IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

A DEVELOPER CENTERED BUG PREDICTION MODEL

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ABSTRACT

Software bugs are a critical challenge in the development lifecycle, impacting product quality, user satisfaction, and maintenance costs. Traditional bug prediction models often focus on static code metrics or historical bug data, without considering the developer-centric context. This paper proposes a Developer-centered bug prediction model that leverages both code-level features and developer-specific behavioral patterns to enhance prediction accuracy. The model integrates features such as code complexity, change history, developer expertise, and commit frequency, using advanced machine learning techniques like ensemble learning and deep neural networks. We validate our approach on real-world datasets from open-source repositories, demonstrating significant improvements over conventional models in terms of precision, recall, and F1-score. The results suggest that incorporating developer-related factors provides a more nuanced understanding of bug-prone code, enabling more targeted and effective bug management strategies.

Keywords: Bug Prediction, Developer-Centric Analysis, Change Scattering, Code Quality Assessment, Predictive modeling, Logistic Regression, Cross-Validation, Code Change Patterns, Developer behavior Analysis, Static Code Analysis, Model Evaluation, Software Reliability.

INTRODUCTION

Bug prediction is a crucial task in software development, aiming to identify defect-prone code areas early in the lifecycle. Traditional models primarily rely on code metrics and historical bug data, often overlooking the influence of developer behavior and context.

A developer-centered bug prediction model addresses this gap by integrating both code-level features and developer-specific factors such as coding patterns, commit history, and expertise. By leveraging machine learning techniques, this model offers a more holistic approach, improving the accuracy of bug detection and enabling targeted interventions. This shift from a purely code-centric to a developer-aware perspective enhances software quality and optimizes resource allocation in development teams.

Bug prediction is an essential task in software maintenance, as it allows teams to allocate resources effectively and focus their efforts on problematic areas of the codebase. Traditional models rely on static code attributes such as lines of code (LOC), cyclomatic complexity, and code churn. While these metrics provide valuable insights, they do not account for the influence of developer behaviour on software quality. Developers work in teams, collaborate on various tasks, and have different skill levels, which all play a role in defect introduction and resolution. By integrating developer-related attributes, a bug prediction model can offer a

more holistic view of defect-prone areas, making it a valuable tool for software quality assurance.

LITERATURE SURVEY

Zimmermann et al. (2007) [1] emphasized the use of historical defect data to train classifiers for software modules. While this model was effective to some extent, but lacked adaptability across projects and often failed to generalize due to the absence of human-related dynamics in the process.

Kamei et al. (2013) [2] proposed **Just-In-Time (JIT) defect prediction**, using features at the change-level instead of file-level. However, these models often still overlooked the individual **developer's role** and behavioral patterns behind the changes.

Rahman and Devanbu (2013) [3] investigated whether social factors and developer reputation influence software quality. **Developer experience**, **focus**, **task switching**, and **collaboration patterns**.

Hall et al. (2012) [4] This study provides a comprehensive review of fault prediction models, evaluating their performance across different datasets and metrics. It highlights the variability in results and stresses the need for consistent evaluation frameworks.

Kim et al. (2007) [5] The authors propose a history-based fault prediction method using change history logs, demonstrating that historical change metrics can effectively predict future faults in software components.

Menzies et al. (2007) [6] This work applies data mining techniques to static code attributes to construct defect predictors, showing that simple models built from code metrics can perform comparably to complex ones.

Yang et al. (2015) [7] The paper introduces a deep learning-based approach for Just-In-Time (JIT) defect prediction, significantly improving prediction accuracy by automatically learning feature representations from software change data.

Shivaji et al. (2009) [8] This research focuses on feature selection techniques to improve bug prediction accuracy, demonstrating that reducing irrelevant or redundant features enhances classifier performance.

Nam et al. (2018) [9] A systematic review of automated defect prediction techniques is presented, identifying current trends, gaps, and suggesting future directions including deep learning and cross-project prediction.

Zhang & Wu (2018) [10] The study investigates developer-centric features in defect prediction, revealing that incorporating developer behavior and expertise can lead to more accurate and personalized predictions.

