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ML-Enhanced Code Refactoring Recommendations for Improving Software Maintainability

Dr. Rohit Malhotra

Professor, University of Mumbai, India.

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ABSTRACT

Software maintainability is a critical quality attribute influencing the long-term sustainability, scalability, and cost-effectiveness of software systems. Traditional refactoring approaches often rely on manual inspection or rule-based static analysis, which can be time-consuming, inconsistent, and limited in capturing deeper code quality issues. Recent advances in machine learning (ML) provide new opportunities to automate and enhance refactoring recommendations by learning from large codebases, identifying complex patterns, and predicting optimal refactoring strategies. This paper investigates ML-driven approaches for generating code refactoring recommendations aimed at improving maintainability. We review existing techniques, propose an ML-based framework capable of detecting maintainability hotspots and suggesting targeted refactorings, and evaluate its effectiveness through empirical experiments on real-world repositories. Results show that ML-enhanced recommendations outperform traditional methods in accuracy, relevance, and impact on maintainability metrics. The findings highlight the potential of integrating ML into modern development practices to support developers in producing cleaner, more maintainable software systems.

KEYWORDS

Machine Learning for Software Engineering, Code Refactoring, Software Maintainability, Technical Debt, Automated Software Quality Improvement, ML-based Recommendation Systems ,Code Smell Detection, Software Analytics.

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1. INTRODUCTION

1.1. Background and motivation

Software systems today are growing in complexity, size, and longevity, making maintainability one of the most important attributes of software quality. As systems evolve over years or decades, codebases accumulate inconsistencies, technical debt, and structural issues that complicate future modifications. These issues not only increase development cost but also reduce reliability, agility, and team productivity. Refactoring—systematically restructuring code without altering its functionality—has long been recognized as a crucial practice for mitigating these problems. However, performing refactoring at scale remains difficult because it requires expert understanding of code quality, architectural principles, and project context. With modern software development producing vast amounts of code, logs, and version histories, machine learning offers new opportunities to support developers by learning patterns of good design, identifying problematic code more accurately, and recommending optimal refactoring strategies. This growing intersection of ML and software engineering provides the motivation for investigating ML-enhanced refactoring recommendation systems.

1.2. Importance of maintainability in modern software systems

Maintainability directly influences a system's long-term sustainability, cost efficiency, and adaptability to changing user or business requirements. In modern development environments where rapid releases, continuous integration, and large distributed teams are common, maintainability ensures that new features can be added with minimal risk, bugs can be fixed swiftly, and code can evolve without structural degradation. Poor maintainability often leads to increased development time, higher defect rates, and excessive reliance on domain experts to navigate convoluted codebases. Moreover, maintainability has become essential for organizations transitioning to DevOps cultures and microservices architectures, where codebases must remain flexible and modular. Therefore, improving maintainability through advanced refactoring techniques is not merely a quality enhancement practice but a business-critical necessity.

1.3. Limitations of traditional refactoring and static analysis tools

Traditional refactoring tools and static analysis systems rely on manually encoded rules and predefined heuristics to detect code smells or structural issues. While they are useful for identifying obvious anti-patterns, they lack the ability to understand deeper contextual relationships within code or adapt to different programming styles and project-specific conventions. These tools often generate excessive false positives, provide generic recommendations, and cannot learn from historical refactorings or evolving code quality trends. Furthermore, they typically treat code artifacts in isolation, ignoring higher-level semantics, architectural dependencies, and development patterns captured in repositories over time. As a result, many developers either disregard these recommendations or find them insufficiently actionable, highlighting the need for more intelligent, data-driven approaches.

1.4. Emergence of ML techniques in software engineering

With the availability of large-scale open-source repositories, version histories, and code review data, ML techniques have rapidly gained traction in software engineering research and practice. Models such as CodeBERT, Graph Neural Networks, and Transformer-based encoders have demonstrated exceptional capability in representing source code, understanding programming constructs, and identifying semantic relationships. ML techniques enable automated learning from millions of real-world code examples, allowing systems to identify complex patterns that traditional

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rule-based tools cannot capture. For tasks such as bug prediction, code summarization, automated code review, and code smell detection, ML models have shown substantial improvements in accuracy and contextual understanding. This technological evolution sets the foundation for developing ML-driven refactoring recommendation systems that can adapt, learn continuously, and provide more relevant suggestions to developers.

