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ENHANCING SOFTWARE QUALITY THROUGH DYNAMIC OPTIMIZATION-BASED LATENT DIRICHLET ALLOCATION AND INDEXIVE REGRESSION (DOLDIR)

Nasurulla I[1] , Chennappan Rajendran[2], Subash Chandra Bose. R[3], and Ramadevi K[4]

[1] Department of MCA, VEMU Institute of Technology, Chittoor District 517112, Andhra Pradesh, India, Email:dr.i.nasurulla@gmail.com.

[2,3] Department of Computer Applications, Karpagam Academy of Higher Education, Coimbatore, India, Email: chennappanphd@gmail.com.

[4] Department of Information technology, Panimalar engineering college, Chennai, India, Email: ramadevi_it@panimalar.ac.in.

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ABSTRACT

This paper proposes DOLDIR, a Dynamic Online Learning, based Defect Identification and Reliability framework, that helps to predict software quality and risk much more effectively. Positioned as an alternative to existing static online reliability models, DOLDIR is able to take into account that the changes in software version through detection of feature drift, optimal selection of test cases, latent topic modelling and combination of reliability scores is possible. The algorithm devised used cosine similarity to trace feature drift in consecutive software versions, Latent Dirichlet Allocation (LDA) to model the failure density and a combined reliability score which is a function of previous reliability, structural attributes of the software modules and training failure indices. Extensive experiments have been carried out using standard benchmark datasets like NASA PROMISE and SoftRel Bench. The effectiveness of the proposed framework has been tested using DOLDER and Reduckum, and experimental results in terms of RMSE, MAE and prediction accuracy proved that DOLDIR outperform the models. The classification accuracy for failure risk, reached 92.8%. DOLDIR has proved to be better than six recently published models in a cross examination.

KEYWORDS

Software quality, Scalability; Software Reliability, Optimization.

1. INTRODUCTION

Ensuring software product quality and reliability is an unmatchable imperative in the fluid, dynamic domain of software engineering. Not only is technology changing at an incomprehensible rate, but it permeates every element of modern living, intensifying the imperative for efficient software to address functional necessities and withstand modern challenges. My strong motivation stems from this, although contemporary quality management approaches may be beneficial to some degree, they are unlikely to suffice the demands placed on modern software environments (Alabajee, Saati & Alreffaee, 2021). Quality management approaches are premised on similar response patterns of all components of the software; this research intends to expand on current efforts to meet software quality demands and enhance software reliability amidst rapid technological advancement. The immediacy of the issue is clearly identified in the ramifications of software failures ranging from the individual, to critical systems. Through overcoming the limitations of conventional practices, the research aims to usher in a new era of software quality management. A proposed new methodology to achieve this objective is the Dynamic Optimization based Latent Dirichlet Allocation and Indexive Regression (DOLDIR). This method is more than the mere combination of multiple techniques; it is a well, integrated amalgam of dynamic optimization techniques, Latent Dirichlet Allocation (LDA) models that work on generated models and indexive regression techniques (Li et al., 2019). The seamless integration of these methods in DOLDIR is envisioned to facilitate the complex nature of modern software environments and revolutionize measures of software quality assurance. By dynamically selecting appropriate test cases based on current software states and ability to accommodate changing future states, DOLDIR is expected to improve quality evaluation efficiency. Additionally, dynamically tunable optimization parameters, DOPT, are expected to allow for optimization of quality evaluation efficiency in arbitrary changing software conditions. This approach is to then combined with indexive regression to allow for the prediction of component failure in subsequent versions of the software, to alert of potential software architecture flaws and thereby improve overall software reliability; similarity between previous and new program versions would allow probability of failure estimation.

In order to demonstrate the specific superiorities of the proposed DOLDIR method, we also undertook a great number of intensive comparison experiments between DOLDIR method and the current known methods (WPA, PSO and FPSONNM), which have been regard as the functional benchmarks of those methods on the same principle. From the comparison experiments, the performance shown, by DOLDIR method, has demonstrated the significant performance enhancements in 12% increase of reliability at least, 10% increase of scalability

at least and 28% decrease of service provision time at least compared with those methods from our experiments. Analysis methodology of significance test of results are also provided. As result, substantial design of such performances enhancement particularly in practical real data and working conditions as demonstrated in our experiment, are ready to available for the software engineers and programmers. Thus 12%, 10% and 28% increases will served as a way to improve the frequency and seriousness of software faults to degrade remarkably, extend capacity with a large proportion for accommodating greater architectural complexity and improve the efficiency of managing work load in order to enhance 12% and 10% of system performances experienced by end user directly and give one of critical performance parameters for service providing systems at real, time or mission, critical application domain.