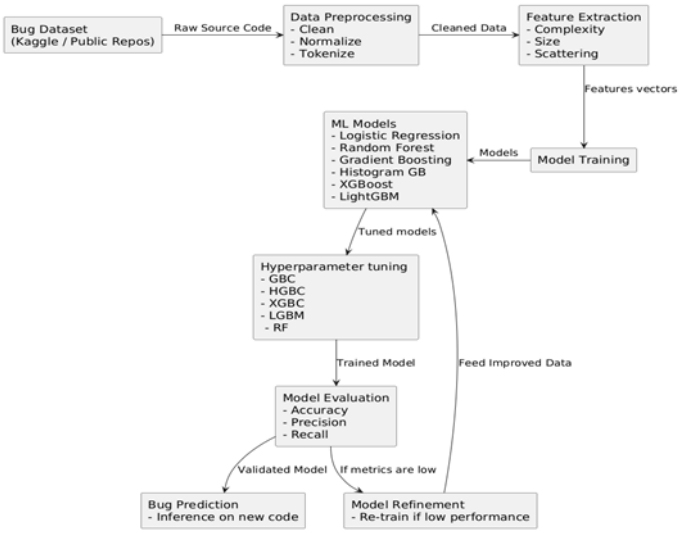
EXISTING SYSTEM

Current bug prediction systems primarily focus on static code metrics, historical defect data, and machine learning algorithms like decision trees, SVMs, and neural networks. Models such as **BUGZILLA**, **JPredict**, and **SZZ Algorithm** have been widely used to identify defect-prone code areas based on code complexity, change history, and commit patterns. However, these systems often overlook the impact of developer-specific factors like coding habits, expertise, and collaboration patterns.

While some recent models attempt to integrate developer behavior, they still lack a comprehensive approach that effectively combines code features with developer-centric insights. This gap highlights the need for a **developer-centered bug prediction model** to improve accuracy and contextual relevance in defect de

- Ignorance of Human Factors
- Lack of Developer Focus Consideration

PROPOSED SYSTEM ARCHITECTURE



The proposed developer-centered bug prediction model aims to address the limitations of existing defect prediction systems by integrating developer-centric attributes alongside traditional code-based and process-based metrics. This approach enhances the accuracy, interpretability, and applicability of defect prediction while promoting proactive defect management in software development.

The primary objective of the proposed system is to incorporate developer-related factors such as coding behaviour, expertise, collaboration patterns, and workload distribution into the bug prediction framework. By leveraging these insights, the model provides a more holistic view of defect introduction, allowing software teams to mitigate risks more effectively.

Key Features of the Proposed System: Developer-Centered Bug Prediction Model

1. **Integrated Data Analysis:** Combines code metrics with developer-specific data (e.g., commit history, coding patterns).
2. **Advanced Machine Learning Algorithms:** Utilizes models like ensemble learning and deep neural networks for accurate bug prediction.
3. **Developer Behaviour Insights:** Analyzes developer activity to identify patterns linked to defect-prone code.
4. **Real-Time Prediction:** Provides timely identification of bug-prone areas during the development process.
5. **Continuous Learning:** Adapts to new data, improving prediction accuracy over time.
6. **Scalability & Flexibility:** Supports large-scale projects and integrates with version control systems like Git.

METHODOLOGY

The developer-centered bug prediction model follows a systematic approach to enhance defect detection accuracy by integrating code-level features with developer-specific data. The methodology involves the following steps:

- **Data Collection**: Gather datasets from software repositories, including code metrics, commit history, and developer activity.
- **Data Preprocessing**: Clean & preprocess the data to handle missing values, normalize features, & remove noise.
- **Feature Selection**: Identify relevant features such as code complexity, change frequency, developer expertise, and code review patterns
- **Model Development:** Apply machine learning algorithms like ensemble methods, decision trees, and neural networks to build predictive models.
- **Evaluation Metrics:** Assess the model using metrics like accuracy, precision, recall, and F1-score to measure its effectiveness.
- **Result Analysis:** Compare the developer-centered model's performance with traditional models to highlight improvements.

