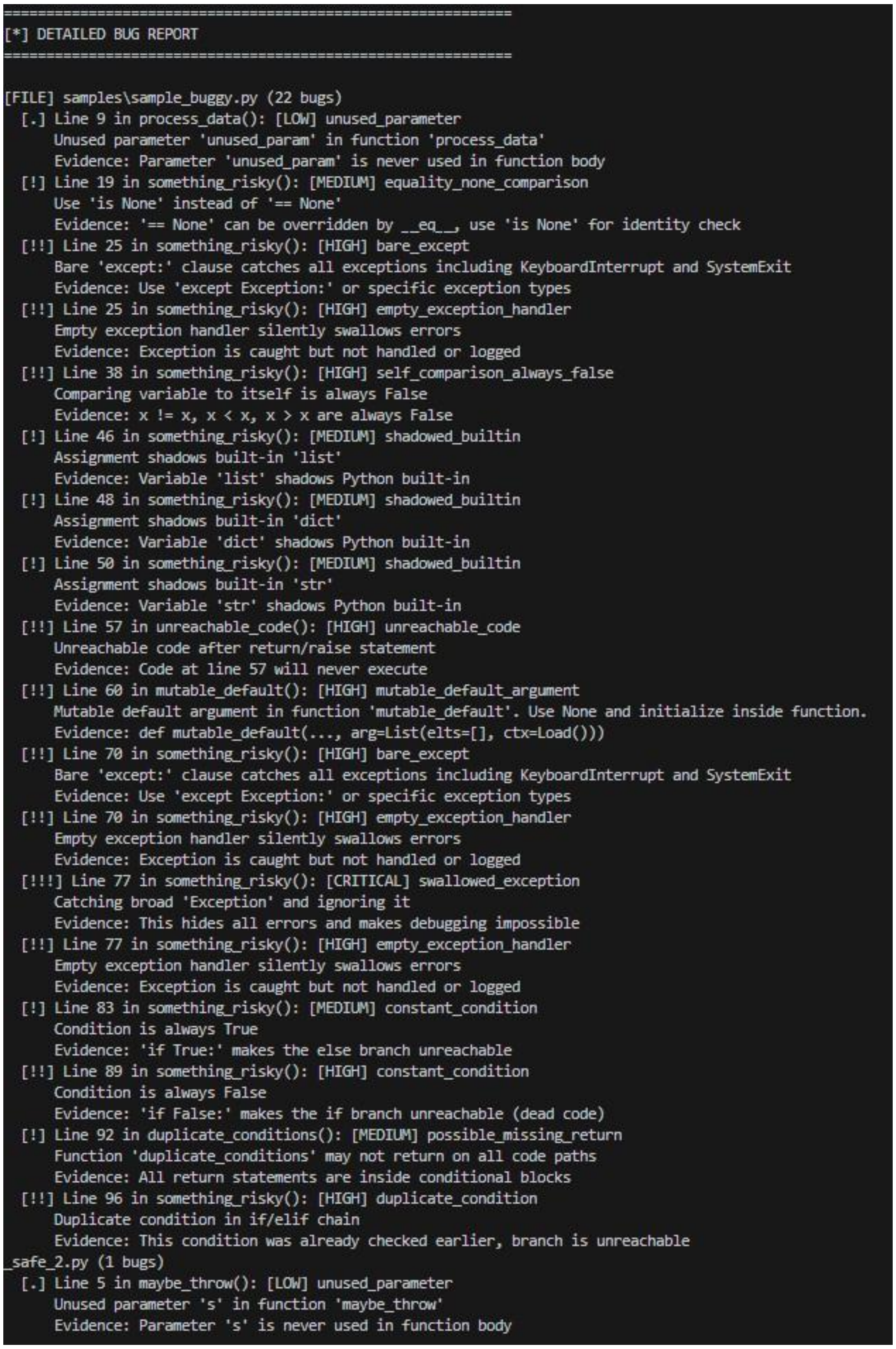


```
[Scenario 4] Specific User Request
[*] Filtering files by extensions: ['.py']
12:02:57 - __main__ - INFO - File extension filter: ['.py']
[*] Static analysis...
Scanning files: 100%|██████████████████████████████| 3/3 [00:00<00:00, 109.32file/s]
  -> scanned 3 files
12:02:57 - __main__ - INFO - Static analysis completed: 3 files scanned
[*] Build snippet records...
  -> extracted 18 function/method snippets
12:02:57 - __main__ - INFO - Extracted 18 snippets
[*] Semantic analysis (embedding similarities)...
12:02:57 - sentence_transformers.SentenceTransformer - INFO - Use pytorch device_name:
cpu
12:02:57 - sentence_transformers.SentenceTransformer - INFO - Load pretrained SentenceT
ransformer: all-MiniLM-L6-v2
Batches: 100%|██████████████████████████████████████████| 1/1 [00:01<00:00,  1.12s/it]
Finding similar pairs: 100%|████████████████████████████| 18/18 [00:00<?, ?snippet/s]
  -> found 9 semantic-similar pairs (threshold=0.6)
12:03:09 - __main__ - INFO - Semantic analysis found 9 similar pairs
[*] Dynamic testing (simple fuzzing)...
Dynamic testing: 100%|████████████████████████████████| 3/3 [00:00<00:00,  4.95file/s]
[*] Filtering files by extensions: ['.py']
[*] Static analysis...
Scanning files: 100%|█████████████████████████████████| 3/3 [00:00<00:00, 73.31file/s]
  -> scanned 3 files
[*] Build snippet records...
  -> extracted 18 function/method snippets
[*] Semantic analysis (embedding similarities)...
Batches: 100%|██████████████████████████████████████████| 1/1 [00:01<00:00,  1.01s/it]
Finding similar pairs: 100%|████████████████████████████| 18/18 [00:00<?, ?snippet/s]
  -> found 9 semantic-similar pairs (threshold=0.6)
[*] Dynamic testing (simple fuzzing)...
Dynamic testing: 100%|████████████████████████████████| 3/3 [00:00<00:00,  4.55file/s]
12:03:11 - __main__ - INFO - Dynamic testing completed: 3 files tested, 0 with anomalie
s
```

