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Original Article

Intelligent Version Control Conflict Resolution Using ML

Robert Miller

Software Engineering Manager, TechNova Inc, USA.

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ABSTRACT

Version control systems are essential for collaborative software development, but merge conflicts remain a persistent challenge, often leading to delays, errors, and increased maintenance effort. Traditional conflict resolution methods rely heavily on manual intervention, which is time-consuming and error-prone, especially in large, distributed teams. This paper proposes an intelligent, machine learning-based approach to automatically detect, classify, and resolve version control conflicts. By leveraging historical commit data, code change patterns, and contextual information from source code and documentation, the proposed system predicts optimal resolutions and provides recommendations to developers. Experiments on open-source and industrial repositories demonstrate the effectiveness of ML models in reducing conflict resolution time, improving accuracy, and supporting team productivity. The study highlights the potential of AI-driven tools to transform collaborative software development and minimize merge-related risks.

KEYWORDS

Version Control, Merge Conflicts, Machine Learning, Conflict Resolution, Collaborative Software Development, Software Engineering Automation.

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1. INTRODUCTION

1.1. Importance of Version Control in Modern Software Development

Version control systems (VCS) are foundational to modern software engineering, enabling teams to collaboratively develop, manage, and maintain codebases. By tracking changes, managing branches, and facilitating code integration, VCS tools like Git, SVN, and Mercurial ensure that multiple developers can work concurrently without overwriting each other's work. They also maintain a historical record of code evolution, supporting rollback, auditing, and traceability. In large-scale and distributed software projects, version control is indispensable for coordinating development efforts, ensuring code quality, and supporting continuous integration and deployment pipelines. Efficient version control directly influences productivity, maintainability, and the ability to quickly respond to changes in requirements or technology.

1.2. Challenges Posed by Merge Conflicts

Despite their benefits, version control systems are prone to merge conflicts when multiple developers modify the same portion of code or interact with interdependent modules. Merge conflicts can be textual, arising from overlapping edits in code lines; semantic, caused by changes that break the program's logic or behavior; or structural, involving modifications to file hierarchies, classes, or APIs. Resolving conflicts manually is often time-consuming, error-prone, and requires deep contextual knowledge of the codebase. In distributed teams or large-scale projects, unresolved conflicts can delay development, introduce defects, and increase maintenance costs. These challenges highlight the need for automated, intelligent tools that can assist developers in managing and resolving conflicts efficiently.

1.3. Motivation for ML-Based Intelligent Conflict Resolution

Machine learning (ML) offers a promising approach to intelligent conflict resolution by leveraging historical commit data, code patterns, and contextual information to predict optimal resolutions. Unlike traditional rule-based methods, ML models can learn from past resolution strategies, understand complex code semantics, and adapt to diverse project contexts. By automating conflict detection and suggesting resolution strategies, ML can reduce developer effort, minimize human errors, and accelerate the integration process. Moreover, intelligent tools can provide actionable recommendations that not only resolve conflicts but also maintain code quality, consistency, and adherence to project standards.

1.4. Objectives and Contributions of the Paper

The primary objective of this paper is to develop an ML-based framework for intelligent conflict resolution in version control systems. Key contributions include the design of a conflict detection and classification mechanism, the extraction of informative features from code changes and commit history, the development of predictive ML models for suggesting resolution strategies, and the integration of a decision support module that assists developers. The paper also evaluates the framework on real-world datasets to demonstrate its effectiveness in improving resolution accuracy, reducing conflict resolution time, and supporting collaborative software development. Overall, the

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study aims to provide a scalable, adaptive, and practical solution to the longstanding problem of merge conflicts.

2. BACKGROUND AND RELATED WORK

2.1. Overview of Version Control Systems (Git, SVN, Mercurial)

Version control systems are software tools that manage changes to source code and related files over time. Git, SVN (Subversion), and Mercurial are widely used systems, each with unique features. Git, a distributed version control system, allows developers to maintain local repositories, enabling offline work and flexible branching strategies. SVN is a centralized system that emphasizes linear history and controlled access to a single repository, while Mercurial provides a distributed model similar to Git but focuses on simplicity and performance. These tools provide essential functionality for collaborative development, including branching, merging, conflict detection, and history tracking. Understanding the operational principles of these systems is crucial for designing intelligent conflict resolution mechanisms.

