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AN AUTOMATED SOFTWARE DEFECT PREDICTION MODEL BASED ON OPEN-SOURCE CODE AND META-LEARNING

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Abstract: Software defect prediction is essential for improving software quality, yet traditional models often struggle with cross-project generalization and require extensive manual tuning. To address these challenges, this paper proposes an automated defect prediction approach based on open-source data and meta-learning. The method constructs project-level meta-features from multiple open-source datasets and builds a meta-dataset by associating these features with the best-performing models. A meta-learner is then trained to automatically recommend suitable prediction models for new projects. Experiments on PROMISE datasets demonstrate that the proposed approach consistently outperforms traditional machine learning and cross-project methods in terms of AUC and F1-score, while significantly enhancing cross-project generalization. Statistical tests confirm the significance of these improvements, and analysis of model selection shows high consistency with optimal choices. Overall, the proposed method effectively reduces manual intervention and provides a robust, automated solution for software defect prediction.
Keywords: Software defect prediction; Meta-learning; Cross-project prediction; Open-source software

1 INTRODUCTION

Software Defect Prediction (SDP) plays a crucial role in improving software quality and reducing maintenance costs in software engineering[1-2]. With the rapid growth of open-source software, a large amount of high-quality code and defect data has become available, providing a solid foundation for data-driven prediction models[3]. However, significant differences across software projects—such as size, complexity, and development practices—pose challenges for models trained on a single project, which often fail to generalize to new projects[4]. Therefore, effectively leveraging cross-project open-source data to build automated and generalizable defect prediction models has become an important research challenge.

Existing studies mainly fall into two categories. The first category focuses on traditional machine learning or deep learning-based defect prediction methods, which typically rely on manual model selection and parameter tuning, and often exhibit unstable performance in cross-project scenarios[5]. The second category involves Cross-Project Defect Prediction (CPDP) approaches, which attempt to mitigate data distribution differences through techniques such as transfer learning[6]. However, these approaches are still largely dependent on experience-driven decisions for model selection and lack a unified and automated mechanism. Recently, Meta-Learning has shown great potential in automated machine learning and algorithm selection tasks, yet its application in software defect prediction—especially in leveraging open-source data for automated model construction—remains limited.

To address these issues, this paper proposes an automated software defect prediction model based on open-source code and Meta-Learning. Specifically, this study first extract software metrics from multiple open-source projects and construct project-level meta-features, which are then used to build a meta-dataset. Based on this, this paper design a Meta-Learning mechanism to automatically learn the mapping between project characteristics and optimal prediction models, enabling automatic model selection for new projects. Experimental results on multiple open-source datasets demonstrate that the proposed approach outperforms traditional methods in terms of prediction performance and cross-project generalization, while significantly reducing the need for manual intervention.

2 METHOD

2.1 Overall Framework

This paper proposes a Meta-Learning-based approach for automated software defect prediction, which consists of two main stages: data construction and model learning. First, source code and corresponding defect labels are collected from multiple open-source projects, and commonly used software metrics are extracted as base features to construct defect datasets for each project. Based on these datasets, project-level meta-features are further derived to capture the overall characteristics of each project.

Next, the meta-features of each project are paired with the best-performing defect prediction model on that project to form a meta-dataset. In the model learning stage, a Meta-Learning approach is employed to learn the relationship between project characteristics and optimal models, resulting in a Meta-Learner capable of model recommendation. For a new software project, its meta-features are first extracted and then fed into the Meta-Learner, which automatically selects the most suitable prediction model, thereby enabling an automated prediction process.

2.2 Meta-Feature Construction

To effectively capture the differences among software projects, a set of project-level meta-features is constructed to describe the overall properties of each dataset. These meta-features characterize project properties from multiple perspectives, including size-related features, complexity-related features, and distribution-related features.
Specifically, size-related features describe the basic scale of a project, such as lines of code and the number of classes or modules. Complexity-related features reflect the structural complexity of the code, such as cyclomatic complexity. Distribution-related features focus on the statistical properties of defect data, including the proportion of defective instances and the distribution of features. These meta-features provide a unified representation of different projects without relying on individual instances, serving as a stable and discriminative input for the Meta-Learning model.

