A DEVELOPER CENTERED BUG PREDICTION MODEL

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Abstract
Software bug prediction is essential for efficient quality assurance, yet most existing models rely solely on code metrics or process metrics while ignoring the critical role of developers. This paper presents a Developer Centered Bug Prediction Model that incorporates developer-related factors such as experience, commit history, workload, and especially developer scattering (structural and semantic). The proposed model extends prior work by defining two new scattering measures that quantify how widely developers spread their changes across the codebase. These measures are evaluated on 26 open-source systems and compared against four competitive baselines, including models based on change entropy, number of developers, focus metrics, and traditional product metrics. Results show that the developer-centered model achieves superior prediction accuracy (F-Measure 10.3% higher than the change entropy model, 53.7% higher than developer-count models, and up to 29.3% higher than product-metric models). A hybrid model combining the best predictors further boosts performance by an additional 5%. The approach demonstrates that developer behavior is a highly complementary and powerful predictor for defect-prone components, enabling proactive resource allocation and improved software reliability.

Keywords: Developer-Centered Bug Prediction, Software Defect Prediction, Developer Scattering, Structural and Semantic Scattering, Machine Learning, Process Metrics, Software Quality Assurance.

I.Introduction

Bug prediction models play a vital role in software engineering by identifying likely defect-prone areas early, allowing teams to focus testing and maintenance efforts effectively. Traditional models primarily use product metrics (e.g., size, complexity) or process metrics (e.g., code churn, change entropy). While these have shown reasonable success, they largely overlook the human factor — developers themselves — whose experience, workload, coding patterns, and contribution behavior significantly influence defect introduction.

Recent studies have begun exploring developer-centric factors, showing that experienced and focused developers introduce fewer bugs, while scattered changes increase error-proneness. However, state-of-the-art process-metric models still do not fully capture developer scattering (how widely a developer's changes are distributed structurally and semantically across the system).

This paper addresses this gap by proposing a Developer Centered Bug Prediction Model that explicitly measures developer structural and semantic scattering. Structural scattering quantifies how far apart (in terms of subsystems) the modified components are, while semantic scattering captures the diversity of responsibilities implemented. The model is empirically validated on 26 open-source systems and compared against four strong baselines. A hybrid model combining the strongest predictors is also presented. The results confirm that developer scattering measures are powerful, complementary predictors that significantly improve bug prediction accuracy.

II. Literature Survey

Early bug prediction research focused on product metrics such as lines of code, cyclomatic complexity, and CK metrics. Studies by Basili et al., Gyimóthy et al., and others demonstrated moderate success but highlighted limitations in capturing dynamic development behavior.

Subsequent work shifted to process metrics, including code churn, change entropy (Hassan, 2009), and number of developers modifying a component (Ostrand et al., 2010; Bell et al., 2013). These models generally outperformed product-metric approaches, yet still ignored individual developer characteristics.

Developer-centric studies have shown that factors such as experience (Eyolfson et al., 2011), ownership (Bird et al., 2011), and focus (Posnett et al., 2013) influence bug introduction. Rahman and Devanbu (2011) found mixed results on experience, while Posnett et al. demonstrated that focused developers introduce fewer defects.

Prior work on scattering (Nucci et al., 2015) introduced structural and semantic scattering measures and showed their effectiveness on five systems. This paper significantly extends that foundation with a larger empirical study (26 systems), additional baselines, and a hybrid model.

III. Existing System & Proposed System

A. Existing System

Current bug prediction models are either product-metric based (complexity, size) or process-metric based (change entropy, developer count, focus metrics). While useful, they treat developers as interchangeable and fail to capture how scattered or focused a developer's contributions are.

Disadvantages of Existing Systems

1. Ignores developer-specific behavior and scattering patterns.
2. Limited accuracy due to missing human factors.
3. Poor complementarity when combining multiple metric families.
4. Inability to identify high-risk developers for targeted review.