2.2. Nature And Types of Merge Conflicts (Textual, Semantic, Structural)

Merge conflicts arise when concurrent changes to a codebase cannot be automatically reconciled by the version control system. Textual conflicts occur when two developers modify the same lines of code, leading to overlapping edits. Semantic conflicts arise when changes do not directly overlap but result in logical inconsistencies, such as method signature changes that break downstream calls. Structural conflicts involve changes to the organization of code, such as file renames, directory restructuring, or modifications to class hierarchies. Each type of conflict presents distinct challenges for resolution, requiring an understanding of both code syntax and program semantics. Effective intelligent tools must detect these different conflict types and provide context-aware resolution strategies.

2.3. Traditional Conflict Resolution Methods (Manual, Rule-Based, Heuristic)

Traditionally, conflict resolution relies on manual intervention or simple automated heuristics provided by version control systems. Manual resolution requires developers to inspect conflicting code segments, understand the impact of changes, and merge modifications carefully. Rule-based approaches apply predefined strategies, such as “take the latest change” or “prefer incoming changes,” but often fail in complex or semantic conflicts. Heuristic techniques, like textual similarity or line-based merging, improve automation but still struggle with logical inconsistencies and contextual nuances. While these methods provide a baseline solution, they are limited in scalability, adaptability, and accuracy, especially for large or distributed teams working on complex software systems.

2.4. Existing AI/ML Approaches in Version Control and Conflict Resolution

Recent research has explored AI and ML techniques to automate conflict resolution. Supervised learning models have been applied to predict conflict resolution strategies based on historical commit data and code change patterns. Sequence models, such as RNNs and Transformers,

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have been used to capture the contextual dependencies in code, enabling semantic understanding for better resolution suggestions. Some studies incorporate static code analysis or hybrid approaches combining rules and ML to improve reliability. These methods show promise in reducing resolution effort and improving accuracy, but their effectiveness depends on data quality, feature engineering, and the diversity of training datasets.

2.5. Research Gaps and Limitations of Current Techniques

Despite progress, current AI/ML approaches face several limitations. Many models rely on small or project-specific datasets, limiting generalization across different programming languages and development practices. Feature extraction often focuses on textual changes without fully capturing semantic or structural aspects of code. Moreover, existing tools rarely integrate real-time recommendations within development workflows, reducing practical usability. There is also a lack of comprehensive evaluation against diverse conflict types, making it difficult to assess model reliability in real-world scenarios. These gaps highlight the need for a holistic, scalable, and context-aware framework for intelligent conflict resolution.

3. PROBLEM DEFINITION

3.1. Definition of the Version Control Conflict Resolution Problem

The version control conflict resolution problem involves detecting, classifying, and resolving conflicts that arise when multiple developers modify overlapping or interdependent portions of a codebase. The goal is to produce a merged code state that maintains correctness, consistency, and adherence to project standards. This problem is complex due to the interplay of textual, semantic, and structural conflicts, and the need to consider the broader context of project dependencies, historical changes, and developer intentions. Solving this problem automatically requires understanding both code syntax and semantics, as well as learning patterns from historical conflict resolution data.

3.2. Inputs: Conflicting Code Segments, Commit History, Developer Metadata

The proposed system takes multiple inputs to predict effective conflict resolutions. Conflicting code segments provide the immediate textual context of the conflict. Commit history supplies chronological information about changes, including which files and modules have been modified, the sequence of edits, and prior resolutions. Developer metadata, such as authorship, expertise, and contribution patterns, helps contextualize changes and predict the most likely successful resolution strategy. Collectively, these inputs provide a comprehensive view of the conflict, enabling the machine learning model to make informed and context-aware predictions.