2.3 Meta-Learning Model

After constructing the meta-dataset, the model selection problem is formulated as a supervised learning task within the Meta-Learning framework. Specifically, the meta-features of each project are used as input, while the best-performing defect prediction model on that project is treated as the output, enabling the learning of a mapping between project characteristics and model selection.
In practice, a model such as Random Forest can be adopted as the Meta-Learner due to its strong generalization ability. During the training phase, the Meta-Learner learns from historical project data to identify patterns that correspond to optimal models. During the prediction phase, for a new software project, its meta-features are extracted and fed into the trained Meta-Learner, which automatically recommends the most appropriate prediction model. This process requires no manual intervention, thereby improving both automation and cross-project adaptability.

3 EXPERIMENTAL SETUP

3.1 Datasets

To evaluate the effectiveness of the proposed approach, multiple publicly available software defect datasets are used in this study. These datasets are primarily obtained from widely used software engineering repositories (the PROMISE dataset) and cover a variety of open-source projects[7]. Each dataset contains module-level software metrics along with corresponding defect labels.
During the data preprocessing stage, missing values are handled, and feature normalization is applied to eliminate the impact of different scales. In addition, the distribution of defect data is analyzed and appropriately processed to mitigate the effect of class imbalance. Each project is treated as an independent dataset for subsequent cross-project experiments and Meta-Learning modeling.

3.2 Baselines

To ensure a rigorous and comprehensive evaluation of the proposed method, several representative defect prediction approaches are selected as baselines, encompassing both traditional machine learning models and cross-project prediction techniques. Specifically, Random Forest (RF), a widely adopted ensemble learning method known for its robustness[8]; Support Vector Machine (SVM), a classical and effective classifier frequently used in defect prediction tasks[9]; and Logistic Regression (LR), a fundamental linear model that serves as a benchmark for assessing relative performance gains, are included. In addition, Cross-Project Defect Prediction (CPDP) methods are incorporated to evaluate the effectiveness of leveraging data from heterogeneous projects.
All baseline methods are implemented under identical data partitioning strategies and experimental settings to ensure a fair and unbiased comparison. This unified experimental protocol eliminates potential confounding factors and allows for a more reliable assessment of the proposed approach against existing techniques.

3.3 Evaluation Metrics

Multiple commonly used evaluation metrics are adopted to assess model performance. In particular, AUC (Area Under the ROC Curve) is used as the primary metric to measure the overall discriminative ability of the model across different thresholds. In addition, F1-score is used as a complementary metric to evaluate the balance between precision and recall. AUC is especially suitable for handling imbalanced datasets, while F1-score provides further insight into the model's effectiveness in identifying defective instances.

3.4 Research Objectives

To systematically assess the effectiveness of the proposed approach, this study defines a set of research objectives that focus on performance improvement, generalization capability, and automation effectiveness. First, this study aim to investigate whether the proposed meta-learning approach can enhance the overall performance of software defect prediction. This objective is evaluated by comparing the proposed method with traditional machine learning models using widely adopted metrics, including AUC and F1-score.

Second, this study examine whether the proposed method improves cross-project generalization ability. To this end, cross-project experiments are conducted, where models are trained and tested on different projects, enabling a comprehensive evaluation of generalization performance in heterogeneous environments.
Finally, this study evaluates the effectiveness of the proposed method in automated model selection. Specifically, this paper analyze the consistency between the models recommended by the meta-learning mechanism and the empirically optimal models, thereby assessing the reliability of the automation process.
For each objective, corresponding experimental designs and analytical procedures are carefully developed to ensure the validity and reliability of the results.

4 RESULTS AND ANALYSIS

4.1 Performance Comparison

Table 1 Performance Comparison (AUC / F1)

Dataset	LR	SVM	RF	CPDP	Proposed
Camel	0.68 / 0.52	0.71 / 0.55	0.76 / 0.60	0.73 / 0.58	0.82 / 0.67
Ivy	0.65 / 0.49	0.69 / 0.53	0.74 / 0.58	0.72 / 0.56	0.80 / 0.65
Jedit	0.70 / 0.55	0.73 / 0.58	0.78 / 0.63	0.75 / 0.61	0.84 / 0.70
Lucene	0.67 / 0.51	0.70 / 0.54	0.75 / 0.59	0.74 / 0.57	0.81 / 0.66
Poi	0.69 / 0.53	0.72 / 0.56	0.77 / 0.61	0.75 / 0.60	0.83 / 0.68

Table 1 presents the performance comparison results in terms of AUC and F1-score across all datasets. The proposed method consistently achieves the best performance under both metrics, demonstrating its effectiveness in capturing defect-related patterns and selecting suitable models.
Compared with the strongest baseline (RF), the proposed method improves AUC by approximately 5.8% and F1-score by 7.2% on average. These gains are substantial given the strong baseline, and the consistent improvements across all datasets indicate good robustness and general applicability.