1.5. Research objectives and scope

This study aims to investigate how machine learning can enhance code refactoring recommendations with a particular focus on improving software maintainability. The primary objective is to design a framework that automatically identifies maintainability issues, predicts refactoring opportunities, and recommends specific improvements tailored to the context of the codebase. The research explores various ML techniques, including supervised learning, unsupervised clustering, and deep learning models, to determine their effectiveness in analyzing code. The scope includes developing the conceptual architecture, implementing feature extraction mechanisms, evaluating models using real-world datasets, and comparing the proposed approach with traditional static analysis systems. While the study focuses on maintainability, the findings may extend to broader aspects of software quality such as readability, complexity reduction, and technical debt management.

1.6. Structure of the paper

The remainder of the paper is organized into several key sections that collectively build the foundation for the proposed ML-enhanced refactoring framework. The Literature Review explores past research on maintainability metrics, refactoring principles, and machine learning applications in code analysis. The Framework section describes the architecture, data processing pipeline, feature extraction strategies, and ML models forming the core of the system. The Experimental Setup outlines datasets, evaluation methods, and baseline tools used for comparison. The Results and Discussion section analyzes the performance and impact of the proposed system. Finally, the paper concludes by summarizing contributions and highlighting potential avenues for future research.

2. LITERATURE REVIEW

2.1. Code maintainability metrics and quality attributes

Maintainability is typically assessed through quantifiable software metrics and qualitative attributes that measure how easily code can be understood, modified, and extended. Common maintainability metrics include cyclomatic complexity, coupling and cohesion measures, lines of code, Halstead metrics, code duplication ratios, and maintainability indexes. These metrics help quantify design quality and identify potential problem areas. Quality attributes such as readability, modularity, extensibility, and testability also influence maintainability but are harder to measure with static rules alone. Furthermore, modern codebases are affected by architectural constraints, dependency structures, and evolving development practices, all of which can impact maintainability. Existing literature emphasizes the importance of combining quantitative metrics with contextual, semantic, and historical data—something that machine learning approaches are uniquely positioned to handle.

2.2. Overview of refactoring practices and common code smells

Refactoring involves small, behavior-preserving transformations aimed at improving a system's internal structure. Common refactoring operations include Extract Method, Rename Variable, Replace Conditional with Polymorphism, and Decompose Class. These actions target "code

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smells," which are indicators of underlying design flaws. Examples of code smells include Long Method, God Class, Feature Envy, Duplicate Code, and Large Parameter List. Although refactoring can significantly enhance maintainability, identifying the exact need for refactoring and choosing the most appropriate technique remains challenging. Developers often rely on intuition, experience, and manual inspection, which may lead to inconsistency and oversight in large codebases. The literature underscores the need for automated tools to systematically detect smells and recommend effective refactoring actions.

2.3. Traditional rule-based and static analysis methods

Static analysis tools such as PMD, Checkstyle, and SonarQube use predefined rules and heuristics to identify code smells and design issues. While these tools support automated detection, they are fundamentally limited by their rule-based nature. They cannot recognize patterns that fall outside predefined rules, and they fail to adapt to different coding styles or evolving design practices. Many of their rules are language-specific, resulting in inconsistent performance across languages and frameworks. Additionally, static analysis tools typically operate syntactically rather than semantically, which restricts their ability to detect deeper architectural inconsistencies or context-dependent issues. Research indicates that these tools often produce false positives and lack personalization, making their outputs less effective in guiding refactoring decisions.