3.3. Expected Outputs: Resolved Code, Conflict Classification, Resolution Suggestions

The system outputs include a merged code segment that resolves the conflict while maintaining program correctness, a classification of the conflict type (textual, semantic, or structural), and recommended resolution strategies or actions. These outputs guide developers by reducing manual effort, ensuring higher accuracy, and providing insights into why a particular resolution is

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suggested. Additionally, the system may provide confidence scores or alternative resolution options, supporting developers in making final decisions and maintaining control over the codebase.

3.4. Challenges: Context Understanding, Code Semantics, Diverse Programming Languages, Multi-Developer Scenarios

Resolving conflicts intelligently faces multiple challenges. Context understanding requires interpreting not just the immediate code changes, but also how they interact with the broader codebase and project dependencies. Capturing code semantics, including function behavior and program logic, is critical for resolving semantic conflicts. Diverse programming languages and coding styles introduce variability that can reduce model generalization. Multi-developer scenarios add complexity due to differing development practices, priorities, and intentions. Addressing these challenges is essential for building an intelligent, reliable, and widely applicable conflict resolution system.

4. PROPOSED ML-BASED FRAMEWORK

4.1. Overall Architecture of the Intelligent Conflict Resolution System

The proposed framework integrates conflict detection, feature extraction, machine learning-based prediction, and decision support into a unified system. It begins with identifying and classifying conflicts in the codebase, extracts informative features from code changes, commit history, and developer activity, and feeds them into ML models to predict resolution strategies. The outputs are presented to developers through a recommendation module that highlights suggested resolutions, conflict types, and potential impacts. The architecture is designed for scalability, adaptability, and real-time integration with development workflows, ensuring practical usability in collaborative environments.

4.2. Modules

4.2.1. Conflict Detection and Classification

This module automatically identifies merge conflicts and classifies them into textual, semantic, or structural types. Detection involves parsing changes, comparing versions, and recognizing overlapping edits or structural modifications. Classification informs the resolution strategy, as different conflict types require different handling techniques. Accurate detection and classification are foundational to the system, ensuring that subsequent ML predictions are contextually relevant and reliable.

4.2.2. Feature Extraction from Code Changes and Commit History

Feature extraction transforms raw inputs into informative attributes for machine learning models. From code changes, features include line-level modifications, syntactic patterns, and semantic embeddings. From commit history, features include change frequency, file modification patterns, and prior resolutions. Developer metadata, such as experience and module ownership, is also incorporated. Together, these features enable the ML model to learn patterns that correlate with successful conflict resolutions.

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4.2.3. Machine Learning Model for Predicting Resolution Strategies

The ML model predicts optimal conflict resolution strategies based on extracted features. Supervised learning methods, sequence models, or hybrid approaches can be used to capture both textual and semantic aspects of code changes. The model outputs recommended actions, including code merges, refactoring suggestions, or alternative conflict resolutions, with associated confidence scores. This predictive capability reduces manual effort, improves accuracy, and supports faster integration in collaborative projects.

4.2.4. Decision Support and Recommendation Module

The decision support module presents ML predictions to developers in an interpretable and actionable manner. It highlights suggested resolutions, provides explanations for model recommendations, and allows developers to review alternative strategies. This module bridges the gap between automated prediction and human decision-making, ensuring that developers remain in control while benefiting from AI-driven assistance. Visualizations and interactive interfaces enhance usability and adoption in real-world development workflows.

4.3. Data Sources: Open-Source Repositories, Collaborative Development Histories

The framework leverages rich datasets from open-source repositories such as GitHub and Bitbucket, as well as industrial projects with collaborative version histories. These data sources provide diverse examples of conflicts, coding styles, and resolution strategies, enabling ML models to generalize across multiple contexts. Historical commit logs, issue trackers, and developer metadata offer the necessary context for accurate prediction, ensuring the system's effectiveness in real-world scenarios.

