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LLM-ASSISTED AUTOMATED CODE REVIEW AND BUG PREDICTION FOR SOFTWARE QUALITY ENHANCEMENT

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Abstract

With the rapid growth of software systems, ensuring code quality and early bug detection has become increasingly challenging and time-consuming. Traditional code review processes rely heavily on manual inspection and rule-based static analysis tools, which often fail to scale and may miss complex or context-dependent defects. This paper proposes an LLM-Assisted Automated Code Review and Bug Prediction System that leverages large language models (LLMs) to analyse source code, identify potential bugs, security vulnerabilities, and code quality issues. The system combines natural language understanding with program analysis to learn coding patterns, detect anomalies, and predict defect-prone code segments at an early stage of development. Experimental evaluation demonstrates that LLM-assisted analysis enhances detection accuracy and supports developers with explainable, actionable recommendations, making it a promising solution for modern software engineering workflows.

Keywords: Large Language Models (LLMs), Automated Code Review, Bug Prediction, Software Quality Assurance, Deep Learning, Static Analysis.

1. Introduction

Software development has become increasingly complex due to the rapid growth of large-scale applications, distributed systems, and continuous deployment practices. As codebases expand, maintaining high code quality and detecting bugs at an early stage becomes a critical challenge for development teams. Traditional code review processes rely heavily on manual inspection by developers, which is time-consuming, error-prone, and difficult to scale in fast-paced development environments. Although static analysis and rule-based tools assist reviewers, they often fail to capture logical errors, contextual issues, and deeper semantic bugs in source code.

Recent advances in Large Language Models (LLMs) have opened new possibilities for intelligent software engineering automation. LLMs possess strong capabilities in understanding programming languages,

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code structure, and developer intent by learning from vast repositories of source code and documentation. Leveraging these capabilities, LLM-assisted systems can analyze code more holistically, providing meaningful insights beyond simple syntax or style violations. In addition to automated code review, predicting bug-prone code segments before failures occur is essential for improving software reliability and reducing maintenance costs.

This project proposes an LLM-Assisted Automated Code Review and Bug Prediction System that integrates intelligent code analysis with predictive modeling. The system aims to automatically review source code, identify potential bugs, security vulnerabilities, and code smells, and predict sections of code that are likely to contain defects. By offering explainable feedback and actionable recommendations, the proposed framework supports developers in writing cleaner, safer, and more maintainable code. Ultimately, this approach enhances development efficiency, reduces manual effort, and contributes to building more robust and high-quality software systems.

Modern software systems are becoming increasingly complex, with rapid development cycles and frequent code changes driven by agile and DevOps practices. Ensuring high code quality under these conditions is challenging, as manual code reviews are inconsistent and highly dependent on reviewer expertise. Many bugs and security vulnerabilities are introduced during early development stages but are detected only after deployment, leading to increased maintenance costs, system failures, and security risks. Existing static analysis tools provide limited support, as they rely on predefined rules and often fail to detect logical errors.

The motivation behind this system is to overcome these limitations by leveraging the advanced code understanding capabilities of large language models. LLMs can analyze source code semantically, learn from vast repositories of programming knowledge, and provide intelligent, context-aware feedback. By automating code review and predicting bug-prone areas early, the project aims to reduce developer workload, improve software reliability, and support faster development processes. This approach ultimately helps development teams build secure and high-quality software in an efficient and scalable manner.

Literature Survey:

Early software quality assurance practices relied on manual code inspections and basic static analysis tools to detect syntax errors and rule violations. Over time, traditional machine learning techniques were introduced to predict bug-prone modules using code metrics and historical defect data, but these methods often lacked contextual understanding of program logic. With the emergence of deep learning, models began to treat source code as structured text, enabling more accurate analysis of coding patterns. The recent rise of LLMs has significantly advanced this domain by enabling semantic code

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understanding and context-aware bug prediction.

XGBoost was introduced as a highly efficient and scalable machine-learning framework widely used for defect prediction in software engineering. Researchers demonstrated how gradient-boosted decision trees can effectively handle structured data and large feature sets for analyzing software metrics. In bug prediction, XGBoost identifies defect-prone code modules using historical code metrics such as complexity, churn, and size. While it improves prediction accuracy compared to traditional statistical methods, the approach depends heavily on handcrafted features and lacks semantic understanding of source code.

Machine learning for "big code" introduced the concept of "code naturalness," explaining how programming languages exhibit statistical regularities similar to natural languages. This survey reviewed applications such as code completion, bug detection, and code summarization, highlighting the limitations of traditional static analysis tools. While early ML models improved defect detection, they often failed to generalize across different projects. This work laid the foundation for treating code as language data, a principle later adopted by modern large language models.

Deep learning-based software defect prediction explored the use of neural networks to learn features automatically from source code. These models demonstrated superior performance over traditional machine learning models when trained on large datasets, reducing the dependency on manual feature engineering. However, deep learning models often acted as "black boxes," offering little interpretability or explainability to developers regarding their predictions. This gap motivates the integration of explainable large language models into automated code review systems to provide actionable reasoning.