2.4. Machine learning techniques applied to code analysis

Machine learning has been increasingly applied to a wide range of software engineering tasks, demonstrating significant potential in understanding source code beyond explicit rules. Supervised learning models are used to predict code smells, bugs, or refactoring actions based on labeled datasets. Unsupervised models identify anomalies, code clusters, and deviations from typical patterns, making them suitable for exploratory analysis. Deep learning techniques, especially neural models trained on large code corpora, provide semantically rich embeddings that capture relationships within code and across entire projects. Tools like Code2Vec, CodeBERT, and Graph Neural Networks have shown impressive performance in representing syntactic and structural properties of programs. This body of research forms the foundation for developing ML-driven refactoring recommendation systems that learn from real-world refactoring practices.

2.5. Gaps in current research and opportunities

Despite the progress in ML-based code analysis, significant gaps remain in integrating these techniques into practical refactoring workflows. Many existing approaches focus on isolated tasks such as smell detection without providing actionable refactoring recommendations. Others lack interpretability, making developers hesitant to trust automated suggestions. Additionally, most studies use small or artificially labeled datasets, limiting the generalizability of their models. There is also limited research on workflow integration, such as embedding ML-based recommendations into IDEs or CI/CD systems. These gaps present opportunities to develop holistic, context-aware refactoring recommendation systems that combine data-driven insights with practical developer needs.

3. ML-ENHANCED REFACTORING RECOMMENDATION FRAMEWORK

3.1. Architecture of the proposed framework

The proposed framework is designed as a modular and extensible architecture that integrates multiple components to process source code, extract meaningful features, apply machine learning models, and generate actionable refactoring recommendations. The architecture begins with a data

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ingestion layer that collects code from repositories, parses abstract syntax trees (ASTs), and gathers historical commit information. A preprocessing module cleans and normalizes the data, preparing it for feature extraction. The feature extraction module transforms source code into multiple representations, such as numerical metrics, syntactic structures, and semantic embeddings. These representations are fed into various ML models that analyze code quality, detect maintainability issues, and predict appropriate refactoring techniques. The output is then passed to a recommendation engine that prioritizes suggestions based on severity, maintainability impact, and developer context. Finally, integration modules allow the system to embed itself within development environments to deliver real-time recommendations.

3.2. Dataset acquisition and preprocessing (source code, ASTs, metrics, code smells)

The effectiveness of ML-based refactoring recommendations relies heavily on high-quality datasets derived from real-world software repositories. Dataset acquisition involves collecting source code from open-source platforms, mining version histories, and extracting labeled examples of refactoring actions. Preprocessing includes parsing raw code into abstract syntax trees, computing structural and complexity metrics, and identifying code smells using baseline tools for initial labeling. Additional steps such as tokenization, normalization, and noise removal ensure consistency across languages and projects. Preprocessing also includes resolving dependencies, handling incomplete code fragments, and segmenting large files into meaningful units for analysis. The final dataset contains structured data linking code artifacts to quality metrics, semantic representations, and past refactoring operations—forming a robust foundation for training ML models.

3.3. Feature extraction approaches

Feature extraction is a crucial step that converts raw code into machine-understandable representations. Static code metrics such as cyclomatic complexity, coupling, cohesion, and maintainability index provide quantitative insights into structural quality. Structural and syntactic features derived from ASTs capture the organization of code elements, control flows, and dependencies between classes or methods. These features help ML models understand patterns that reflect code smells or maintainability problems. Semantic embeddings represent code using deep learning models trained on massive corpora, capturing high-level meaning and contextual relationships. Models like CodeBERT or Graph Neural Networks learn embeddings that reflect not only syntax but also semantics, enabling the detection of subtle issues and more accurate prediction of refactoring actions. Combining these complementary features allows the framework to achieve a richer and more holistic understanding of code quality.

3.4. Machine learning models for prediction

The framework leverages multiple ML paradigms to ensure accurate and adaptable refactoring predictions. Supervised learning models such as decision trees, random forests, and neural networks are trained on labeled datasets containing examples of code smells and associated refactoring actions. These models learn to classify problematic code segments and predict the most appropriate refactoring operations. Unsupervised clustering techniques help identify outliers or unusual code patterns that may represent emerging maintainability issues not covered by known smell categories. Deep learning models, particularly those based on Transformers or graph architectures, provide high-level semantic reasoning and can capture global code dependencies. Combining these models enables robust detection of diverse maintainability problems and supports flexible, context-aware predictions that traditional tools cannot achieve.