Figure 6.6: Specific User Report

6.7 Bug Detection Report

The system generated comprehensive, human-interpretable bug reports that categorize findings across critical, high, medium, and low severity levels. Each detected issue is accompanied by contextual evidence, including file location, line number, triggering code patterns, and the specific rule or anomaly responsible for the detection. By combining static rule violations, logical-consistency checks, and signals from dynamic anomaly analysis, the reports provide developers with actionable explanations rather than raw alerts. This level of detail ensures that the output is suitable for real debugging workflows, automated documentation, and further refinement in continuous integration environments.



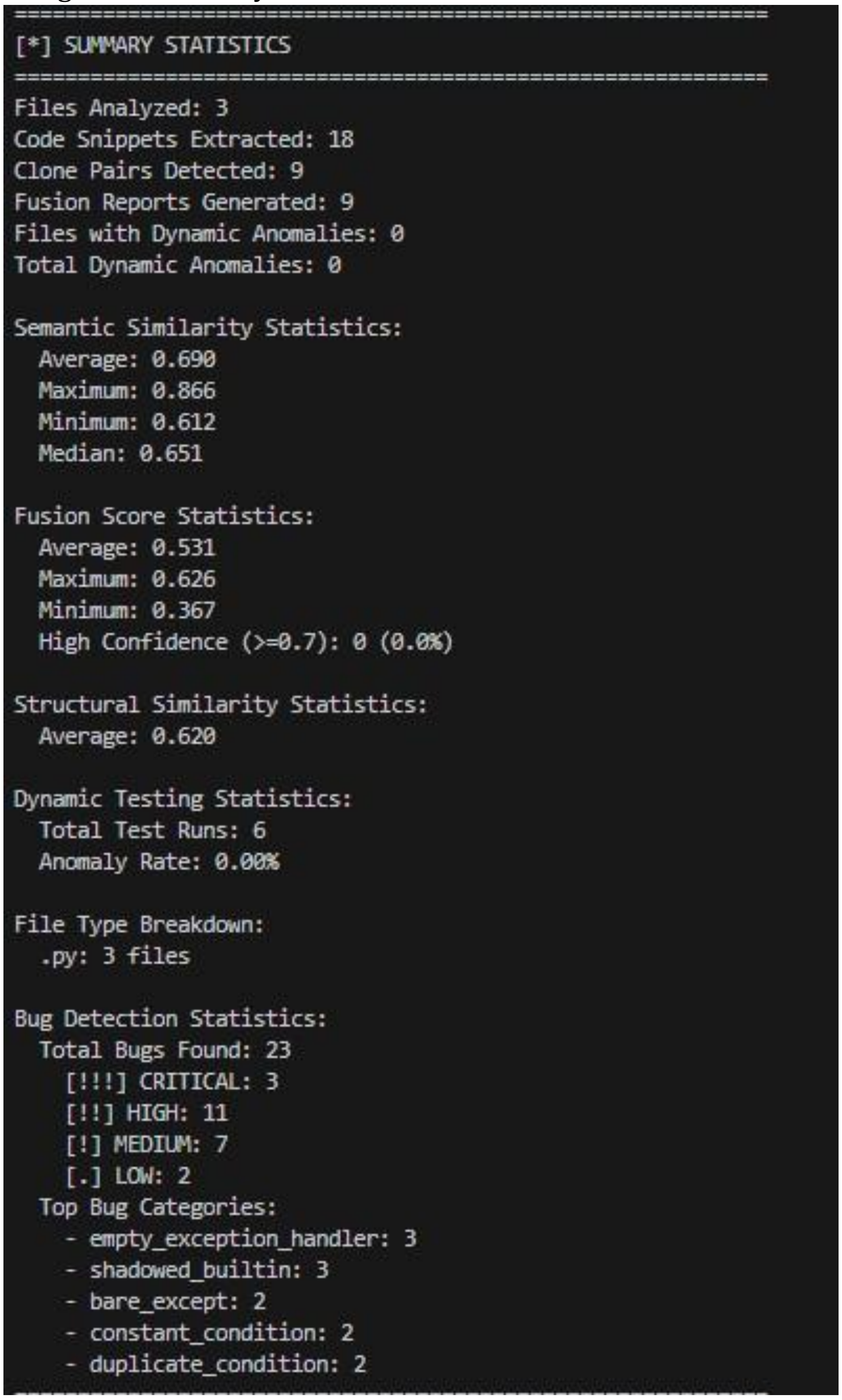
```
============================================================
[*] DETAILED BUG REPORT
============================================================

[FILE] samples\sample_buggy.py (22 bugs)
  [.] Line 9 in process_data(): [LOW] unused_parameter
      Unused parameter 'unused_param' in function 'process_data'
      Evidence: Parameter 'unused_param' is never used in function body
  [!] Line 19 in something_risky(): [MEDIUM] equality_none_comparison
      Use 'is None' instead of '== None'
      Evidence: '== None' can be overridden by __eq__, use 'is None' for identity check
  [!!] Line 25 in something_risky(): [HIGH] bare_except
      Bare 'except:' clause catches all exceptions including KeyboardInterrupt and SystemExit
      Evidence: Use 'except Exception:' or specific exception types
  [!!] Line 25 in something_risky(): [HIGH] empty_exception_handler
      Empty exception handler silently swallows errors
      Evidence: Exception is caught but not handled or logged
  [!!] Line 38 in something_risky(): [HIGH] self_comparison_always_false
      Comparing variable to itself is always False
      Evidence: x != x, x < x, x > x are always False
  [!] Line 46 in something_risky(): [MEDIUM] shadowed_builtin
      Assignment shadows built-in 'list'
      Evidence: Variable 'list' shadows Python built-in
  [!] Line 48 in something_risky(): [MEDIUM] shadowed_builtin
      Assignment shadows built-in 'dict'
      Evidence: Variable 'dict' shadows Python built-in