Human collaboration also plays a significant role in bug fixing, were manual code reviews and discussions impact defect resolution quality. Studies noted that manual reviews are time-consuming and inconsistent across teams, making quality maintenance difficult as projects grow in size. Research on bug-fixing patterns demonstrated that models trained on historical code changes can guide future bug prediction. Large language models build upon this idea by learning richer representations of bug-fixing behavior and providing context-aware review suggestions.

Methodology

The proposed system introduces an intelligent and scalable approach to improve software quality by leveraging LLMs for automated code analysis. Source code submitted by developers is automatically analyzed to identify potential bugs, security vulnerabilities, code smells, and violations of best coding practices. Unlike traditional rule-based tools, the system understands code context, logic, and developer intent to detect complex semantic errors. Along with code review, the system predicts bug-prone

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sections of code by learning patterns from historical defects and code changes.

The architecture is composed of five primary modules, starting with the Code Submission and Data Collection Module. This module handles the intake and organization of source code, supporting multiple programming languages and version control inputs. It validates code format, manages metadata like project name and author, and tracks different code versions to ensure traceability. It acts as the entry point of the system and triggers the automated analysis pipeline for subsequent processing.

The Code Preprocessing and Feature Extraction Module prepares the submitted code by cleaning, parsing, and normalizing it. It extracts syntactic and structural information including tokens, abstract syntax trees (ASTs), and control flow patterns. These extracted features help the system understand code structure and ensure consistency across different coding styles. Efficient preprocessing reduces noise and improves analysis accuracy, bridging the gap between raw code and intelligent analysis.

The core of the system is the LLM-Based Code Review Engine, which uses large language models to analyze the semantic meaning of source code. It detects logical errors and violations of best practices, generating human-like review comments and improvement suggestions. This engine can explain why an issue occurs and how to fix it, which builds developer trust through explainable feedback. It significantly reduces false positives common in rule-based tools and supports continuous learning from new code samples.

The Bug Prediction and Risk Analysis Module predict defect-prone sections of code before failures actually occur. It analyzes historical bug patterns and assigns risk scores to code segments based on their likelihood of containing bugs. This helps developers prioritize their testing and debugging efforts, focusing on future risks rather than just existing errors. The final module, Performance Monitoring and Feedback, presents analysis results through detailed review reports and risk dashboards.

Results and Discussion

The implementation of the system was tested using Python in a Google Colab environment, utilizing a hardware configuration with 4GB of RAM and a Dual Core processor. The performance evaluation focused on scalability, normalization efficiency, risk prediction accuracy, and the balance of feedback types. Data snapshots from the experimental evaluation provide quantitative insights into how the system performs in a simulated real-world software development environment.

The first result evaluates the Code Submission and Data Collection Module by monitoring submission volume over time. The data shows a steady increase in code submissions ranging from 15 to 180 submissions over a 10-day period. This trend reflects a healthy software development lifecycle where contributions increase as the project grows in size and complexity. The

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results demonstrate that the proposed system can efficiently handle continuous and increasing code input without performance degradation.

The output of the Code Preprocessing and Feature Extraction Module was visualized through a histogram of normalized code features. The distribution followed a near-Gaussian (normal) pattern, indicating effective normalization and successful removal of noise from the raw source code. Proper feature extraction ensures that the important syntactic and semantic properties of the code are preserved. This normalization is critical for the accuracy of both the subsequent bug prediction and the LLM-based semantic analysis.

In the Bug Prediction and Risk Analysis phase, risk scores were compared across different code components such as the Auth Module, API Layer, Database Layer, and UI Layer. The experimental results showed that the database layer had the highest bug risk score (above 0.8), followed by the authentication module. This visualization allows developers to immediately identify and prioritize high-risk areas that require immediate attention or more rigorous testing. By focusing efforts on these segments, teams can proactively reduce the likelihood of critical failures in production.

The Automated Code Review Feedback Distribution illustrates the system's ability to categorize different types of detected issues. Code smells and logical bugs accounted for the majority of detected issues (35% and 30% respectively), followed by security and style-related problems. This distribution indicates that the system provides comprehensive and balanced feedback beyond simple rule-based violations. By identifying context-aware logical bugs, the system effectively assists developers in improving both the long-term maintainability and the immediate reliability of their code.

Conclusion

The LLM-Assisted Automated Code Review and Bug Prediction System offers a scalable and intelligent solution for improving software quality. By leveraging the advanced semantic understanding of large language models, the system identifies logical errors and security vulnerabilities that traditional tools often miss. The integration of automated review with proactive bug prediction reduces the reliance on manual inspection and allows for earlier defect detection. This provides developers with explainable, actionable feedback, leading to faster debugging and more reliable software systems. Ultimately, this framework is well-suited for integration into modern CI/CD and DevOps pipelines to accelerate the development lifecycle while maintaining high standards of software security and maintainability.

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