Table 1: Example Features Extracted for ML Model

Feature Category	Description	Example Values
Code Change Features	Characteristics of code	Lines added/removed, code churn, syntax changes
Commit History Features	Historical patterns of changes	Frequency of commits, prior conflict occurrence, file ownership
Developer Metadata	Information about contributors	Experience level, number of previous merges, module expertise
Semantic Features	Embeddings capturing code meaning	Function similarity scores, AST-based embeddings

Table 2: Evaluation Metrics for Conflict Resolution

Metric	Description	Formula / Interpretation
Resolution Accuracy	Percentage of conflicts correctly resolved	(Correct Resolutions / Total Conflicts) × 100
Developer Acceptance Rate	Fraction of ML suggestions accepted by developers	(Accepted Suggestions / Total Suggestions) × 100
Time Saved	Average reduction in resolution time per	Manual Time – ML-Assisted Time

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	conflict	
F1-Score	Harmonic mean of precision and recall for classification	2 × (Precision × Recall) / (Precision + Recall)

5. MACHINE LEARNING TECHNIQUES USED

5.1. Supervised Learning: Classification of Conflict Types and Resolution Strategies

Supervised learning is a foundational technique for predicting merge conflict resolution. Using labeled datasets of past conflicts and their successful resolutions, models such as decision trees, random forests, and support vector machines (SVMs) can classify the type of conflict (textual, semantic, or structural) and suggest appropriate resolution strategies. These models learn patterns from historical commit data, code changes, and developer actions, enabling them to generalize to new conflicts. Supervised learning is particularly effective for structured datasets where outcomes are known, providing interpretable predictions that developers can trust when automating conflict resolution.

5.2. Sequence Models (Rnns, Transformers) for Understanding Code Context

Merge conflicts often require understanding the broader context of code, including dependencies, function calls, and control flow. Sequence models such as Recurrent Neural Networks (RNNs) and Transformer architectures can capture these contextual relationships. RNNs are capable of modeling sequential dependencies in code lines or commits, while Transformers, with their attention mechanisms, can process long-range dependencies and capture semantic similarities between code segments. These models are particularly useful for resolving semantic conflicts where overlapping edits do not occur but logic inconsistencies arise, allowing the system to make context-aware recommendations.

5.3. Reinforcement Learning (Optional) for Adaptive Resolution Suggestions

Reinforcement learning (RL) can be applied to enable adaptive conflict resolution, where the system learns optimal strategies through trial and error over multiple resolution scenarios. By defining reward functions based on successful merge outcomes, reduced developer intervention, or minimal introduced errors, RL models can iteratively improve their conflict-handling policies. While optional, this approach allows the system to adapt to evolving codebases, team practices, and programming languages, providing more robust recommendations over time.

5.4. Hybrid Approaches Combining ML with Static Analysis or Rule-Based Heuristics

Hybrid approaches leverage both data-driven ML predictions and domain knowledge encoded in static analysis tools or rule-based heuristics. For example, while ML models predict resolution strategies, static analysis can ensure that the suggested merge does not introduce compilation errors, logical inconsistencies, or API violations. Combining heuristics with ML improves reliability, interpretability, and safety, particularly in industrial projects where incorrect merges can have significant consequences. This approach balances automation with developer oversight.

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5.5. Feature Engineering and Embedding Techniques for Code Representation

Feature engineering is critical for effective ML-based conflict resolution. Features may include textual characteristics of code changes, structural information from the abstract syntax tree (AST), commit metadata, and developer activity logs. Embedding techniques, such as code2vec or Graph Neural Networks (GNNs), transform code into dense vector representations capturing semantic and structural information. Proper feature selection and representation improve model accuracy, allow handling of diverse programming languages, and ensure that both syntactic and semantic aspects of conflicts are incorporated into the ML predictions.

6. EVALUATION AND EXPERIMENTS

6.1. Dataset Description

The system is evaluated using datasets from open-source repositories such as GitHub and industrial repositories with rich version histories. The datasets include conflicts across multiple programming languages, varying project sizes, and different types of merge conflicts (textual, semantic, structural). Each conflict entry contains code segments from both branches, commit history, developer metadata, and the manually or historically resolved merge result. This diversity ensures that ML models are tested under realistic and challenging scenarios, supporting generalization across different development environments.

6.2. Experimental Setup and Model Training

Experiments involve preprocessing the data, extracting relevant features, and splitting the dataset into training, validation, and test sets. Supervised models are trained on labeled conflicts to predict resolution strategies, while sequence models like RNNs and Transformers are trained on sequential code data to capture context. Hyperparameter tuning, cross-validation, and ablation studies are conducted to identify optimal model configurations. Some experiments also test hybrid and reinforcement learning approaches to evaluate their adaptability and robustness in dynamic project settings.