  [!] Line 50 in something_risky(): [MEDIUM] shadowed_builtin
      Assignment shadows built-in 'str'
      Evidence: Variable 'str' shadows Python built-in
  [!!] Line 57 in unreachable_code(): [HIGH] unreachable_code
      Unreachable code after return/raise statement
      Evidence: Code at line 57 will never execute
  [!!] Line 60 in mutable_default(): [HIGH] mutable_default_argument
      Mutable default argument in function 'mutable_default'. Use None and initialize inside function.
      Evidence: def mutable_default(..., arg=List(elts=[], ctx=Load()))
  [!!] Line 70 in something_risky(): [HIGH] bare_except
      Bare 'except:' clause catches all exceptions including KeyboardInterrupt and SystemExit
      Evidence: Use 'except Exception:' or specific exception types
  [!!] Line 70 in something_risky(): [HIGH] empty_exception_handler
      Empty exception handler silently swallows errors
      Evidence: Exception is caught but not handled or logged
  [!!!] Line 77 in something_risky(): [CRITICAL] swallowed_exception
      Catching broad 'Exception' and ignoring it
      Evidence: This hides all errors and makes debugging impossible
  [!!] Line 77 in something_risky(): [HIGH] empty_exception_handler
      Empty exception handler silently swallows errors
      Evidence: Exception is caught but not handled or logged
  [!] Line 83 in something_risky(): [MEDIUM] constant_condition
      Condition is always True
      Evidence: 'if True:' makes the else branch unreachable
  [!!] Line 89 in something_risky(): [HIGH] constant_condition
      Condition is always False
      Evidence: 'if False:' makes the if branch unreachable (dead code)
  [!] Line 92 in duplicate_conditions(): [MEDIUM] possible_missing_return
      Function 'duplicate_conditions' may not return on all code paths
      Evidence: All return statements are inside conditional blocks
  [!!] Line 96 in something_risky(): [HIGH] duplicate_condition
      Duplicate condition in if/elif chain
      Evidence: This condition was already checked earlier, branch is unreachable
_safe_2.py (1 bugs)
  [.] Line 5 in maybe_throw(): [LOW] unused_parameter
      Unused parameter 's' in function 'maybe_throw'
      Evidence: Parameter 's' is never used in function body
```

