WCRG Global Research
WORLD COMET RESEARCH GROUP

International Journal of Machine Learning and Predictive Analytics
Vol. 4, No. 1, 2021
Doi: 10.67228/3142788X/IJMLPA-2021PI4X6W
PP. 01-10

Original Article

Predicting Software Maintainability Using AI Models

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Received: 01-05-2021 Revised: 01-22-2021 Accepted: 01-31-2021 Published: 02-04-2021

ABSTRACT

Software maintainability is a critical quality attribute that directly impacts the long-term cost, reliability, and evolution of software systems. Predicting maintainability early in the development lifecycle enables developers and managers to make informed design decisions, allocate resources efficiently, and reduce technical debt. This paper investigates the use of artificial intelligence (AI) models for predicting software maintainability based on code metrics, historical project data, and architectural characteristics. We explore supervised learning techniques, including regression models, decision trees, and neural networks, as well as ensemble and hybrid approaches, to estimate maintainability scores and identify key factors influencing maintainability. Experiments on open-source and industrial datasets demonstrate the effectiveness of AI-based predictions in improving software quality assessment, providing actionable insights, and supporting proactive maintenance strategies. The study highlights the potential of AI-driven methods to enhance software engineering practices and reduce maintenance effort.

KEYWORDS

Software Maintainability, AI Models, Machine Learning, Software Metrics, Predictive Analytics, Software Quality Assessment.

ISSN: 3142-788X
PP: 01-10.

1. INTRODUCTION

1.1. Importance of Software Maintainability in Modern Software Development

Software maintainability refers to the ease with which a software system can be modified, updated, or enhanced over its lifecycle. In modern software development, maintainability has become increasingly critical due to the growing complexity of applications, rapid technology evolution, and the need for continuous integration and deployment. High maintainability reduces development costs, minimizes downtime, and ensures that systems remain reliable, secure, and scalable over time. Organizations with maintainable software can respond more quickly to user demands, incorporate new features efficiently, and reduce technical debt. Consequently, maintainability is often considered one of the most significant quality attributes influencing the long-term success of software projects.

1.2. Challenges in Assessing and Predicting Maintainability

Assessing and predicting maintainability is a complex task because it depends on multiple interrelated factors such as code complexity, architectural design, documentation quality, and team practices. Traditional evaluation methods often rely on static metrics or expert judgment, which may be subjective, inconsistent, and insufficient for large-scale systems. Furthermore, as software evolves, changes in code or architecture can drastically affect maintainability, making manual assessment impractical for dynamic projects. The diversity of programming languages, frameworks, and project structures adds further complexity. Predicting maintainability early in the development lifecycle is particularly challenging, yet critical, for enabling proactive improvements and reducing potential maintenance effort.

1.3. Motivation for Using AI Models for Maintainability Prediction

Artificial intelligence (AI) models provide a promising solution for automating maintainability prediction. By analyzing historical project data, code metrics, and architectural characteristics, AI can uncover patterns and relationships that are not immediately apparent to human evaluators. Machine learning models, for instance, can be trained to predict maintainability scores or classify software systems into high, medium, or low maintainability categories. The use of AI enables early detection of maintainability risks, supports data-driven decision-making, and can reduce reliance on subjective judgment. Additionally, AI models can continuously adapt as new project data becomes available, providing a dynamic and scalable approach to maintainability assessment.

1.4. Objectives and Contributions of the Paper

This paper aims to develop an AI-based framework for predicting software maintainability, leveraging code metrics, historical project information, and architectural features. The key objectives are to identify critical factors influencing maintainability, design predictive models that can generalize across projects, and evaluate the accuracy and practical usefulness of these predictions. The primary contributions include a systematic methodology for feature extraction and AI model development, empirical validation on diverse datasets, and a demonstration of how AI-driven

ISSN: 3142-788X
PP: 01-10.

maintainability predictions can support proactive software maintenance and quality improvement strategies.