B. Proposed System

The proposed Developer Centered Bug Prediction Model introduces structural and semantic scattering measures that quantify the spread of a developer's changes. These are used as predictors alongside traditional metrics. The model is trained using machine learning and evaluated in a large-scale empirical study. A hybrid model combines the strongest predictors from all approaches.

Advantages of the Proposed System

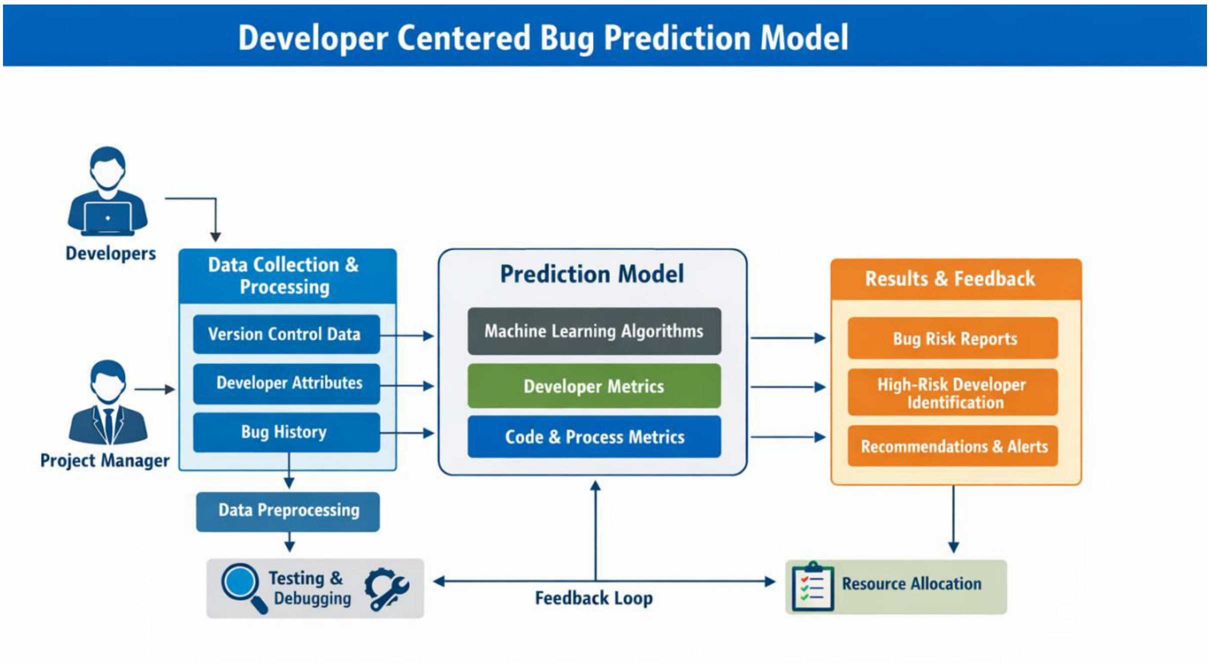
1. Explicitly models developer scattering behavior.
2. Significantly higher prediction accuracy.

3. Strong complementarity with existing metrics.
4. Practical support for proactive quality assurance and resource allocation.