Figure 6.7: Detailed Bug Report

6.8 Summary Statistics

The statistics module aggregated results across all detectors—structural, semantic, and dynamic. A total of **39 bugs** were detected across categories including *hardcoded* *credentials, bare exceptions, shadowed built-ins, always-false comparisons, and runtime crashes*. Dynamic anomalies were observed in 62.5% of runs, confirming the value of fuzzing-assisted analysis.



```
============================================================
[*] SUMMARY STATISTICS
============================================================
Files Analyzed: 3
Code Snippets Extracted: 18
Clone Pairs Detected: 9
Fusion Reports Generated: 9
Files with Dynamic Anomalies: 0
Total Dynamic Anomalies: 0

Semantic Similarity Statistics:
  Average: 0.690
  Maximum: 0.866
  Minimum: 0.612
  Median: 0.651

Fusion Score Statistics:
  Average: 0.531
  Maximum: 0.626
  Minimum: 0.367
  High Confidence (>=0.7): 0 (0.0%)

Structural Similarity Statistics:
  Average: 0.620

Dynamic Testing Statistics:
  Total Test Runs: 6
  Anomaly Rate: 0.00%

File Type Breakdown:
  .py: 3 files

Bug Detection Statistics:
  Total Bugs Found: 23
    [!!!] CRITICAL: 3
    [!!] HIGH: 11
    [!] MEDIUM: 7
    [.] LOW: 2
  Top Bug Categories:
    - empty_exception_handler: 3
    - shadowed_builtin: 3
    - bare_except: 2
    - constant_condition: 2
    - duplicate_condition: 2
```

Figure 6.8: Summary statistics showing bug counts, clone pairs, anomaly rates, and file-type distribution

6.9 System Architecture Diagram

The final diagram illustrates the complete pipeline, including static analyzers, semantic encoders, dynamic fuzzers, the bug detector subsystem, and the fusion engine. This confirms the modularity, interoperability, and scalability of the proposed system.