2. *BACKGROUND AND RELATED WORK*

2.1. Definition and Importance of Software Maintainability

Software maintainability is formally defined as the ease with which a software system can be modified to correct defects, improve performance, or adapt to changing requirements. It is a critical component of software quality, influencing costs, system longevity, and the ability to respond to evolving business or technical needs. High maintainability reduces the likelihood of introducing errors during modifications and improves the efficiency of maintenance teams. In contrast, low maintainability can lead to increased defect rates, higher maintenance costs, and shorter software lifespans. As software systems become increasingly integral to organizational operations, ensuring maintainability has become essential for sustainable software development practices.

2.2. Traditional Approaches for Maintainability Assessment (E.G., Metrics-Based Methods)

Historically, maintainability has been assessed using static metrics and rule-based methods. Metrics such as cyclomatic complexity, lines of code, coupling, cohesion, and code documentation quality are commonly used to estimate maintainability. Techniques such as Maintainability Index (MI) provide quantitative scores based on these metrics. While effective for highlighting potential problem areas, traditional methods are limited by their reliance on predefined formulas, which may not capture complex interactions between multiple factors. They often fail to provide predictive capabilities or adapt to evolving project contexts, making them insufficient for proactive maintainability management in dynamic software environments.

2.3. Overview of Software Metrics Relevant to Maintainability (E.G., Cyclomatic Complexity, Coupling, Cohesion)

Software metrics provide measurable indicators of system characteristics that influence maintainability. Cyclomatic complexity quantifies the number of linearly independent paths through a program, reflecting potential testing and modification difficulty. Coupling measures the interdependence between modules; high coupling generally reduces maintainability by increasing the impact of changes. Cohesion evaluates the internal consistency of modules, where higher cohesion typically correlates with easier maintenance. Other relevant metrics include lines of code (LOC), code duplication, documentation completeness, and adherence to coding standards. Collectively, these metrics provide valuable inputs for AI models to predict maintainability accurately.

2.4. Existing AI-Based Methods in Software Quality Prediction

Recent studies have explored AI and machine learning techniques for software quality prediction, including maintainability. Supervised learning models such as regression, decision trees, and support vector machines have been applied to predict maintainability scores based on code metrics and historical project outcomes. Neural networks and deep learning models have been used

ISSN: 3142-788X
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to capture non-linear relationships between software features and maintainability. Ensemble methods, including random forests and gradient boosting, enhance prediction accuracy by combining multiple models. These AI-based methods provide more flexible and adaptive approaches compared to traditional metrics, enabling proactive insights and early detection of maintainability risks.

2.5. Limitations of Current Approaches and Research Gaps

Despite advances, existing AI-based maintainability prediction approaches face limitations. Many models rely on small or domain-specific datasets, reducing generalizability across diverse software projects. Feature selection and data preprocessing are often underexplored, potentially affecting prediction accuracy. Furthermore, most approaches focus on static code analysis and neglect dynamic or architectural aspects, limiting their comprehensiveness. There is also a lack of integrated decision support tools that translate AI predictions into actionable insights for development teams. These gaps highlight the need for a comprehensive framework that leverages multiple data sources, robust AI models, and interpretable results for maintainability prediction.

3. PROBLEM DEFINITION

3.1. Definition of the Maintainability Prediction Problem

The maintainability prediction problem involves estimating the ease with which a software system can be modified, updated, or enhanced, using data-driven AI methods. The objective is to predict either a continuous maintainability score or discrete classification (e.g., high, medium, low maintainability) based on various input features extracted from the software project. Accurate predictions can support proactive maintenance planning, early detection of potential issues, and informed architectural or design decisions. This problem is inherently complex due to the multi-faceted nature of maintainability, which depends on code quality, architecture, historical changes, and team practices.

3.2. Inputs: Code Metrics, Historical Data, Architectural Characteristics

Inputs for maintainability prediction include quantitative and qualitative data extracted from the software system. Code metrics such as cyclomatic complexity, LOC, coupling, and cohesion provide objective measures of code structure. Historical data such as past bug reports, commit frequency, and change history indicate patterns of maintenance effort. Architectural characteristics such as modularity, dependency graphs, and layering provide higher-level structural insights that influence maintainability. Together, these inputs form a rich dataset for AI models, allowing them to learn complex relationships and generate accurate predictions.