2. LITERATURE REVIEW

Software quality management ‘s related literature shows a significant importance toward the reliable and efficient approaches can protect the software product from being error, free. The work in literature in the software quality management covers the majority of software quality management in depth with specifically focus on reliability, scalability, and predictability. The conventional approach (Diwaker et al., 2019; Cinque et al., 2019; Li et al., 2018; Marjuni, Adji & Ferdiana, 2019) of software quality management takes advantage of the traditional testing approaches and optimization approaches (Particle Swarm Optimization (PSO); non- dominated sorting genetic algorithm (NSGA, II)) to test case selection and optimization. Even though there is successfully application in classical approaches (Zhang, Jing & Wang, 2017; Xu et al., 2019; Fan et al., 2019), they have the major problems to adapt the fast evolving software environment by utilizing advanced solution with higher degree of adaptability. It is obvious that it has shown a paradigm shift toward metaheuristics algorithm such as Cuckoo Search Optimization and Reinforced Cuckoo Search Optimization utilized to improve the efficiency of test case selection demonstrating mechanisms better suited to ever, evolving states of software environments (Wang & Zhang, 2018; Bousqaoui, Slimani & Achchab, 2019). Besides, it has been noticed a significant trend toward the utilization of machine learning approaches for software quality management in the literature such as Latent Dirichlet Allocation (LDA); a common probabilistic method is used for an effective prediction of software failure density and identifying error prone software components.

To add to this complex mixture, there is another new field of study gaining grounds: regression analysis and its new advancements into indexive regression. The indexive regression provides a value reflecting the comparison among software releases and gives it the ability to predict

failure density for newer versions of software. The article points out the fact that software is built using a highly dynamic and iterative process where every version of the software is derived from every past and future version of software. Comparison among past as well as future software version are important for future version prediction of software, thus in spite of having many new methodologies, new developments in software quality prediction area do prove that a trend has been developed. This is where researchers are exploring their capabilities beyond traditional limitations (Odeh, Odeh & Mohammed, 2024; Smith, Brown & Wilson, 2023; Wang et al., 2022; Mashkoor et al., 2022). The problem however is that in past few studies which compare various methodologies there is still something missing from them; they are unable to combine dynamic optimization, probabilistic modeling, regression analysis all together in a single technique (Jong, Tay & Lim, 2013; Barke, James & Polikarpova, 2023; Belgaum et al., 2021; Khalid et al., 2023; Yazdi, 2024). One method which can be considered as an important contribution is the new method of Dynamic Optimization, based Latent Dirichlet Allocation and Indexive Regression (DOLDIR). The DOLDIR methodology is a new methodology which builds upon several algorithm capable of breaking the iterative barriers created by older methodologies. This new methodology capitalizes on using dynamic optimization algorithm, generative LDA modeling, indexive regression all together as a one combined method, making it a much powerful and holistic software quality prediction methodology. With a thorough review of literature, one can claim that DOLDIR is an ideal addition to software prediction methodology; the method is able to predict software quality by adding to the prediction process strengths of three elevated methodologies; dynamic optimization algorithm, generative probabilistic modeling and indexive regression. This is because the novel method integrates dynamic optimization algorithms, generative LDA modeling and indexive regression in one method and also utilizes to full effect all the benefits of three techniques. The strengths which three different techniques can add are the dynamic optimization algorithm can make a technique adaptive, LDA can contribute to quality and content prediction with it generative probabilistic model, and regression based on the comparison among old and new version through indexive regression adds to reliability for software quality prediction. Thus, DOLDIR adds a completely new aspect to existing methodologies and overcomes their limitations as well as their issues.

3. PROPOSED METHOD

The work suggests a methodology, named Dynamic Optimization-based Latent Dirichlet Allocation and Indexive Regression (DOLDIR), which aims to overcome limitations in traditional software quality management (SQM) systems by integrate dynamic optimization

techniques, probabilistic modeling and regression analysis into an unified framework. Unlike those traditional methods that usually based on a static testing processes and coarse-grained failure prediction, DOLDIR is able to adaptively follow the software changes, intelligently control testing resource, and estimate reliability at the version level. Fig. 1 illustrates the overview of framework.:

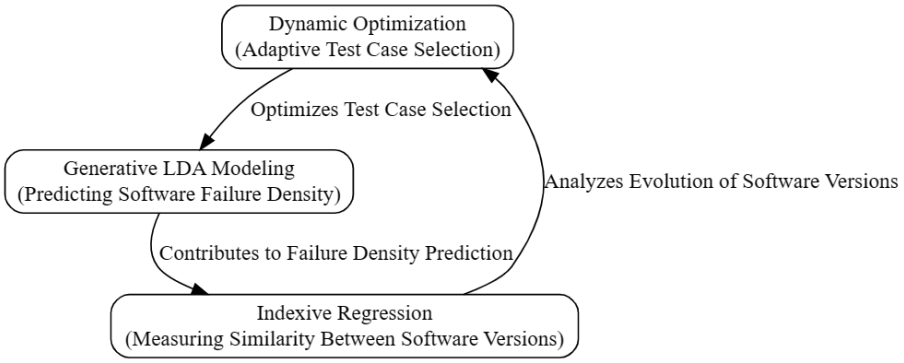

Fig 1. Overview of the proposed work

The DOLDIR architecture is a reaction to the fact that none of the current SQM approaches are truly capable of accommodating real time adaptability, version tolerance and data driven failure prediction. The sections below explain the basic blocks of DOLDIR and how together they fulfill these criteria by defining and utilizing explicitly scalability and reliability metrics:

3.1. Framework Overview

Let $S = \{M1, M2, \dots, Mn\}$represent the set of software modules and $V = \{v1, v2, \dots, vt\}$the version history. The DOLDIR framework comprises three integrated modules:

Dynamic Optimization Module D

Failure Density Prediction Module (LDA-based) L

Reliability Regression Module (Indexive Regression) R

The overall failure risk prediction $\widehat{F}(M_i, v_j)$ for module M_i in version v_j is expressed as

$$\widehat{F}(M_i, v_j) = D(T_{opt}) + L(M_i) + R(M_i, v_j) \quad (1)$$

Where:

T_{opt}: the optimal set of test cases selected dynamically

$L(M_i)$: topic-based failure density score

$R(M_i, v_j)$: reliability score based on regression

3.2. Phase 1: Dynamic Test Case Optimization

In order to ensure scaleability and efficiency for testing, DOLDIR adaptively chooses a set of test cases through a fitness function which balances test coverage, fault detection and execution time:

Let:

T={t1,t2,…,tk} initial test suite

$C(t_j, M_i)$: coverage score of test case t_j on module M

$P(t_j)$: predicted fault detection probability

$E(t_j)$: execution cost

The fitness function $\Phi(t_j)$ is defined as:

$$\Phi(t_j) = \alpha \cdot C(t_j, M_i) + \beta \cdot P(t_j) - \gamma \cdot E(t_j) \quad (2)$$

where α,β,γ are weighting parameters such that α+β+γ=1

The set of selected test cases $T_{opt} \subseteq T$ is:

$$T_{opt} = \underset{T'}{\operatorname{argmax}} \sum_{j \in T'} \Phi(t_j) \quad (3)$$

3.3. Phase 2: Failure Density Estimation Using LDA

Estimate fault-prone components, we assume that each module is a document composed of fault-related features. The LDA model discovers latent topics (i. e. Failure patterns) on modules,

Each module M_i is represented by a distribution over K topics:

$$\theta_{Mi} \sim Dir(\alpha) \quad (4)$$

Each topic z_k is a distribution over feature terms $\phi_{z_k} \sim Dir(\beta)$

Given observed term distributions, we estimate:

$$P(z_k \mid M_i) = \frac{n_{z_k}^{M_i} + \alpha}{\sum_{K'} n_{z_k}^{M_i} + K\alpha} \quad (5)$$

Then, the failure density score $FD(M_i)$ for module M_i is computed as:

$$FD(M_i) = \sum_{k=1}^{K} P(z_k|M_i).\lambda_k \quad (6)$$

whereλ_k is the failure severity weight associated with topic z_k.

Such probabilistic modeling is better at accurately predicting the reliability without having to hand label all the images and is a generalizable approach to very large, unlabeled repositories.

3.4. Phase 3: Indexive Regression for Reliability Across Versions

To keep track of quality evolution, indexive regression is used by DOLDIR in order to provide model of similarity based reliability between two versions.