RESULTS & ANALYSIS

```
train.describe().T
```

	count	mean	std	min	25%	50%	75%	max
loc	101763.0	37.347160	54.600401	1.0	13.00	22.00	42.00	3442.00
v(g)	101763.0	5.492684	7.900855	1.0	2.00	3.00	6.00	404.00
ev(g)	101763.0	2.845022	4.631262	1.0	1.00	1.00	3.00	165.00
iv(g)	101763.0	3.498826	5.534541	1.0	1.00	2.00	4.00	402.00
n	101763.0	96.655995	171.147191	0.0	25.00	51.00	111.00	8441.00
v	101763.0	538.280956	1270.791601	0.0	97.67	232.79	560.25	80843.08
l	101763.0	0.111634	0.100096	0.0	0.05	0.09	0.15	1.00
d	101763.0	13.681881	14.121306	0.0	5.60	9.82	18.00	418.20
i	101763.0	27.573007	22.856742	0.0	15.56	23.36	34.34	569.78
e	101763.0	20853.589876	190571.405427	0.0	564.73	2256.23	10193.24	16846621.12
b	101763.0	0.179164	0.421844	0.0	0.03	0.08	0.19	26.95
t	101763.0	1141.357982	9862.795472	0.0	31.38	125.40	565.92	935923.39
lOCode	101763.0	22.802453	38.541010	0.0	7.00	14.00	26.00	2824.00
lOComment	101763.0	1.773945	5.902412	0.0	0.00	0.00	1.00	344.00
lOBlank	101763.0	3.979865	6.382358	0.0	1.00	2.00	5.00	219.00
locCodeAndComment	101763.0	0.196604	0.998906	0.0	0.00	0.00	0.00	43.00
uniq_Op	101763.0	11.896131	6.749549	0.0	8.00	11.00	16.00	410.00
uniq_Opnd	101763.0	15.596671	18.064261	0.0	7.00	12.00	20.00	1026.00
total_Op	101763.0	57.628116	104.537660	0.0	15.00	30.00	66.00	5420.00
total_Opnd	101763.0	39.249698	71.692309	0.0	10.00	20.00	45.00	3021.00
branchCount	101763.0	9.839549	14.412769	1.0	3.00	5.00	11.00	503.00