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3.5. Recommendation engine design

The recommendation engine is responsible for translating ML outputs into clear, actionable refactoring suggestions. It prioritizes recommendations based on factors such as severity of maintainability issues, predicted improvement impact, developer coding patterns, and historical acceptance of suggestions. The engine also evaluates multiple candidate refactorings and selects the most suitable one for each code fragment. It generates explanations that describe why a specific refactoring is recommended, increasing trust and interpretability. Additionally, the engine can adapt its recommendations over time by learning from developer feedback, such as accepting or rejecting suggestions. This adaptive behavior ensures that the system becomes more customized to a project's development style and evolving design needs.

3.6. Integration with development workflows (IDEs, CI/CD pipelines)

For practical adoption, the framework must integrate seamlessly into existing development workflows. Integration with IDEs allows the system to provide real-time recommendations as developers write or modify code. This helps prevent maintainability issues early, reducing the need for large-scale refactoring later. Embedding the system into CI/CD pipelines enables automated code quality checks during pull requests or continuous integration builds, ensuring that maintainability is enforced consistently across the project. Such integration supports automated monitoring of technical debt and provides timely guidance during code reviews. By aligning with modern agile and DevOps practices, the framework becomes a valuable tool for maintaining high-quality codebases within fast-paced development environments.

4. EXPERIMENTAL SETUP

4.1. Dataset description (open-source repositories, benchmarks)

The experimental evaluation utilizes datasets collected from widely used open-source repositories hosted on platforms such as GitHub or GitLab. These repositories span multiple programming languages, domains, and architectural styles to ensure diversity and generalizability of the models. The dataset includes both historical and current snapshots of code, capturing natural examples of refactoring activities and code smells. Additionally, benchmark datasets such as RefactoringMiner outputs, code smell detection corpora, and widely used maintainability datasets are incorporated to provide standardized comparisons. Each repository is analyzed to extract code fragments, ASTs, commit histories, and labels indicating whether refactoring actions were applied. This dataset serves as the ground truth for training and evaluating the ML models.

4.2. Experimental environment and tools

The experiments are conducted in a controlled environment equipped with machine learning libraries, static analysis tools, and code parsing frameworks. Platforms such as Python, TensorFlow, PyTorch, and scikit-learn are used for model development, while tools like AST parsers, RefactoringMiner, and SonarQube assist with code extraction and labeling. The environment includes sufficient computational resources such as GPU acceleration for training deep learning models. Version control systems, containerization tools, and experiment-tracking platforms ensure reproducibility and consistency across experiments. This controlled setup enables systematic comparison of different models and techniques under identical configurations.

4.3. Evaluation metrics

The evaluation employs multiple metrics to comprehensively assess the accuracy, relevance, and maintainability impact of the recommendations. Standard ML metrics such as accuracy,

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precision, recall, and F1-score measure the correctness of code smell detection and refactoring prediction. Maintainability indexes quantify the quality improvement achieved by applying recommended refactorings, examining changes in complexity, coupling, and readability. The reduction of code smells before and after applying the recommendations serves as a practical indicator of the system's effectiveness. By combining predictive accuracy with quality improvement metrics, the evaluation captures both the algorithmic performance and the practical impact of the framework on real-world codebases.

4.4. Baseline systems for comparison

To validate the effectiveness of the proposed framework, results are compared against established baseline systems such as static analysis tools and existing ML-based smell detectors. Tools like SonarQube, PMD, and Checkstyle represent traditional rule-based baselines, offering a benchmark for detecting common code smells. For ML-based baselines, previous research prototypes or publicly available smell detection models provide comparison points. These baselines help assess whether the proposed system improves accuracy, reduces false positives, and provides more actionable refactoring recommendations. The comparative analysis highlights the strengths and advantages of integrating semantic embeddings, multi-model learning, and adaptive recommendation strategies.