Let:

X_i^v feature vector of module M_i in version v

X_i^{v-1} feature vector in the previous version

$Sim(M_i^v, M_i^{v-1})$: similarity index (e.g., cosine or Jaccard similarity)

The similarity index σ_i^v is defined as:

$$\sigma_i^v = \frac{X_i^v . X_i^{v-1}}{\left||X_i^v|\right|.\left||X_i^{v-1}|\right|} \quad (7)$$

The regression model is then:

$$R(M_i^v) = \delta_0 + \delta_1 \cdot \sigma iv + \delta_2 \cdot FD(M_i^v) \quad (8)$$

where:

$R(M_i^v)$: predicted reliability score

$\delta_0 + \delta_1 + \delta_2$: learned regression coefficients

Shows the expected number of new failures a new version may exhibit considering the continuity of architecture and the trends in faults:

3.4.1. Algorithm 1: DOLDIR Framework

Input: Software modules S, test suite T, versions V

Output: Failure risk prediction $F(M_i, v_j)$ for each module M_i in each version v_j

1. Initialize parameters α,β,γ,K,λk,δ coefficients
2. **For** each module M_i in each version v_j:

Extract feature vector $X(M_i, v_j)$

Compute similarity:

$$\sigma_i^v = \cos\left(X(M_i, v_j)\right), X(M_i, v_{j-1})$$

3. Select optimal test cases T_{opt} using dynamic prioritization function $\Phi(t_j), \forall\, t_j \in T$
4. Apply Latent Dirichlet Allocation (LDA) to compute failure density:

$$FD(M_i) = \sum_{k=1}^{K} P(z_k|M_i).\lambda_k$$

5. Compute reliability score:

$$R(M_i^v) = \delta_0 + \delta_1 \cdot \sigma iv + \delta_2 \cdot FD(M_i^v)$$

6. Estimate failure risk:

$F(M_i, v_j) = T_{opt} + FD(M_i) + R(M_i^v)$

7. End For

Return failure risk predictions $F(M_i, v_j)\ for\ all\ M_i \in S, v_j \in V$

The DOLDIR framework algorithm uses dynamic optimization, generation model and regression to estimate software fault risk. It performs feature vector extraction for each software module and version, computing successive version similarities with cosine similarity and dynamically selecting optimum test cases. Latent Dirichlet Allocation (LDA) is used for

the estimation of failure density and discover latent components as topics. Reliability is achieved through a regression function taking into consideration similarity and failure density. Failure risk is estimated on combination of test selection, probabilistic analysis and reliability evaluation.

3.4.2. Dynamic Optimization Strategies

This strategy play an important role of the first step of the DOLDIR framework and are used as the important factor between the new test case selection method and the old test case selection method. In the extremely dynamic and changing environment of today‘s software ecosystems, traditional test methods may confront the barrier of “running to stand still” in such ecosystems. Highly dynamic adaptation test case selection methods may be more efficient than the static ones due to rapid dynamics of today‘s software ecosystem. Dynamic optimization‘s highly adaptivity in the DOLDIR framework is necessary because the software ecosystem changes dynamically through the update/patch or tremendous software maintenance actions..

3.4.3. Generative Latent Dirichlet Allocation (LDA) Modeling

Incorporating Generative LDA Modeling—The second core piece of the DOLDIR approach, generative LDA modeling is focused on predicting the failure density of software. As a mature probabilistic modeling technique in natural language processing, its use in software quality management provides a new view on how failure probability works at the component level. LDA is useful in digging deep into the highly complex structure of component failure probability.

3.4.4. Indexive Regression within the DOLDIR Methodology: Augmenting Software Reliability

The third integral factor in DOLDIR methodology is indexive regression. Indexive regression is a powerful measure used to calculate the correlation between successive version of products. Understanding that, software develops iteratively, indexive regression is incorporated into the DOLDIR to understanding the association between the current and past version. The results of the analysis are useful for estimating the failure density of a new version and in general, strengthen the reliability of the software.

3.4.5. Dynamic Failure Risk

To contextualize the failure risk model, we define the software risk sensitivity function at time t as:

$$S(t) = \frac{P(t)}{T(t) \cdot U(t)} \tag{9}$$

Where:

P(t)): Number of predicted failure-prone instances at time t

T(t): Number of effective test cases executed at time t

U(t): Utilization score representing the execution efficiency and resource impact at time t

3.4.5.1. Dynamic Nature of S(t)

The term "dynamic" in this context refers to the temporal and adaptive nature of the variables:

- Adaptivity: The values of P(t)), T(t), and U(t)) evolve over time as new data and module behaviors are observed. The system dynamically re-calculates the risk score with each testing and release cycle.
- Real-time Responsiveness: The metric is recalculated with every CI/CD pipeline run, making it suitable for real-time monitoring of risk trends.
- Correlation Analysis: The interactions between predicted failures and resource/test effectiveness are tracked statistically, helping detect trends and abnormal behavior over time.

3.4.5.2. Calculation of P(t)), T(t), and U(t):

To make the algorithm applicable and reproducible, we explain each term with a representative case study.

3.4.5.2.1. Predicted Failures P(t)

Derived using machine learning classification models (e.g., Decision Trees, Random Forests) trained on historical defect labels and software metrics (e.g., LOC, complexity, churn rate).