Figure 1: Exploratory Data Analysis

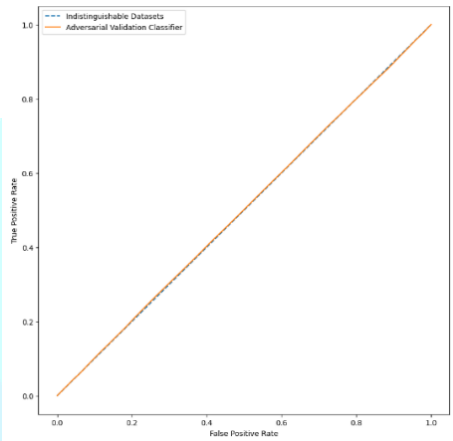


Figure 2: Training-Test Adversarial Validation

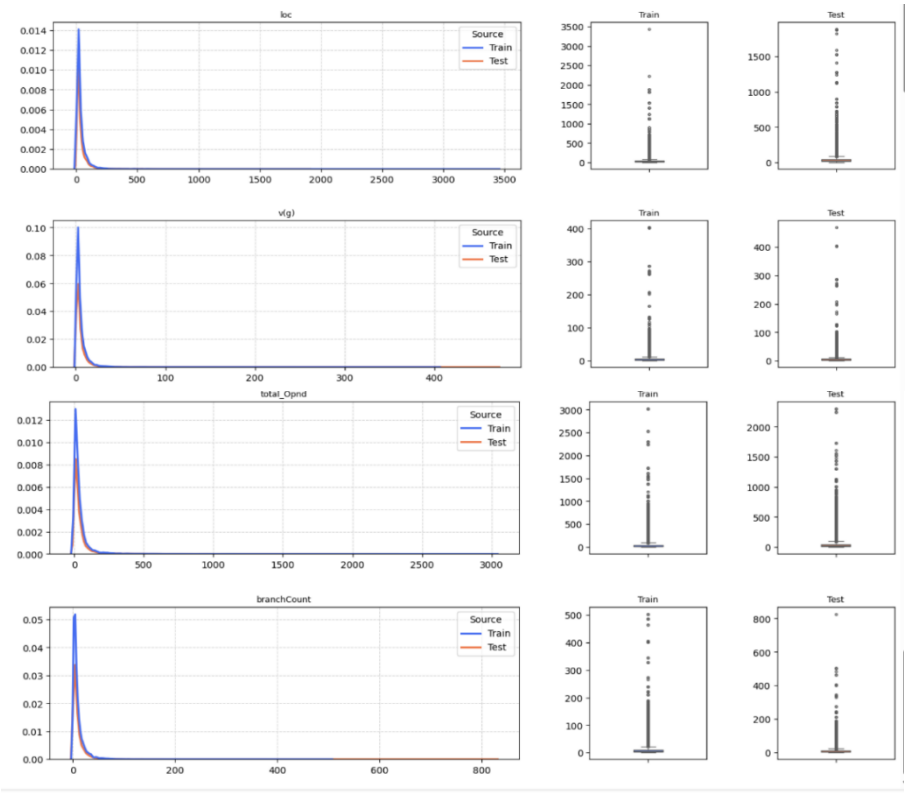


Figure 3: Feature Distribution Analysis - Train vs Test Dataset

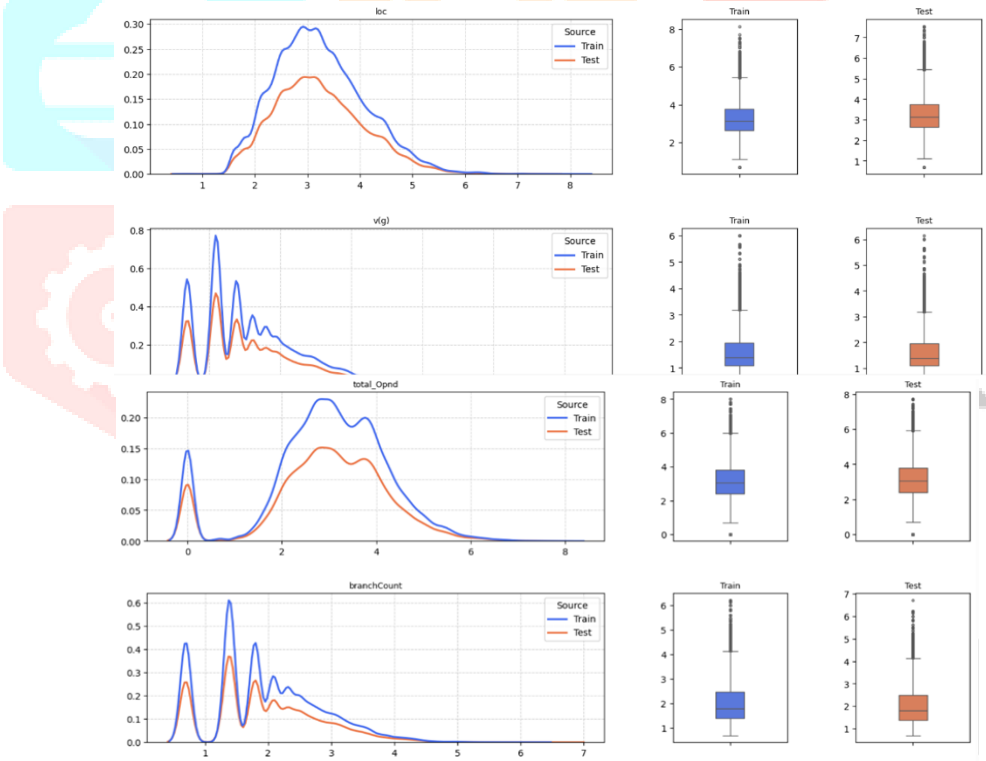
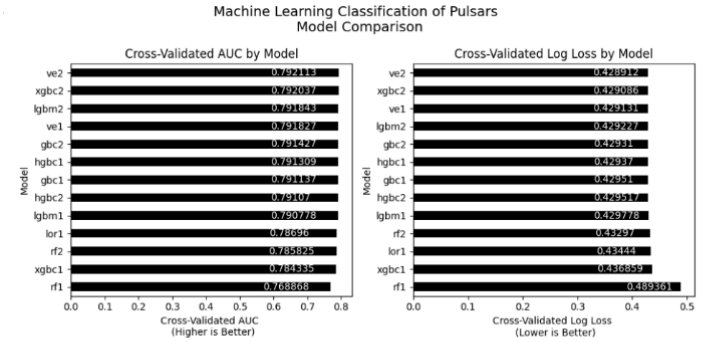