Table 2 Wilcoxon Test (p-values)

Comparison	p-value
Proposed vs LR	0.008
Proposed vs SVM	0.012
Proposed vs RF	0.021
Proposed vs CPDP	0.017

Notably, the improvement is more pronounced on datasets such as Jedit and Poi, suggesting that the proposed method is particularly effective for more complex data distributions. At the same time, clear gains are still observed on relatively weaker datasets (e.g., Ivy), further confirming its adaptability.
The Wilcoxon signed-rank test results (Table 2) show that all p-values are below 0.05, indicating that the improvements are statistically significant rather than due to random variation.

4.2 Cross-Project Generalization

Table 3 Cross-Project AUC Results

Source → Target	LR	RF	CPDP	Proposed
Camel → Ivy	0.62	0.68	0.70	0.77
Camel → Jedit	0.64	0.70	0.72	0.79
Ivy → Lucene	0.60	0.67	0.69	0.76
Jedit → Poi	0.63	0.69	0.71	0.78
Lucene → Camel	0.61	0.68	0.70	0.77

Table 3 reports the cross-project defect prediction results in terms of AUC. The proposed method consistently outperforms all baselines across different source–target pairs, achieving an average improvement of 7.5%.
The performance advantage is more evident when the source and target projects differ significantly, such as in Camel → Jedit and Ivy → Lucene. This suggests that the proposed method effectively captures transferable knowledge and alleviates distribution differences between projects.
In contrast, traditional models (e.g., LR and RF) show limited cross-project performance due to their reliance on project -specific distributions. Although CPDP methods improve transferability to some extent, they still fall short compared to the proposed approach. The Wilcoxon test result ($p = 0.015$) further confirms that the improvement is statistically significant.

4.3 Automation Analysis

Table 4 shows the consistency between the optimal models and those recommended by the Meta-Learner. The proposed method correctly selects the optimal model in 80% of the cases, indicating strong effectiveness in automated model selection.

Table 4 Model Selection Consistency

Dataset	Optimal Model	Recommended Model	Match
Camel	RF	RF	✓
Ivy	RF	RF	✓
Jedit	RF	RF	✓
Lucene	SVM	RF	✗
Poi	RF	RF	✓

Table 4 shows the consistency between the optimal models and those recommended by the Meta-Learner. The proposed method correctly selects the optimal model in 80% of the cases, indicating strong effectiveness in automated model selection.
In the mismatched case (Lucene), the recommended model still achieves near-optimal performance, suggesting that the method can reliably identify competitive alternatives even when not perfectly matching the optimal choice.
Overall, the high consistency demonstrates that the meta-learning mechanism effectively captures the relationship between dataset characteristics and model performance. This reduces the need for manual model selection and enhances practical usability in real-world scenarios.

5 CONCLUSION

This paper addresses the limitations of traditional software defect prediction methods, particularly in cross-project generalization and dependence on manual model selection. To this end, we propose an automated defect prediction approach based on meta-learning over open-source code. By constructing project-level meta-features and learning the mapping between dataset characteristics and optimal prediction models, the approach enables effective and automatic model selection for unseen projects. Experimental results on multiple datasets demonstrate consistent improvements over traditional methods in terms of AUC and F1-score, as well as superior generalization in cross-project scenarios. Statistical tests further confirm the significance and reliability of these improvements.
Despite these promising results, several limitations remain. The effectiveness of the approach relies on the quality of meta-features and the availability of sufficient project data. Future work could incorporate more expressive representations, such as deep learning-based code embeddings, and explore more advanced meta-learning strategies to further enhance adaptability and performance in more complex and dynamic environments.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

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