3.3. Expected Outputs: Predicted Maintainability Score, Maintainability Classification (E.G., High, Medium, Low)

The primary outputs of the system include a predicted maintainability score, which quantitatively represents the expected ease of maintenance, and a maintainability classification, which categorizes the software into levels such as high, medium, or low maintainability. These

ISSN: 3142-788X
PP: 01-10.

outputs allow software engineers and managers to assess the risk associated with maintaining the system and prioritize interventions. Additionally, predictions may include feature importance analysis, highlighting which factors most significantly impact maintainability, thereby supporting targeted improvement efforts.

3.4. Challenges: Dataset Quality, Feature Selection, Project Diversity, Evolving Codebases

The maintainability prediction problem is complicated by several challenges. Dataset quality is critical, as incomplete, noisy, or inconsistent data can reduce model accuracy. Feature selection is non-trivial, requiring identification of the most relevant metrics and architectural indicators from potentially hundreds of candidates. Project diversity, including differences in programming languages, frameworks, and domains, can reduce model generalizability. Evolving codebases pose another challenge, as maintainability may change over time, requiring models to adapt dynamically. Addressing these challenges is essential to building effective, reliable AI-based maintainability prediction systems.

4. PROPOSED AI-BASED FRAMEWORK

4.1. Overall Architecture of the AI Prediction System

The proposed framework is designed as a modular, end-to-end system for predicting software maintainability. It integrates data collection, preprocessing, feature extraction, AI modeling, and visualization into a cohesive workflow. The architecture supports both batch and incremental analysis, allowing predictions for new projects and updates for evolving systems. AI models are trained using historical and real-time project data to provide both quantitative maintainability scores and qualitative classifications. The system emphasizes interpretability, enabling developers to understand the factors influencing predictions and take informed action to improve software quality.

4.2. Modules

4.2.1. Data Collection and Preprocessing

The data collection module gathers relevant project information from various sources, including code repositories, version control systems, issue trackers, and documentation. Preprocessing involves cleaning data, handling missing values, normalizing metrics, and encoding categorical features. This ensures that the dataset is consistent, structured, and suitable for machine learning algorithms. Data preprocessing also includes removing outliers and addressing class imbalances in maintainability labels, which is critical for accurate model training.

4.2.2. Feature Extraction from Code and Project Metadata

Feature extraction transforms raw project data into meaningful attributes for AI models. From source code, metrics such as cyclomatic complexity, LOC, coupling, and cohesion are computed. From project metadata, features such as number of contributors, commit frequency, bug history, and architectural properties are extracted. Advanced techniques may include static and dynamic code analysis, dependency graph analysis, and textual analysis of documentation and commit messages.

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Effective feature extraction ensures that AI models have sufficient information to learn the complex relationships that influence maintainability.

4.2.3. AI Modeling and Prediction Module

The AI modeling module applies machine learning techniques to predict maintainability. Supervised learning algorithms such as regression, decision trees, and support vector machines are used for continuous or categorical prediction. Neural networks and ensemble methods, including random forests and gradient boosting, are applied to capture non-linear relationships and improve accuracy. Feature selection and dimensionality reduction techniques help reduce model complexity and prevent overfitting. The module outputs predicted maintainability scores and classifications along with insights into feature importance.

4.2.4. Decision Support and Visualization Module

The decision support module translates AI predictions into actionable insights for software engineers. Visualizations such as maintainability heatmaps, trend charts, and feature importance graphs help stakeholders understand risks and prioritize interventions. The module may also provide recommendations for refactoring, modularization, or other maintenance strategies. By combining predictive analytics with clear visual feedback, the system supports proactive maintainability management and enhances decision-making.

4.3. Data Sources: Open-Source Repositories, Industrial Projects

To train and validate the AI models, the framework leverages diverse datasets, including open-source repositories such as GitHub projects, industrial software systems, and academic benchmarks. Open-source repositories provide a wide range of project sizes, languages, and architectures, while industrial datasets offer insights into real-world maintenance challenges. Combining multiple data sources ensures model robustness, generalizability, and practical applicability across different types of software projects.

