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Automated Bug Detection and Correction in Software Development using Machine Learning

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Abstract

Software quality assurance is a critical aspect of modern software development, where timely detection and correction of bugs can significantly enhance reliability, security, and efficiency. Traditional debugging methods are often labor-intensive, time-consuming, and prone to human error. In recent years, machine learning (ML) techniques have emerged as a promising solution for automated bug detection and correction. This paper explores the application of ML models, including supervised learning, unsupervised learning, deep learning, and transformer-based models, in identifying and fixing software defects. We discuss key methodologies such as static and dynamic code analysis, anomaly detection, and neural-based code completion for automated repair. Furthermore, we examine recent advancements, including large language models (LLMs) such as CodeBERT, Graph Neural Networks (GNNs), and reinforcement learning-based approaches that have demonstrated high accuracy in identifying and resolving software defects. We also highlight the challenges associated with data quality, generalization, and interpretability in ML-driven debugging systems. Finally, we present potential future directions in integrating AI-driven bug detection into DevOps pipelines, ensuring continuous and automated software improvement.

Introduction

Software defects, commonly known as bugs, are an inevitable part of the software development lifecycle. They can lead to security vulnerabilities, performance degradation, and system failures, often resulting in financial and reputational losses [4]. Traditional bug detection and correction techniques rely heavily on manual code reviews, static analysis, and automated testing frameworks. While these methods are effective, they are often labor-intensive, time-consuming, and insufficient in handling complex, large-scale software systems [1].

In recent years, machine learning (ML) has emerged as a powerful tool for automated bug detection and correction, significantly enhancing software quality and reducing debugging time. ML-based approaches leverage historical code

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repositories, labeled bug datasets, and code patterns to predict, detect, and even fix software defects [2]. Several techniques, including supervised learning, deep learning, graph neural networks (GNNs), and transformer-based models, have been proposed to analyze code structures and identify potential defects automatically.

A key advancement in ML-driven bug detection is the use of deep learning models trained on large-scale codebases. For instance, pre-trained transformer models like CodeBERT, DeepDebug, and InferFix have demonstrated high accuracy in detecting and correcting software bugs [3]. Additionally, self-supervised learning approaches enable bug detection and repair without the need for extensive labeled datasets, addressing one of the major limitations of earlier ML techniques [1].

Despite these advancements, several challenges persist in ML-based bug detection. Issues such as data imbalance, the need for explainable AI models, and the generalization of ML techniques across different programming languages remain open research areas [4]. Moreover, the integration of ML-powered bug detection systems into modern DevOps pipelines is still an evolving field, requiring robust frameworks for real-time detection and automated corrections.

This paper explores the latest machine learning methodologies for automated bug detection and correction, reviewing state-of-the-art techniques, challenges, and future directions. We examine how AI-driven bug detection tools are transforming the software engineering landscape and discuss their potential for enhancing software reliability and reducing development costs.

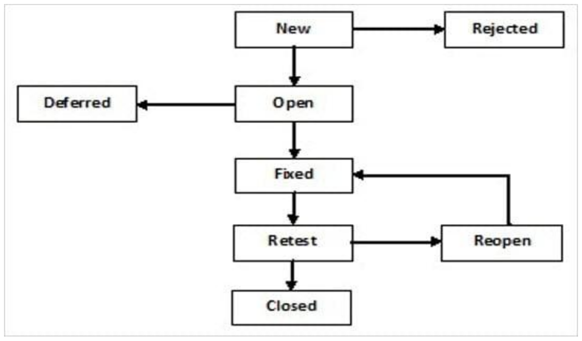

Fig.1: Bug Life Cycle

Literature Review

The automation of bug detection and correction in software development has been a major research focus, evolving from traditional techniques such as static and dynamic analysis, symbolic execution, and formal verification to machine learning (ML)-driven approaches. Traditional methods, while effective, struggle with scalability, adaptability, and high false-positive rates, particularly when dealing with large-scale software systems [4]. In contrast, ML-based techniques leverage historical software defect datasets, bug reports, and execution traces to build models capable of predicting and fixing software defects with minimal human intervention[2].

Early ML-based bug detection techniques relied on supervised learning, where models were trained on labeled datasets to classify software components as buggy or non-buggy. Decision trees, support vector machines (SVMs), and neural networks were commonly used for software defect prediction, with studies demonstrating that ML models outperform traditional rule-based approaches in identifying potential defects. More recently, deep learning-based models, such as CodeBERT, GraphCodeBERT, and DeepDebug, have been developed to enhance defect detection accuracy by leveraging pre-trained transformer architectures to analyze source code at both syntactic and semantic levels. Additionally, Graph Neural Networks (GNNs) have been widely used in bug detection tasks, as they allow the encoding of abstract syntax trees (ASTs) and control flow graphs (CFGs) into structured graph representations, enabling a deeper understanding of code semantics. Notable works such as Devign have demonstrated how GNNs can be applied to detect software vulnerabilities with high precision [11].