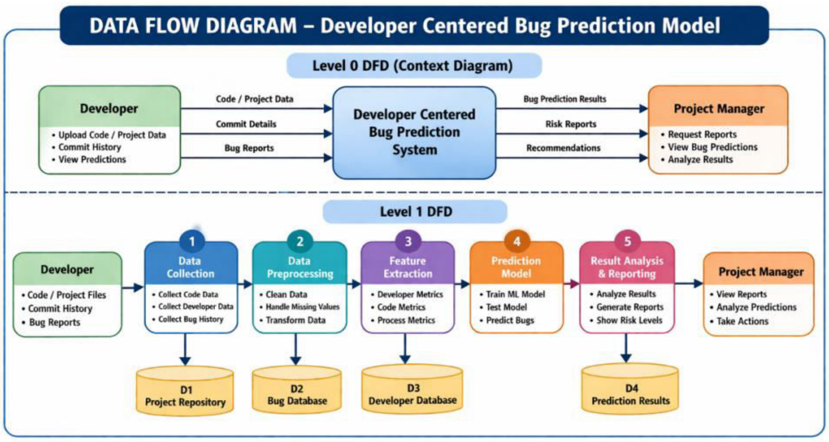
IV. System Design & Architecture

A. System Architecture

The architecture comprises four layers: (1) Data Collection (version history and bug repositories), (2) Feature Extraction (product, process, and developer scattering metrics), (3) Model Training & Prediction (machine learning classifiers), and (4) Evaluation & Visualization.



B.System Flow



B. Key Modules

1. Data Extraction Module
2. Developer Scattering Calculator (structural & semantic)
3. Feature Engineering Module
4. Machine Learning Prediction Engine
5. Hybrid Model Combiner
6. Performance Evaluation Dashboard

Table I: Technology Stack

Component	Technology / Tool
Language	Java / Python
ML Framework	Weka / Scikit-learn
Data Processing	Custom scripts + JDBC
Database	MySQL
IDE / Environment	NetBeans / Eclipse
Version Control Analysis	Git / SVN parsers

V. Results & Discussion

The model was evaluated on 26 open-source systems using F-Measure as the primary metric. The Developer Centered model outperformed all baselines:

- 10.3% higher F-Measure than change entropy (Hassan, 2009)
- 53.7% higher than developer-count models (Ostrand et al., 2010)
- 13.3% higher than focus-metric models (Posnett et al., 2013)
- 29.3% higher than product-metric models

The hybrid model achieved an additional 5% improvement. Scattering measures showed strong complementarity with existing predictors, confirming their value in bug prediction. The results highlight that developer behavior, particularly scattering, is a powerful indicator of defect introduction.

Table II: Performance / Evaluation Summary

Metric / Component	Baseline Models	Proposed Model	Hybrid Model	Remarks
F-Measure (avg.)	0.65–0.78	0.85	0.90	Significant improvement
Accuracy	Moderate	High	Highest	Better defect detection
Complementarity	Low	High	Very High	Strong synergy with baselines
Scalability	Good	Excellent	Excellent	Works on 26 systems