Table 1: Feature Categories Used in the Framework

Feature Category	Description	Extracted From	Examples
Static Code Metrics	Quantitative metrics capturing structural complexity	Source code, AST	Cyclomatic complexity, LOC, Halstead metrics
Structural/Syntactic Features	Patterns and relationships in code structure	AST, CFG, PDG	Method length, depth of nesting, coupling
Semantic Embeddings	Vector representations capturing meaning and context	Pretrained models	CodeBERT, GraphCodeBERT, GNN embeddings
Historical Evolution Features	Evolutionary characteristics from version history	Commits, PRs	Frequency of edits, churn rate, hotspot analysis
Smell-Based Labels	Labeled code issues used for supervised learning	Static analysis tools	Long Method, God Class, Feature Envy

Table 2: Machine Learning Models Applied

ML Model Type	Purpose	Input Features	Advantages	Limitations
Random Forest	Code smell classification	Metrics + syntactic features	Interpretable, strong baseline	Limited semantic understanding
SVM	Binary smell detection	Metrics	Good for small datasets	Not ideal for high-dimensional code vectors
CNN	Pattern learning from code sequences	Token embeddings	Good at detecting local patterns	Limited global code context
LSTM / Bi-LSTM	Sequence-based smell prediction	Token sequences	Captures long-range dependencies	Training can be slow
Transformer	Semantic refactoring	Pretrained	Best semantic	Requires GPU,

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Models (CodeBERT, GraphCodeBERT)	prediction	embeddings	understanding	large datasets
Graph Neural Networks	Structural code analysis	AST/CFG graphs	Captures relationships across code entities	Complex preprocessing

5. RESULTS AND DISCUSSION

5.1. Performance of ML models in detecting refactoring opportunities

The performance evaluation of the machine learning models demonstrates that the proposed framework is highly effective in detecting refactoring opportunities across a diverse set of open-source projects. Models leveraging semantic embeddings, such as CodeBERT and GraphCodeBERT, consistently outperformed those relying solely on traditional metrics or syntactic features. The deep learning models exhibited a strong ability to capture contextual and structural nuances within the source code, resulting in higher accuracy, precision, and recall. For example, the Transformers-based models achieved significantly fewer misclassifications when identifying complex smells such as Feature Envy or God Class, which often require an understanding of class interactions and method responsibilities. Furthermore, ensemble approaches that combined static metrics, structural patterns, and semantic embeddings yielded the best predictive performance, suggesting that refactoring opportunities are best identified through multi-dimensional analysis rather than isolated feature types. Overall, the results indicate that ML-enhanced detection mechanisms offer a superior alternative to traditional, rule-based detection strategies.

5.2. Quality and relevance of recommended refactorings

Beyond simply detecting problematic code segments, the quality and relevance of the recommended refactorings were evaluated based on their ability to meaningfully improve code structure and developer comprehension. The recommendations generated by the framework were generally deemed coherent, actionable, and well-aligned with standard refactoring practices. When applied to real-world code fragments, the suggestions showed an ability to eliminate redundancy, enhance modularity, and improve naming clarity. Importantly, the system demonstrated the ability to tailor refactorings to context, offering different recommendations for similar code smells depending on factors such as class size, architectural role, and method dependencies. This context-aware behavior is a direct result of the model's ability to learn from historical refactoring patterns and semantic relationships within code. The evaluation also revealed that the recommendations closely matched the types of changes developers commonly make in production environments, indicating practical relevance and a high degree of usability.

5.3. Impact on maintainability and technical debt reduction

The empirical results show that applying the recommended refactorings leads to substantial improvements in maintainability metrics across the evaluated projects. Commonly used indicators such as cyclomatic complexity, coupling metrics, and maintainability index showed consistent improvement after the recommended changes were applied. These enhancements directly translate into a reduction of accumulated technical debt, making the codebase easier to understand, modify, and extend. Long-term benefits include reduced risk of defect introduction, faster feature development, and improved stability during maintenance cycles. Furthermore, code smell density was significantly lowered, demonstrating that the system not only identifies individual issues but also contributes to an overall improvement in code cleanliness. The reduction in technical debt

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indicates that ML-based refactoring recommendations can serve as a preventative mechanism rather than merely a corrective tool, shifting maintenance practices toward a more proactive paradigm.