6.3. Evaluation Metrics: Resolution Accuracy, Developer Acceptance Rate, Time Saved

The effectiveness of the system is measured using multiple metrics. Resolution accuracy quantifies the percentage of conflicts correctly resolved by the ML model compared to ground truth. Developer acceptance rate measures the fraction of ML suggestions accepted in practice, reflecting trust and usability. Time saved evaluates the reduction in manual conflict resolution effort, providing practical insights into productivity gains. Additional metrics, such as precision, recall, and F1-score, are used for classification tasks, while sequence-based predictions are assessed using similarity measures between predicted and actual resolved code.

6.4. Results and Analysis

Experimental results indicate that ensemble and hybrid ML models perform best in predicting correct conflict resolutions, with high resolution accuracy and developer acceptance rates. Sequence models, particularly Transformers, excel at resolving semantic conflicts due to their ability to capture

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long-range code dependencies. Feature importance analysis reveals that commit metadata, code change patterns, and AST-based embeddings are critical for accurate predictions. The analysis highlights strengths, weaknesses, and scenarios where the system is most effective, providing guidance for further optimization and deployment in real development workflows.

6.5. Case Studies or Example Conflict Scenarios

Illustrative case studies demonstrate the system's practical application. For instance, a textual conflict in a Python project is automatically merged with minimal developer intervention, while a semantic conflict in a Java module is correctly resolved using Transformer-based predictions. These examples show how the system reduces manual effort, minimizes errors, and provides interpretable recommendations, enhancing collaboration and productivity in both open-source and enterprise development environments.

7. DISCUSSION

7.1. Insights from Experiments

The experiments reveal that ML-based conflict resolution can significantly reduce manual effort and increase resolution accuracy, particularly when combining supervised learning with context-aware sequence models. Sequence models are crucial for capturing semantic conflicts, while hybrid approaches improve reliability by incorporating rule-based checks. Feature analysis confirms the importance of both code-level and developer-level features in achieving robust predictions.

7.2. Comparison with Traditional Manual or Heuristic-Based Resolution Methods

Compared to manual resolution, the proposed system is faster, more consistent, and less error-prone. Traditional rule-based methods often fail in semantic or structural conflicts, while the ML-based system adapts to diverse scenarios and learns from historical patterns. However, manual intervention remains important for extremely complex conflicts, suggesting that the ML system is best used as a decision-support tool rather than a fully autonomous replacement.

7.3. Benefits, Limitations, and Practical Implications for Software Teams

The primary benefits include reduced conflict resolution time, higher accuracy, and actionable recommendations for developers. Limitations involve dependence on high-quality historical data, model generalization across programming languages, and computational requirements for sequence models. In practice, integrating the system into IDEs, continuous integration pipelines, or code review tools can streamline development, improve collaboration, and reduce the risk of faulty merges, enhancing overall software quality.

8. CONCLUSION AND FUTURE WORK

8.1. Summary of Contributions

This paper presents a machine learning-based framework for intelligent version control conflict resolution. The framework combines conflict detection, feature extraction, supervised and sequence-based ML models, and hybrid techniques with decision support to provide accurate and

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context-aware conflict resolution suggestions. Experimental results on real-world datasets demonstrate the system's effectiveness in reducing manual effort, improving resolution accuracy, and supporting collaborative software development.

8.2. Potential Improvements (Real-Time Conflict Prediction, IDE Integration, Multi-Language Support)

Future enhancements could include real-time conflict prediction as developers work, seamless integration with popular IDEs and version control platforms, and support for multiple programming languages to improve generalization. Incorporating continuous learning from new commits and developer feedback can further enhance accuracy and adaptability.

8.3. Future Research Directions

Future research may explore reinforcement learning for adaptive, long-term conflict resolution strategies, graph-based models for better semantic understanding of code, and transfer learning to leverage knowledge across projects. Additionally, investigating interpretability techniques to explain model predictions will increase developer trust and adoption.

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