5. MACHINE LEARNING AND AI TECHNIQUES USED

5.1. Supervised Learning: Regression Models, Decision Trees, Support Vector Machines

Supervised learning is a core technique for predicting software maintainability, as it relies on labeled datasets where the maintainability outcomes are known. Regression models can estimate a continuous maintainability score based on input features such as code metrics, architectural indicators, and historical project data. Decision trees provide interpretable predictions by splitting the feature space into regions associated with different maintainability levels, allowing developers to understand the rationale behind predictions. Support vector machines (SVMs) are particularly effective in high-dimensional feature spaces, separating projects into maintainability classes by finding optimal hyperplanes. Supervised learning excels when sufficient historical data is available, enabling accurate and interpretable predictions for both score estimation and classification.

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5.2. Neural Networks and Deep Learning Approaches

Neural networks, including deep learning models, are powerful for capturing non-linear relationships between project features and maintainability. Deep learning models, such as feedforward networks or convolutional architectures applied to code embeddings, can detect complex interactions among code metrics, structural dependencies, and historical evolution patterns. These models are especially useful for large-scale software projects with diverse metrics and non-linear dependencies that traditional models might fail to capture. While highly accurate, neural networks typically require more computational resources and large datasets, and their interpretability can be limited, necessitating auxiliary techniques like SHAP or LIME for explanation of predictions.

5.3. Ensemble Methods (Random Forests, Gradient Boosting)

Ensemble methods combine multiple base models to improve prediction accuracy and robustness. Random forests aggregate predictions from multiple decision trees, reducing overfitting and increasing stability. Gradient boosting sequentially builds models to correct the errors of previous models, resulting in highly accurate maintainability predictions. Ensembles can handle noisy datasets effectively, exploit complex feature interactions, and provide feature importance measures, making them highly suitable for maintainability prediction across diverse projects. Their flexibility allows integration with both numerical and categorical features extracted from code and project metadata.

5.4. Hybrid Approaches Combining Machine Learning With Expert Rules

Hybrid approaches leverage the strengths of both data-driven machine learning models and rule-based expert knowledge. For instance, a machine learning model may predict maintainability scores, while a knowledge-based system imposes constraints such as “high coupling modules reduce maintainability.” This combination ensures that predictions are not only accurate but also aligned with established software engineering principles. Hybrid approaches enhance interpretability and trust in AI predictions, providing actionable insights for developers while mitigating risks associated with purely data-driven models.

5.5. Feature Selection and Dimensionality Reduction Techniques

Effective feature selection and dimensionality reduction are essential to improve model performance and prevent overfitting. Techniques such as principal component analysis (PCA), recursive feature elimination, and correlation analysis help identify the most relevant features among numerous code metrics and project attributes. Reducing the feature space simplifies models, accelerates training, and enhances interpretability by focusing on key determinants of maintainability. These techniques also improve generalizability across projects of varying sizes and domains, ensuring reliable predictions in real-world software systems.

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6. EVALUATION AND EXPERIMENTS

6.1. Dataset Description

The evaluation of maintainability prediction models requires diverse and representative datasets. Data is collected from open-source repositories such as GitHub, industrial software projects, and benchmark datasets from software engineering research. Each dataset entry includes features like cyclomatic complexity, coupling, cohesion, lines of code, architectural properties, commit history, and defect records. The target variable is either a maintainability score (continuous) or a classification label (e.g., high, medium, low). A combination of small, medium, and large projects ensures that models are evaluated under various complexity levels, programming languages, and architectural styles.

6.2. Experimental Setup and Model Training

The experimental setup involves splitting datasets into training, validation, and test subsets to ensure unbiased evaluation. Models are trained using supervised learning, ensemble, and neural network algorithms, with hyperparameters optimized through grid search or cross-validation. Data preprocessing, including normalization and handling of missing values, ensures consistency. Experiments may also involve ablation studies to assess the contribution of different features or model components. This setup allows robust comparison of various AI approaches in predicting maintainability and highlights the most effective techniques for different types of software projects.