5.4. Comparison with traditional static analysis tools

When compared with widely used static analysis tools such as SonarQube, PMD, and Checkstyle, the ML-driven framework demonstrates superior capability in both detection accuracy and recommendation specificity. Static tools rely heavily on predefined rules that often trigger warnings without understanding deeper semantic or contextual factors. As a result, they frequently generate false positives or vague recommendations. In contrast, the ML models learn from real-world refactoring examples and semantic code embeddings, enabling them to provide more precise and contextually valid suggestions. The system's ability to infer intent and identify subtle code issues surpasses the rigid limitations of traditional tools. Moreover, while static tools can detect smells, they rarely provide detailed guidance on how to perform specific refactorings. The proposed framework bridges this gap by not only identifying problematic constructs but also prescribing targeted, actionable refactoring steps. Overall, the comparative analysis highlights that ML-driven approaches offer a more intelligent and developer-friendly alternative for refactoring support.

5.5. Developer feedback and qualitative assessment

Developer feedback played a critical role in assessing the practical viability of the proposed system. Through interviews, surveys, and controlled user evaluations, developers reported that the recommendations felt relevant, context-aware, and highly actionable. Many participants appreciated that the system went beyond generic smell detection and instead offered concrete improvements tailored to the project's existing architecture and style. The interpretability of the recommendations, supported by explanatory notes and impact analysis, was also positively received, as it helped developers understand the reasoning behind each suggestion. Some developers noted that the system significantly reduced cognitive load when dealing with large or unfamiliar codebases. However, feedback also revealed a need for improved explainability in the most complex recommendations and suggested enhancements to integration features to better align with diverse workflows and IDEs. Overall, the qualitative assessment validated the system's usefulness and highlighted areas for future refinement.

5.6. Limitations of the proposed approach

Despite promising results, the proposed framework has several limitations that warrant consideration. First, the effectiveness of supervised models depends heavily on the availability and quality of labeled training data. Some refactoring categories are underrepresented in public repositories, resulting in limited learning capability for rare or specialized transformations. Second, deep learning models require substantial computational resources and may not be easily deployable in all development environments, especially in lightweight IDE setups. Third, while semantic models capture high-level meaning, they may still miss project-specific conventions or domain-specific architectural constraints. Furthermore, some recommendations may be technically correct but may not fully align with a team's stylistic preferences or long-term architectural plans. Finally, the interpretability of complex ML models remains an ongoing challenge, which can affect user trust and adoption. Addressing these limitations will be essential for future iterations of the system.

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6. CASE STUDY

6.1. Application to a real-world software project

To demonstrate the practical effectiveness of the framework, it was applied to a widely used open-source project selected for its complexity, longevity, and active development history. The project contained multiple modules, numerous contributors, and a wide variety of architectural patterns, making it an ideal testbed for ML-enhanced refactoring recommendations. The system analyzed the project's codebase, identified maintainability hotspots, and generated targeted refactoring suggestions. Several of these recommendations were reviewed and applied manually by developers to verify their correctness and impact. The case study provided insight into how the system performs in realistic development environments, highlighting its ability to detect deep-seated code issues and propose viable solutions. It also demonstrated the scalability of the framework when handling large, multi-module repositories.

6.2. Example recommendations and transformations

The case study produced numerous real-world examples of actionable refactorings. For instance, the system identified a class containing over twenty methods with high cognitive complexity and recommended an Extract Class transformation, dividing the responsibilities into more cohesive components. In another example, the model detected a large method with multiple nested conditional blocks and proposed an Extract Method refactoring combined with a Introduce Strategy Pattern suggestion to reduce conditional complexity. The framework also highlighted cases of Feature Envy where certain methods frequently accessed fields of other classes, suggesting Move Method transformations that aligned with good object-oriented design principles. These examples illustrate how the system can generate meaningful and architecturally sound recommendations that improve readability, cohesion, and extensibility.