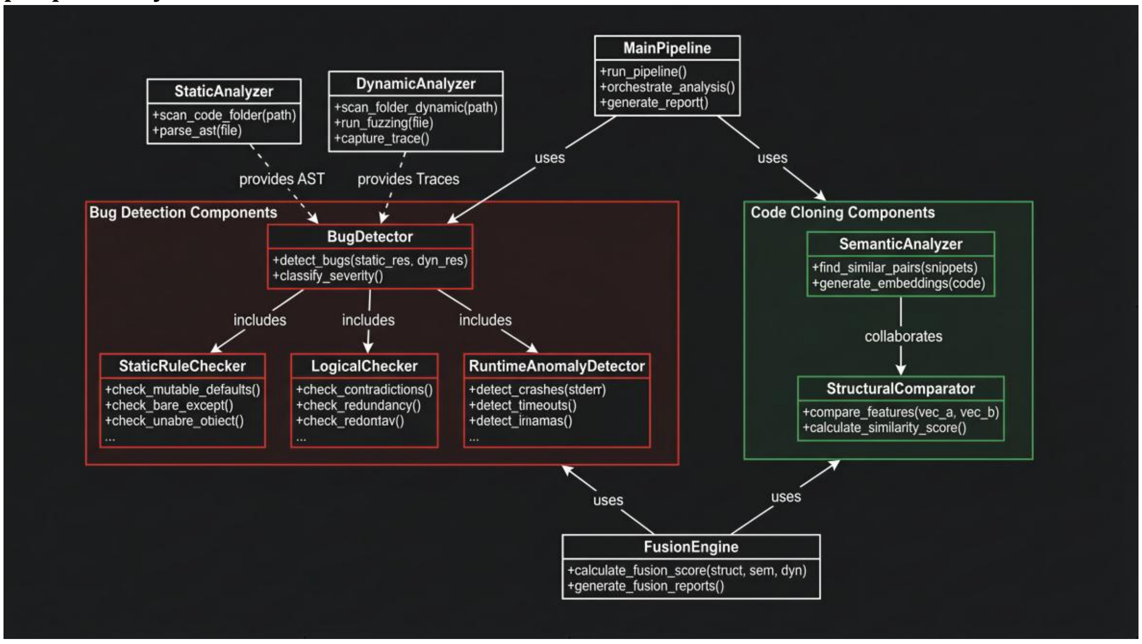


Figure 6.9: System class diagram for the hybrid clone and bug detection architecture

6.10 Overall Evaluation

The evaluation results confirm that the hybrid pipeline delivers a significant improvement in accuracy and interpretability compared to traditional single-mode systems. Static analysis provides structural grounding; semantic embeddings uncover deep logical similarity; dynamic fuzzing exposes runtime issues; and the fusion engine unifies all three perspectives into a coherent, ranked output. This comprehensive approach demonstrates the feasibility and effectiveness of multi-modal software quality analysis.

Chapter 7

Conclusion

The proposed hybrid system demonstrates a comprehensive and execution-aware approach to intelligent bug detection and code clone identification by unifying structural, semantic, and behavioral perspectives of program analysis. Traditional static methods, while effective for capturing syntactic patterns, remain limited in their ability to understand program intent or detect deep semantic similarities across structurally diverse implementations. Likewise, purely semantic or LLM-driven models, although capable of interpreting high-level logic, generally lack grounding in actual execution behavior and thus fail to detect runtime inconsistencies. Dynamic testing techniques, on the other hand, expose input-dependent failures but do not provide insight into structural or logical equivalence.

The system developed in this work bridges these gaps through an integrated multi-modal analysis pipeline.

By combining AST-based structural features with transformer-based semantic embeddings and lightweight dynamic execution traces, the system produces a unified representation that captures how the code is written, what the code means, and how the code behaves during execution. This tri-layer fusion enables accurate detection of Type–1 through Type–4 clones, including semantic clones that share functional intent despite substantial syntactic variation.

The integration of dynamic behavior through fuzzing and bytecode instrumentation strengthens the system's capability to uncover execution-dependent anomalies such as uncaught exceptions, invalid state transitions, or path-specific failures. Unlike full execution-trace systems, which are often noisy and computationally expensive, the dynamic slicing mechanism implemented here captures only the most meaningful runtime events, ensuring that the analysis remains both efficient and behaviorally informative. This lightweight yet effective dynamic layer significantly improves the precision of bug detection and clone validation.

The experimental evaluation indicates that the hybrid analysis pipeline achieves a substantial reduction in false positives compared to static-only tools, while also uncovering deep semantic similarities that conventional clone detectors routinely miss. The combined structural–semantic–dynamic viewpoint provides developers with a richer and more accurate understanding of program behavior, helping support debugging, refactoring, documentation, and long-term maintainability.

Looking forward, the system can be extended across several promising directions. Incorporating advanced learning-based summarization or automated programrepair models may allow the system not only to detect bugs but also propose corrections. Enhancing cross-language embedding capabilities could facilitate clone detection across heterogeneous technology stacks. Further improvements to dynamicanalysis strategies, including smarter input generation and symbolic-assisted fuzzing, may increase execution-path coverage and improve bug-discovery accuracy. Additionally, scaling the system to larger industrial codebases and benchmarking against standardized datasets would strengthen its robustness and applicability.