Figure 4: Skewness Reduction with Log Transform - Visualizing Numerical Features



	Model	Model Alias	Detail	Precision	Recall	F1-score	Cross-Validated Accuracy	Cross-Validated Log Loss	Cross-Validated AUC
0	Logistic Regression	lor1	Default, Scaled	0.671107	0.349220	0.459390	0.812545	0.434440	0.786960
1	Random Forest	rf1	Default, Scaled	0.619687	0.360052	0.455467	0.807956	0.489361	0.768868
2	Gradient Boosting	gbc1	Default, Scaled	0.644163	0.396880	0.491153	0.814952	0.429510	0.791137
3	Histogram-Based Gradient Boosting	hgbc1	Default, Scaled	0.643934	0.388648	0.484734	0.814363	0.429370	0.791309
4	XGBoost	xgbc1	Default, Scaled	0.626189	0.370884	0.465850	0.810638	0.436859	0.784335
5	Light Gradient Boosted Machine	lgbm1	Default, Scaled	0.641590	0.391681	0.486414	0.813862	0.429778	0.790778
6	Gradient Boosting	gbc2	Tuned, Scaled	0.648069	0.392548	0.488937	0.814589	0.429310	0.791427
7	Histogram-Based Gradient Boosting	hgbc2	Tuned, Scaled	0.647482	0.389948	0.486750	0.814097	0.429517	0.791070
8	XGBoost	xgbc2	Tuned, Scaled	0.655298	0.391248	0.489962	0.814952	0.429086	0.792037
9	Light Gradient Boosted Machine	lgbm2	Tuned, Scaled	0.644224	0.393847	0.488841	0.814402	0.429227	0.791843
10	Random Forest	rf2	Tuned, Scaled	0.646583	0.381282	0.479695	0.813459	0.432970	0.785825
11	Voting Ensemble	ve1	GBC2+HGBC2+XGBC2+RF2+LGBM2, Scaled, Soft Voting	0.645390	0.394281	0.489510	0.814992	0.429131	0.791827
12	Voting Ensemble	ve2	GBC2+HGBC2+XGBC2+RF2+LGBM2, Scaled, Weighted S...	0.646515	0.393847	0.489499	0.815011	0.428912	0.792113

Figure 5: Evaluating Models Using Cross-Validated AUC and Log Loss Metrics

```
X_test = pd.read_csv('/content/test.csv', index_col='id')
X_test.columns
```

```
Index(['loc', 'v(g)', 'ev(g)', 'iv(g)', 'n', 'v', 'l', 'd', 'i', 'e', 'b', 't',
       'lOCode', 'lOComment', 'lOBlank', 'locCodeAndComment', 'uniq_Op',
       'uniq_Opnd', 'total_Op', 'total_Opnd', 'branchCount'],
      dtype='object')
```

```
y_prob = ve2.predict_proba(X_test)[:, 1]
submission = pd.DataFrame({'id': X_test.index, 'defects': y_prob})
#submission.to_csv('data/submission.csv', index=False)
submission.to_csv('submission.csv', index=False)
submission.head()
```

	id	defects
0	101763	0.250349
1	101764	0.193368
2	101765	0.662278
3	101766	0.475650
4	101767	0.146661

Figure 6: Final Prediction Output: Bug Occurrence Probability by ID

CONCLUSION

The developer-centered bug prediction model represents an innovative approach to software defect detection by integrating developer-centric metrics with traditional code-based methods. By considering factors such as developer expertise, coding behaviour, and collaboration patterns, this model provides a more comprehensive and accurate prediction mechanism. Unlike conventional models rely primarily on historical defect data, this approach leverages machine learning techniques to analyze real-time code changes and developer activities, enabling early detection of potential defects. This proactive strategy helps development teams address issues before they become critical, ultimately improving software quality and maintainability. The integration of interactive dashboards and visualization tools ensures that developers and project managers can easily interpret defect trends and make informed decisions. Scalability and security are also key aspects of the system, allowing seamless integration into various software development environments while maintaining data privacy and ethical considerations. By fostering a culture of continuous quality improvement, this model not only reduces debugging and maintenance costs but also enhances overall productivity. As organizations increasingly prioritize software reliability, adopting such a developer-focused bug prediction model will be instrumental in shaping the future of software engineering.

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