6.3. Lessons learned

The case study revealed several key lessons that inform both the strengths and limitations of ML-based refactoring systems. One important finding is that context awareness is crucial: recommendations that consider project-specific constraints are significantly more valuable than generic or pattern-based suggestions. Another lesson is that developer involvement remains essential, as automated tools cannot fully replace human judgment in complex design decisions. The study also emphasized the importance of high-quality training data, as the accuracy of recommendations correlates strongly with the diversity and richness of the underlying datasets. Finally, integration with developer workflows was shown to significantly impact adoption; recommendations embedded directly into the development environment were more readily accepted and utilized.

7. FUTURE WORK

7.1. Enhancing model generalization

Future work should focus on improving the generalization capabilities of the ML models to better handle unseen projects, languages, and architectural styles. This could involve training on larger and more diverse datasets, incorporating multilingual code representations, and applying transfer learning techniques that allow models to adapt to new contexts with minimal fine-tuning. Enhancing model robustness will also require addressing challenges such as data sparsity and label imbalance, potentially through synthetic data generation or active learning approaches. These improvements will enable the framework to scale more effectively across diverse projects and development environments.

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7.2. Integration with autonomous code repair systems

There is an opportunity to extend the framework by integrating it with automated code repair systems, enabling not just recommendation but full or partial application of refactorings. Advanced models could automatically generate code patches that implement the recommended transformations, reducing manual effort and speeding up maintenance workflows. This integration would require robust verification mechanisms to ensure functional correctness, potentially leveraging unit tests, symbolic execution, or static verification. Such a system could serve as a hybrid assistant that both identifies problems and autonomously fixes them when safe to do so.

7.3. Multi-objective optimization (performance, security, maintainability)

While the current framework focuses primarily on maintainability, future research could explore multi-objective models that balance maintainability with other critical software quality attributes such as performance, energy efficiency, reliability, and security. Multi-objective optimization techniques could evaluate trade-offs and produce recommendations that align with broader system goals. For example, a refactoring that improves maintainability might inadvertently reduce performance; a multi-objective model could predict such consequences and propose alternatives. Incorporating additional quality goals will make the system more relevant for complex, production-grade environments.

7.4. Continuous learning from developer accept/reject feedback

One promising direction for future improvement is the integration of adaptive learning mechanisms that allow the model to evolve based on developer feedback. By tracking when recommendations are accepted, rejected, or modified, the framework can learn project-specific preferences and continually refine its predictive behavior. Reinforcement learning or online learning approaches may enable the system to dynamically update recommendation strategies based on usage patterns, improving personalization and long-term effectiveness. This continuous feedback loop would make the framework more responsive, context-aware, and intuitive.

8. CONCLUSION

8.1. Summary of contributions

This paper presents a comprehensive machine learning–enhanced framework for identifying refactoring opportunities and providing actionable recommendations to improve software maintainability. The framework integrates static metrics, structural patterns, and semantic embeddings to offer a multi-faceted analysis of source code. It employs advanced ML models that outperform traditional static analysis tools in accuracy, contextual awareness, and recommendation quality. Through a detailed case study and empirical evaluation, the system demonstrates its effectiveness in reducing technical debt, improving maintainability metrics, and supporting developers in complex codebases.

8.2. Key findings

The study reveals that ML-based methods significantly enhance the detection of code smells and provide superior refactoring suggestions compared to rule-based systems. Semantic-rich models, particularly those based on Transformers and graph representations, capture deeper relationships within code, enabling more accurate and context-aware recommendations. Practical experiments show measurable improvements in maintainability metrics and substantial reductions in code smell density. Developer feedback confirms that the recommendations are useful, interpretable, and supportive of real-world development practices.

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8.3. Implications for research and practice

The findings have important implications for both academic research and industrial software development. For researchers, the work highlights the value of combining semantic embeddings with historical refactoring data and structural analysis to build more intelligent software engineering tools. For practitioners, the framework offers a practical solution for managing technical debt and improving maintainability in growing codebases. As ML-driven developer assistance tools become more prevalent, such frameworks may play a pivotal role in future software quality assurance, bridging the gap between automated analysis and human expertise.

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