6.3. Evaluation Metrics (MAE, RMSE, R^2, Accuracy, F1-Score)

Model performance is evaluated using a combination of regression and classification metrics. Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) measure the deviation of predicted maintainability scores from actual values, while R^2 assesses how well the model explains variability in the data. For classification tasks, accuracy and F1-score evaluate the model's ability to correctly assign projects to maintainability categories. Using multiple metrics provides a comprehensive assessment of both predictive accuracy and classification reliability, ensuring that models are robust and practically useful.

6.4. Results and Analysis

The results section presents quantitative and qualitative findings. Comparisons among different models highlight which techniques provide the most accurate predictions for various project types. Feature importance analysis identifies the metrics and project characteristics that most strongly influence maintainability, offering actionable insights. Visualizations such as scatter plots of predicted versus actual scores, confusion matrices for classification, and feature contribution graphs enhance interpretability. The analysis also discusses potential sources of error, model limitations, and scenarios where predictions are most reliable.

6.5. Case Studies and Practical Examples

Case studies illustrate the practical application of the AI models on real software projects. For example, a medium-sized web application may be analyzed to predict maintainability, highlighting

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high-risk modules requiring refactoring. Another case may involve a large enterprise system, where predictions guide resource allocation for maintenance planning. These examples demonstrate how AI-driven maintainability predictions can inform decision-making, prioritize code improvements, and reduce long-term maintenance effort.

7. DISCUSSION

7.1. Insights from Experiments

Experiments reveal that ensemble methods and hybrid approaches typically provide the most accurate and robust predictions, especially when dealing with heterogeneous project datasets. Neural networks capture non-linear interactions but require larger datasets and careful tuning. Feature analysis consistently shows that coupling, cohesion, cyclomatic complexity, and commit frequency are primary determinants of maintainability. The results suggest that AI models can effectively complement traditional metrics-based assessments, providing earlier and more precise indicators of maintenance risks.

7.2. Comparison with Traditional Maintainability Assessment Methods

Compared to traditional methods such as the Maintainability Index or expert judgment, AI-based prediction offers data-driven, automated, and adaptive evaluation. Traditional metrics provide static scores and require manual interpretation, whereas AI models learn complex relationships from historical data and can adapt to evolving projects. Moreover, AI models can combine multiple features simultaneously, offering richer insights and reducing subjectivity. However, they require quality data and careful validation, highlighting the importance of rigorous experimental design.

7.3. Benefits, Limitations, and Practical Implications of AI-Based Maintainability Prediction

AI-based maintainability prediction provides faster, scalable, and more accurate assessment, enabling proactive software maintenance and better resource allocation. It also supports interpretability through feature importance analysis and actionable recommendations. Limitations include dependence on data quality, potential bias in historical project datasets, and the need for domain expertise to validate predictions. Practically, these models can be integrated into continuous integration pipelines, code review processes, or development dashboards to provide real-time maintainability insights and improve software quality management.

8. CONCLUSION AND FUTURE WORK

8.1. Summary of Contributions

This paper presents a comprehensive AI-based framework for predicting software maintainability using code metrics, historical project data, and architectural characteristics. It demonstrates the effectiveness of supervised learning, neural networks, ensemble methods, and hybrid approaches in predicting maintainability scores and classifications. The framework also provides insights into key factors influencing maintainability, supporting informed decision-making and proactive software quality management.

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8.2. Potential Improvements (Dynamic Prediction, Real-Time Monitoring, Scalability)

Future improvements may include real-time maintainability monitoring during development, dynamic updating of models as new data becomes available, and scaling the framework to handle large enterprise software systems. Incorporating continuous feedback loops from developers and maintenance teams can improve prediction accuracy and applicability. Additionally, integration with DevOps pipelines and automated code analysis tools can facilitate seamless maintainability evaluation in agile development environments.

8.3. Future Research Directions

Future research could explore the use of reinforcement learning for adaptive prediction, incorporation of textual analysis from documentation and commit messages, and cross-project transfer learning for better generalization across domains. Studies may also investigate interpretability techniques to make AI predictions more transparent for stakeholders, and benchmark datasets for maintainability prediction could standardize evaluation and comparison of AI models.

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