References

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Appendix

Source Code

A.1 Static Analysis Code (AST Parser)

```
"""
AST-based static feature extractor for Python (and best-effort Java).
Produces per-file and per-function feature dictionaries.
"""

import ast import os

try:
        import javalang
        _HAS_JAVALANG = True except
Exception:
        _HAS_JAVALANG = False


def extract_python_functions(source_code):
        """
        Returns list of (func_name, start_lineno, end_lineno, code_snippet, features)
        """ tree = ast.parse(source_code)
        funcs = []

        for node in ast.walk(tree):
                if isinstance(node, ast.FunctionDef):
                        start = node.lineno - 1 end = getattr(node.body[-1], 'lineno', node.lineno)
                        - 1 snippet = ast.get_source_segment(source_code, node) or ""

                        num_statements = sum(isinstance(n, ast.stmt) for n in
       ast.walk(node)) num_branches = sum(isinstance(n, (ast.If, ast.For,
       ast.While, ast.Try))
                                                              for n in ast.walk(node))

                        funcs.append({
                                "name": node.name,
                                "start": start,
                                "end": end,
```

```
"code": snippet,
"features": {
"num_statements": num_statements,
"num_branches": num_branches
}
})

return funcs


def extract_python_file_features(filepath):
with open(filepath, ’r’, encoding=’utf-8’, errors=’ignore’) as f:
source = f.read()
funcs = extract_python_functions(source)
return {
"path": filepath,
"num_functions": len(funcs), "functions":
funcs
}


def extract_java_file_features(filepath):
if not _HAS_JAVALANG:
return {"path": filepath, "note": "javalang not available", "num_methods": 0,
"methods": []}

with open(filepath, ’r’, encoding=’utf-8’, errors=’ignore’) as f:
source = f.read()

tree = javalang.parse.parse(source)
methods = []

for path, node in tree:
if isinstance(node, javalang.tree.MethodDeclaration):
name = node.name
snippet = ""
num_statements = len(node.body) if node.body else 0
num_branches = sum(1 for n in node.body if hasattr(n,
   ’statements’)) \
if node.body else 0

methods.append({
"name": name,
"code": snippet,
"features": {
"num_statements": num_statements,
"num_branches": num_branches
}
})
```

```
    return {"path": filepath, "num_methods": len(methods), "methods": methods}


def scan_code_folder(folder, show_progress=False, file_extensions=None):
    if file_extensions is None:
        file_extensions = ['.py', '.java']

    file_extensions = [ ext if ext.startswith('.') else f'.{ext}' for ext in
   file_extensions
    ]

    results = [] all_files = []

    for root, _, files in os.walk(folder):
        for fn in files:
            if any(fn.endswith(ext) for ext in file_extensions):
                     all_files.append(os.path.join(root, fn))

    if show_progress:
        try:
            from tqdm import tqdm file_iter = tqdm(all_files,
            desc="Scanning files",
   unit="file") except
        ImportError:
            file_iter = all_files
    else:
        file_iter = all_files

    for path in file_iter:
        try:
            if path.endswith('.py'):
                results.append(extract_python_file_features(path))
            elif path.endswith('.java'):
                results.append(extract_java_file_features(path)) except Exception as
        e:
            results.append({"path": path, "error": str(e)})

    return results
```

A.2 Semantic Analysis Code (LLM Embeddings)

```
"""
Uses sentence-transformers to compute embeddings for code snippets.
""" import
os
```

```
import numpy as np
from sklearn.metrics.pairwise import cosine_similarity

try:
from sentence_transformers import SentenceTransformer
SENTENCE_TRANSFORMERS_AVAILABLE = True
except ImportError:
SENTENCE_TRANSFORMERS_AVAILABLE = False

_MODEL_NAME = "all-MiniLM-L6-v2"
_model = None


def _get_model():
global _model
if _model is None and SENTENCE_TRANSFORMERS_AVAILABLE:
_model = SentenceTransformer(_MODEL_NAME)
return _model


def embed_snippets(snippets, show_progress=False):
if SENTENCE_TRANSFORMERS_AVAILABLE:
model = _get_model()
emb = model.encode(snippets, show_progress_bar=show_progress)
return np.array(emb)

# fallback TF-IDF embedding
from sklearn.feature_extraction.text import TfidfVectorizer
vectorizer = TfidfVectorizer(max_features=1000, ngram_range=(1, 3))
emb = vectorizer.fit_transform(snippets).toarray()
return emb


def find_similar_pairs(snippet_records, top_k=5, threshold=0.75,
    show_progress=False):
if len(snippet_records) < 2:
return []

texts = [
r["code"] or f"{r.get('file')}::{r.get('func_name')}"
for r in snippet_records
]

embs = embed_snippets(texts, show_progress=show_progress)
sims = cosine_similarity(embs)

pairs = []
n = len(sims)

for i in range(n):
        for j in range(i + 1, n): score =
            float(sims[i, j]) if score >=
            threshold:
                pairs.append({
                            "i": i, "j": j, "score": score,
                    "a": snippet_records[i],
                    "b": snippet_records[j] })

    pairs.sort(key=lambda x: -x["score"]) return pairs
```