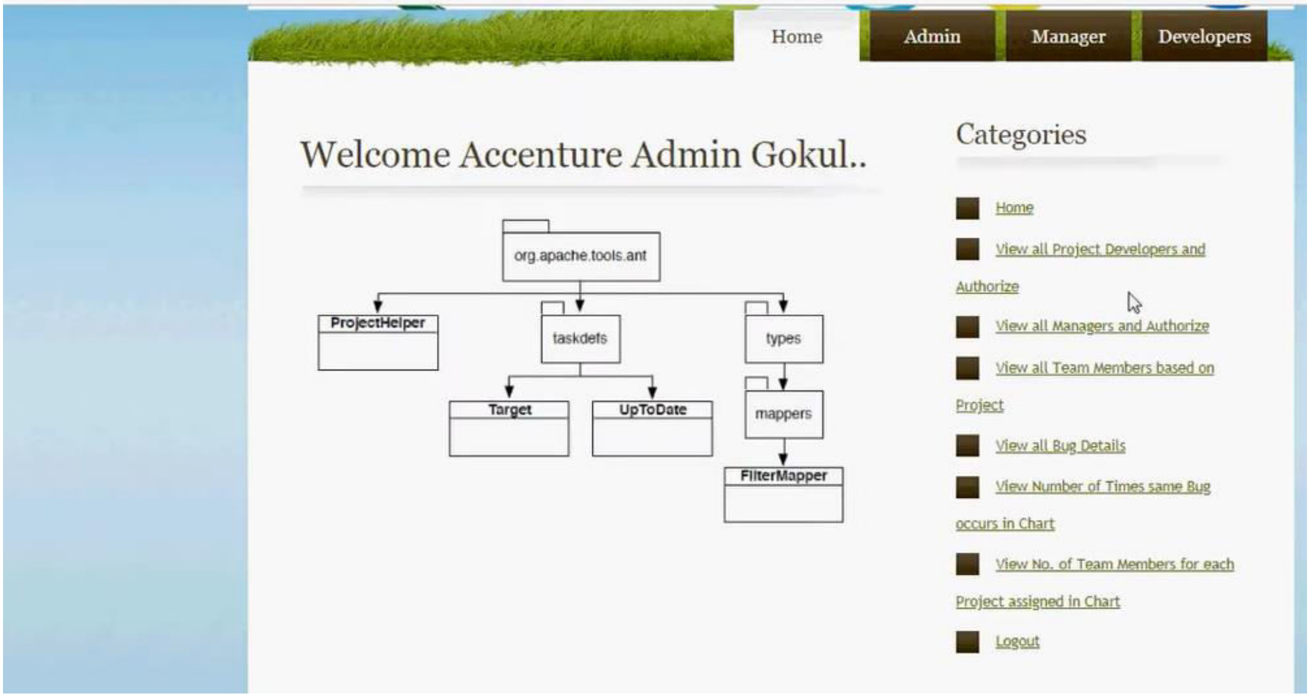


Fig 1:-Admin Home page

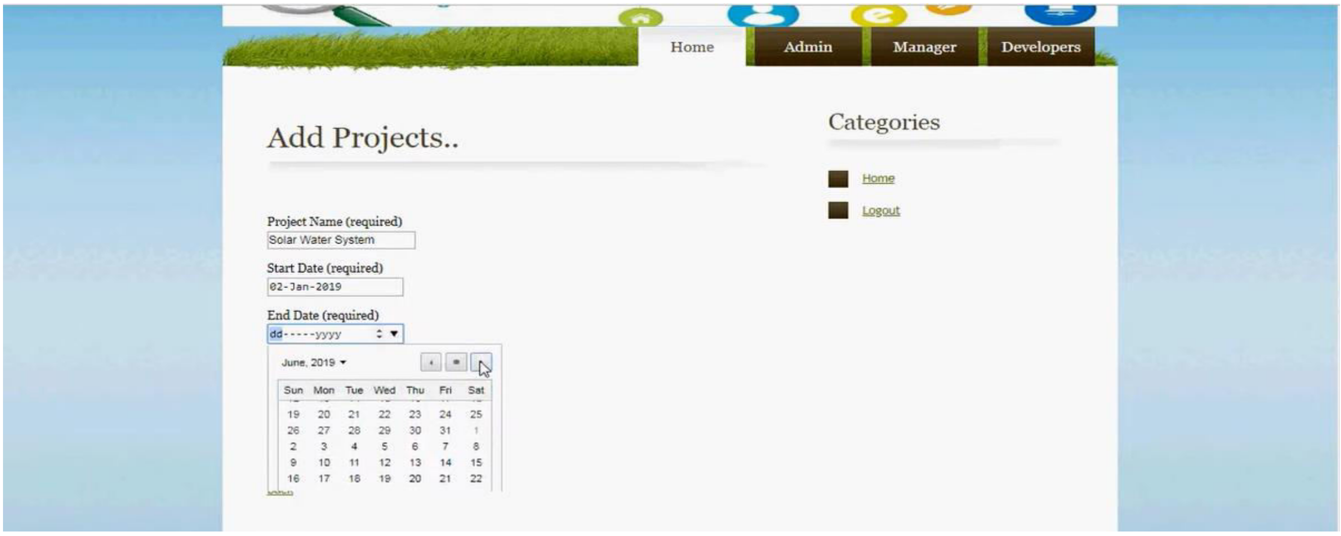


Fig 2:- Adding project Details

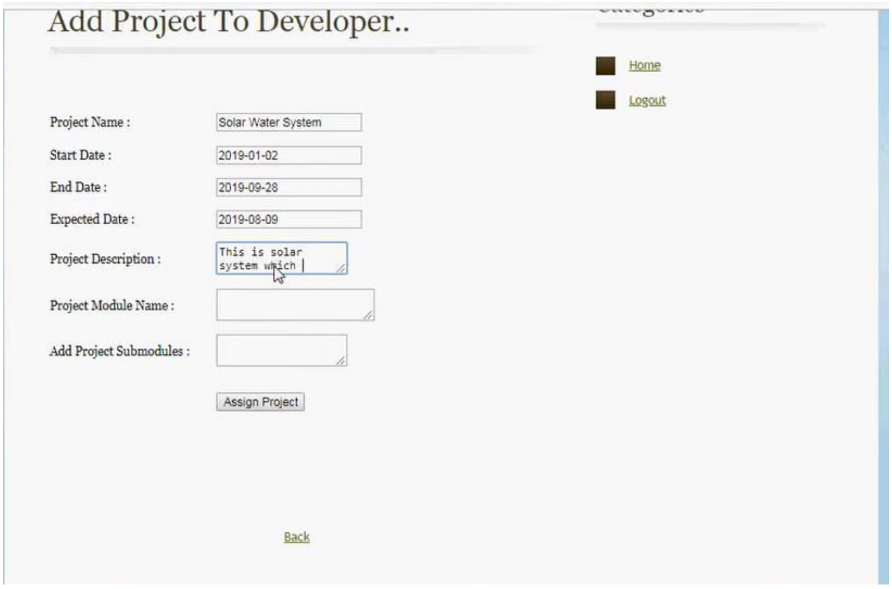


Fig 3:- Assigning project to developer

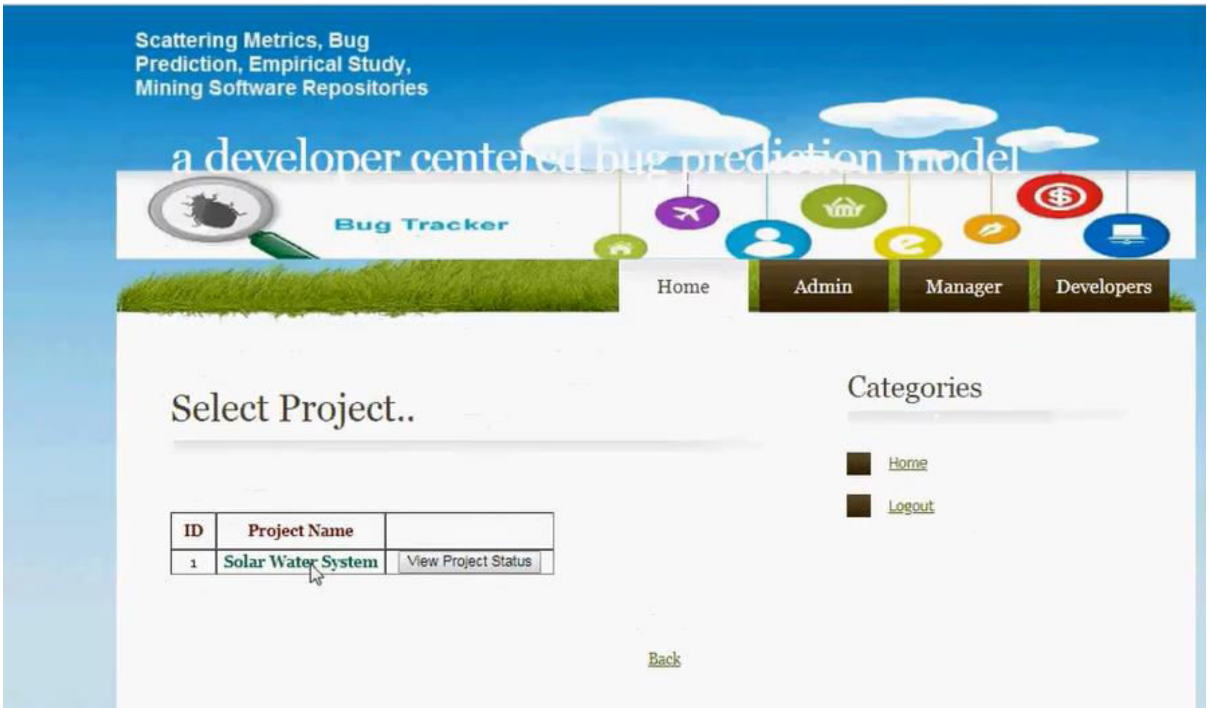


Fig 4:-Viewing the project status

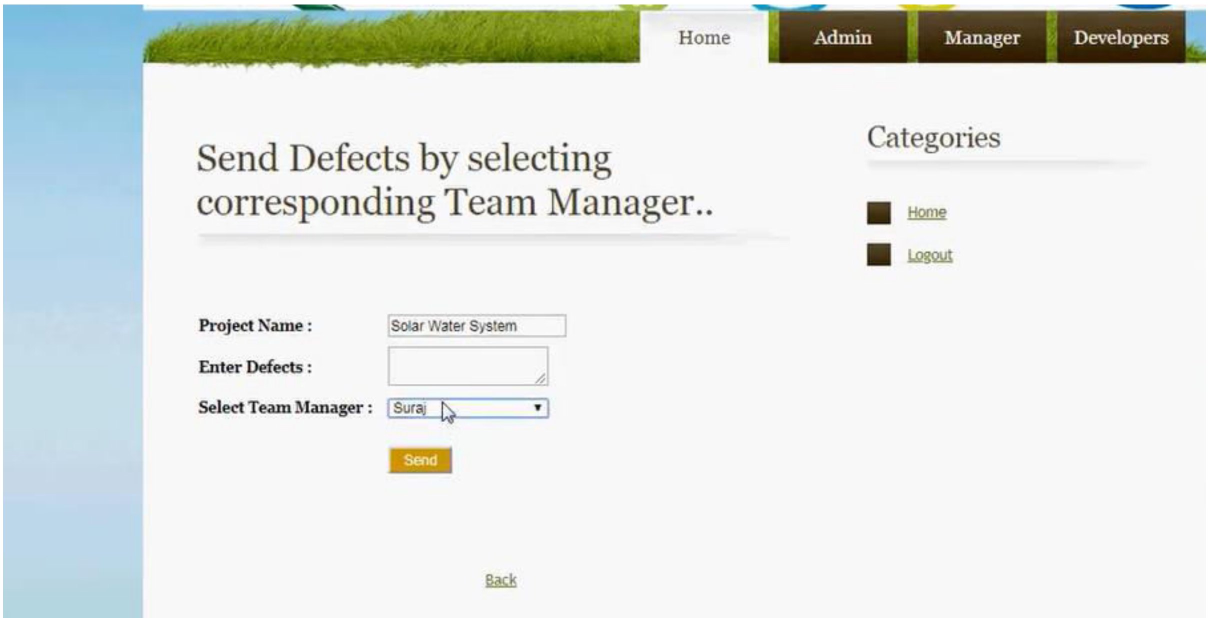


Fig 5:- Sending Defects To Manager

VI. Conclusion

This paper presented a Developer Centered Bug Prediction Model that incorporates novel structural and semantic scattering measures to capture developer behavior. Through a large empirical study on 26 systems, the model demonstrated superior performance over four strong baselines and strong complementarity when combined in a hybrid approach. The results confirm that developer-related factors, especially scattering, are essential for accurate bug prediction. The framework provides actionable insights for project managers to prioritize testing, allocate resources, and improve software quality. Future work will explore finer-grained scattering analysis and real-time integration with development environments.

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