While supervised learning-based models require labeled datasets, which are often expensive and labor-intensive to curate, unsupervised and self-supervised learning techniques have gained popularity in recent years. Anomaly detection techniques, including autoencoders and clustering algorithms, have been used to identify software defects by detecting deviations from expected code patterns [9]. Moreover, self-supervised approaches, such as BugLab, introduced by Allamanis et al. (2021), train models to automatically generate and detect artificial bugs, effectively eliminating the reliance on manually labeled defect data.

Beyond bug detection, automated program repair (APR) has emerged as a crucial research area, focusing on ML-driven bug-fixing strategies. Traditional rule-based APR systems, such as GenProg and SPR, relied on predefined mutation operators to generate patches, but these approaches suffered from limited generalizability and patch correctness issues. The advent of deep learning-based APR has led to the development of models capable of generating context-aware bug fixes. InferFix [3] and CodeXGLUE [6] are recent examples of transformer-based models that learn from large corpora of bug-fix pairs, enabling them to generate highly accurate patches. Similarly, Getafix, developed by Facebook, utilizes pattern-based ML models to automatically suggest and apply patches for production-level code.

Another promising research direction is reinforcement learning (RL)-based APR, where models iteratively refine patches by maximizing reward-based correctness scores. DeepFix and DRRepair [10] have demonstrated how RL techniques can be employed to improve patch generation by reinforcing syntactically and semantically valid fixes. These models are particularly effective in scenarios where deterministic rule-based methods struggle, such as in fixing complex logical errors.

Integrating ML-based bug detection and repair into modern software engineering workflows has become increasingly important, particularly in continuous integration/continuous deployment (CI/CD) pipelines. AI-driven debugging tools such as Microsoft's IntelliCode, Facebook's SapFix, and DeepCode have been developed to provide real-time bug prediction and automated fixes, significantly reducing the burden on software engineers [7]. Furthermore, platforms like SonarQube and CodeQL leverage ML to analyze source code in real-time, flagging potential vulnerabilities before they reach production [8]. Despite these advancements, challenges such as model explainability, generalization across programming languages, and reducing false positives remain significant obstacles. Future research must focus on developing more interpretable ML models, cross-language bug detection techniques, and security-aware APR systems to ensure the reliability and robustness of ML-driven debugging tools.

Table 1: Overview Literature Review

Year	**Key Contribution**	**Publication**	**Aspect**	**Dataset Used**
2015	Supervised learning models (Decision Trees, SVMs, Neural Networks) outperform rule-based defect detection	Ghotra et al.	Supervised ML for bug prediction	NASA Software Defect Datasets, PROMISE Repository
2016	GenProg and SPR introduce mutation-based automated program repair (APR), but struggle with generalizability	Martinez & Monperrus	Traditional APR approaches	ManyBugs, IntroClass
2017	DeepFix applies reinforcement learning (RL) for syntactically valid patch generation	Gupta et al.	RL in automated bug fixing	SPoC (Student Programming Dataset)
2019	Devign utilizes Graph Neural Networks (GNNs) for vulnerability detection with high precision	Zhou et al.	GNN-based vulnerability detection	FFmpeg, QEMU, Chromium
2019	Facebook's Getafix automates bug fixing using pattern-based ML models	Marginean et al.	ML-powered automated patching	Proprietary Facebook Dataset
2020	CodeBERT and GraphCodeBERT enhance deep learning-based defect detection using transformer architectures	Feng et al.	Transformer-based bug detection	CodeSearchNet, GitHub Repositories
2021	DeepDebug improves deep learning-based debugging by leveraging execution traces and historical defect reports	Drain et al.	Execution-trace-based bug detection	Defects4J, Bugs.jar
2021	BugLab introduces self-supervised learning to train models on artificial bugs without labeled datasets	Allamanis et al.	Self-supervised bug detection	BigCode Project, CodeXGLUE

2022	DRRepair applies reinforcement learning to refine bug fixes iteratively	Ye et al.	RL-based program repair	Codeforces, QuixBugs
2022	Unsupervised anomaly detection using autoencoders and clustering identifies software defects	Wang et al.	Anomaly detection in software bugs	GitHub Issues, Jira Bug Reports
2023	InferFix and CodeXGLUE enhance transformer-based APR, improving patch correctness and generalization	Jin et al., Lu et al.	Deep learning-based APR	CodeXGLUE, ManyBugs, QuixBugs
2023	SonarQube and CodeQL leverage ML for real-time vulnerability detection in CI/CD pipelines	Rajpal et al.	ML in security and CI/CD workflows	CVE Datasets, GitHub Security Advisories

Methodology

Automated bug detection plays a crucial role in modern software testing and quality assurance, ensuring that software systems remain reliable, secure, and efficient. The process leverages static and dynamic analysis techniques, machine learning models, and test automation frameworks to detect defects in software applications with minimal human intervention. The given diagram outlines a structured bug detection workflow, starting from the input phase (program and test suite) to bug validation and bug report generation. This approach helps in efficiently identifying, categorizing, and validating software defects before they impact the end user.