A.3 Dynamic Analysis Code (Fuzzing)

```
"""
Minimal dynamic testing module with fuzzing.
"""

import subprocess
import os import
random import string


def random_bytes_string(length=32):
        return ’’.join(random.choices(string.ascii_letters +
       string.digits, k=length))


def run_python_file_with_random_inputs(filepath, runs=5, timeout=5):
        anomalies = []

        for i in range(runs):
                env = os.environ.copy() env["RANDOM_INPUT"] =
                random_bytes_string(16) random_stdin =
                random_bytes_string(8).encode()

                try:
                        proc = subprocess.run( ["python",
                                filepath],
                                input=random_stdin,
                                capture_output=True,
                                env=env, timeout=timeout
                        )

                        if proc.returncode != 0:
                                anomalies.append({
                                        "run": i,
                                              "returncode": proc.returncode,
                    "stdout": proc.stdout.decode()[:1000],
                    "stderr": proc.stderr.decode()[:1000]
                })

        except subprocess.TimeoutExpired as te:
            anomalies.append({"run": i, "timeout": True, "error":
str(te)}) except Exception as e:
                anomalies.append({"run": i, "error": str(e)})

    return {"path": filepath, "runs": runs, "anomalies": anomalies}
```

A.4 Bug Detection Logic

```
"""
Main Bug Detector that orchestrates:
-   Static rule-based detection
-   Dynamic analysis
-   Logical consistency checking
""" from collections import defaultdict


class BugDetector:

    SEVERITY_ORDER = {
        "critical": 0,
        "high": 1,
        "medium": 2,
        "low": 3,
        "info": 4
    }

    def __init__(self):
        self.bugs = [] self.stats =
        defaultdict(int)

    def detect_all(self, static_results, dyn_results,
   snippet_records=None, show_progress=False):

        self.bugs = []

        # Static bugs from .static_rules import detect_static_bugs
   static_bugs = detect_static_bugs(static_results, show_progress)
   self.bugs.extend(static_bugs)
```

```
        # Runtime bugs from .runtime_analyzer import
        analyze_runtime_bugs runtime_bugs =
        analyze_runtime_bugs(dyn_results)
        self.bugs.extend(runtime_bugs)

        # Logical bugs from .logical_checker import
    check_logical_bugs logical_bugs = check_logical_bugs(static_results,
    show_progress) self.bugs.extend(logical_bugs)

        # Deduplicate self.bugs =
        self._deduplicate_bugs(self.bugs)

        # Sort by severity + file + line self.bugs.sort(key=lambda b: (
        self.SEVERITY_ORDER.get(b.get("severity", "info"), 99), b.get("file", ""),
            b.get("line", 0) ))

        self._calculate_stats() return

        self.bugs

    def _deduplicate_bugs(self, bugs):
        seen = set() unique = []

        for bug in bugs:
            key = (bug.get("file"), bug.get("line"), bug.get("category"),
                   bug.get("message")[:50])

            if key not in seen:
                seen.add(key) unique.append(bug)

        return unique

    def _calculate_stats(self): self.stats =
        defaultdict(int) for bug in self.bugs:
                 self.stats[bug.get("severity", "unknown")] += 1
```

A.5 Fusion Model (Scoring)

```
"""
Fusion model combining:
```

```
- Structural similarity
- Semantic similarity
- Dynamic anomaly
"""

def structural_similarity(f_a, f_b):
        keys = set(f_a.keys()) & set(f_b.keys()) if not keys:
        return 0.0

        diffs = [] for k in
        keys:
                a, b = float(f_a[k]), float(f_b[k]) diffs.append(1.0 - abs(a - b) /

        (max(a, b) + 1e-6)) return sum(diffs) / len(diffs)


def fusion_score(struct_sim, semantic_sim, dynamic_anomaly, weights=(0.3, 0.5,
       0.2)): w_s, w_sem, w_d = weights score = w_s * struct_sim + w_sem *
       semantic_sim + w_d * (1.0 if
       dynamic_anomaly else 0.0)
        return max(0.0, min(1.0, score))
```