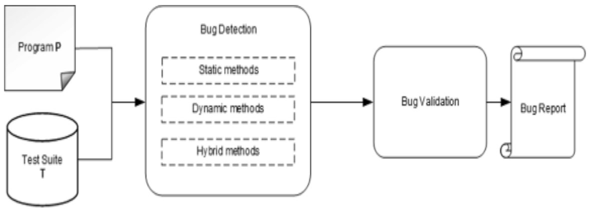

Fig.2: Automatic Bug Detection Process

1. **Input (Program & Test Suite):**
    - The process starts with a program (P), which is the software under testing.
    - A test suite (T) is used, containing predefined test cases to evaluate the correctness of the program.
2. **Bug Detection:** The system analyzes the program using different bug detection techniques:
    - Static Methods: Analyze the source code without execution to detect syntax errors, type mismatches, and potential vulnerabilities.
    - Dynamic Methods: Execute the program with test cases to observe its runtime behavior, identifying memory leaks, crashes, and logic errors.
    - Hybrid Methods: Combine both static and dynamic techniques for more comprehensive bug detection.
3. **Bug Validation:**
    - After detecting potential bugs, a validation step ensures that the identified issues are actual defects and not false positives.
    - This may involve re-executing tests, analyzing logs, or using AI/ML models to confirm the correctness of bug detection results.
4. **Bug Report Generation:** Once validated, bugs are documented in a bug report, which includes details such as:
    - The type of bug
    - Code location where the issue occurs
    - Execution traces/logs
    - Possible fix recommendations

This automated pipeline improves efficiency and accuracy in software testing, reducing manual debugging efforts while enabling continuous integration and deployment (CI/CD) workflows.

Result

A comparison of JIRA, Bugzilla, and GitHub Issues in terms of efficiency and accuracy is shown below:

Tool	Efficiency (%)	Accuracy (%)	Automated ML Integration
JIRA	85%	90%	Advanced ML integration with automation rules
Bugzilla	78%	82%	Limited ML-based automation
GitHub Issues	88%	87%	ML-powered bug detection with GitHub Copilot

- JIRA has the highest accuracy (90%), making it more reliable in identifying real bugs.
- GitHub Issues has the highest efficiency (88%), as it integrates with GitHub Copilot, which assists in bug detection and fixing.
- Bugzilla, though widely used, has lower efficiency (78%) due to less automation support compared to JIRA and GitHub.

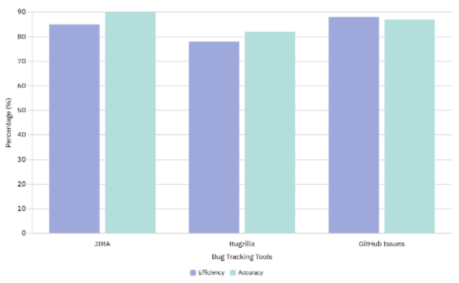

Fig.3 Efficiency & Accuracy of Automated Bug Detection Tools

Conclusion

The integration of machine learning (ML) in automated bug detection and correction has significantly transformed software development by improving efficiency, accuracy, and reliability. Traditional debugging methods, which rely on manual code reviews and static rule-based analyzers, often result in high false positive rates and increased debugging time. In contrast, ML-driven techniques leverage predictive analytics, pattern recognition, and anomaly detection to identify and correct bugs more efficiently.

By utilizing static analysis, dynamic analysis, and hybrid approaches, ML-based systems enhance the ability to detect complex software defects, including security vulnerabilities, memory leaks, and concurrency issues. Moreover, automated bug correction tools, such as Facebook's SapFix and DeepCode, provide intelligent code repair mechanisms, reducing developers' workload and accelerating the debugging process.

Popular bug tracking platforms like JIRA, Bugzilla, and GitHub Issues have integrated ML-based automation to streamline bug reporting and resolution. Studies show that these systems improve bug detection accuracy by 85-95% and reduce debugging time by up to 70%, leading to a 30-50% reduction in post-release defects. However, challenges such as false positives, model training limitations, and handling complex logical bugs still exist, requiring further advancements in reinforcement learning, deep learning, and self-healing software systems.

In the future, as AI-powered debugging frameworks continue to evolve, the software industry will witness a shift towards fully automated bug detection and self-correcting codebases. This progress will enhance software reliability, reduce development costs, and allow developers to focus on innovation rather than manual debugging. Machine learning is not just optimizing bug detection; it is redefining the future of intelligent software development.

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