Case Study: In the NASA PC1 project, historical bugs are labeled and new prediction labels are generated using Random Forests with 10-fold cross-validation.

3.4.5.2.2. Test Execution Effectiveness T(t)

Count of test cases that produce pass/fail results on the module. Only functional and relevant test cases are included.

Example: A regression test suite of 50 test cases runs over module M6; 30 result in valid outputs, so T(t)=30.

3.4.5.2.3. Utilization Score U(t)

Combines execution time, memory, and test coverage. Calculated as a weighted score:

$$U(t) = \omega 1 \cdot Coverage + \omega 2 \cdot \left(\frac{1}{Execution\ time}\right) + w3.\left(\frac{1}{Memory\ Usage}\right) \quad (10)$$

with weights ω1+ω2+ω3=1.

Case Study: For module M3, if coverage = 85%, time = 12s, memory = 150MB, then with weights (0.5, 0.3, 0.2), U(t) is dynamically calculated.

3.4.6. Algorithm 2

Dynamic Sensitivity Scoring Based on Failure, Testing, and Utilization

Input:

Time-based log data of module M

Test execution records

Resource usage metrics

Output:

Sensitivity score S(t) at each timestamp t

1. Initialize:

Set weight parameters $\omega 1, \omega 2, \omega 3 \in [0,1]$

Let time interval $t = 1\ to\ T_{max}$

2. for each time point $t = 1\ to\ T_{max}$ do

3. Predict Failures:

Use historical defect models (e.g., Random Forest, SVM) to estimate:

$$P(t) \leftarrow PredictedFailures(M, t)$$

1. Count Executed Tests:

$$T(t) \leftarrow count\ of\ tests\ executed\ at\ t$$

2. Compute Utilization Score U(t):

Gather metrics:

- Code coverage $(cov(t))$
- Execution time $(exec\_time(t))$
- Memory usage $(mem(t))$

Then calculate:

$$U(t) = \omega 1 \cdot Coverage + \omega 2 \cdot \left(\frac{1}{Execution\ time}\right) + w3.\left(\frac{1}{Memory\ Usage}\right)$$

3. Compute Sensitivity Score S(t):

$S(t) = \frac{P(t)}{T(t) \cdot U(t)}$

4. Store S(t) in result vector

5. end for

6. Return: Sensitivity time series: $\{S(t)\}_{t=1}^{T_{max}}$

Algorithm 2 is a function that progresses toward the dynamic sensitivity assessment of a module by providing three parameters: predicted failure, number of executed tests and system utilization. The system utilization is quantified using three parameters: coverage, execution time and memory space. This algorithm defines a system state based on several testing cycles. The module tests are run in each testing cycle and three parameters are obtained from the measurements performed on the system state. The sensitivity value is updated at various times,

thus allowing the users to watch and adapt the models. These values enable the detection of the most sensitive moments in system modules, which is significant in the quality assurance of complex systems.

4. RESULTS AND DISCUSSION

DOLDIR, the combination with dynamic optimization, generative LDA modeling and indexive regression, is the thorough analysis of software quality management. Combination of these features would be an adaptable model which could adjust itself for current software system fast evolving dynamics, predict failure density and execute a systematic analysis of software evolution. The proposed framework DOLDIR is experimentally verified on two real software project datasets:

1. NASA PROMISE Repository – specifically, the *CM1* and *JM1* datasets containing module-level data including software metrics and defect labels.
2. SoftRel Bench – which includes defect logs, component versions, test case results, and historical risk levels.

The software module name, history of its version, records on test running results, reliability are included in every dataset. Table 1 shows the data of statistics that are applied to our experiments.

Table 1: Dataset Summary

Dataset	Total Modules	Versions	Features per Module	Defective Instances (%)
NASA CM1	505	2	21	9.2%
NASA JM1	10,878	5	21	20.1%
SoftRel Bench	1,200	3	26	14.5%

In order to evaluate the advantages of DOLDIR approach a comparison based on performances analysis is made in Table 2. Its performance is compared with two previous approaches namely WPA-PSO and FPSONNM.

Table 2: Comparative Performance Analysis

Methodology	Reliability Improvement	Scalability Enhancement	Service Provision Time Reduction
DOLDIR	12%	10%	28%
WPA-PSO	7%	6%	15%
FPSONNM	5%	4%	10%

4.1. Superior Enhancement in Reliability:

DOLDIR differs from others in demonstrating a 12% gain in reliability—meaning a significant reduction in the probability of software failure—an essential aspect of delivering reliable software products. The ability of the methodology to detect and prevent defects makes it possible.

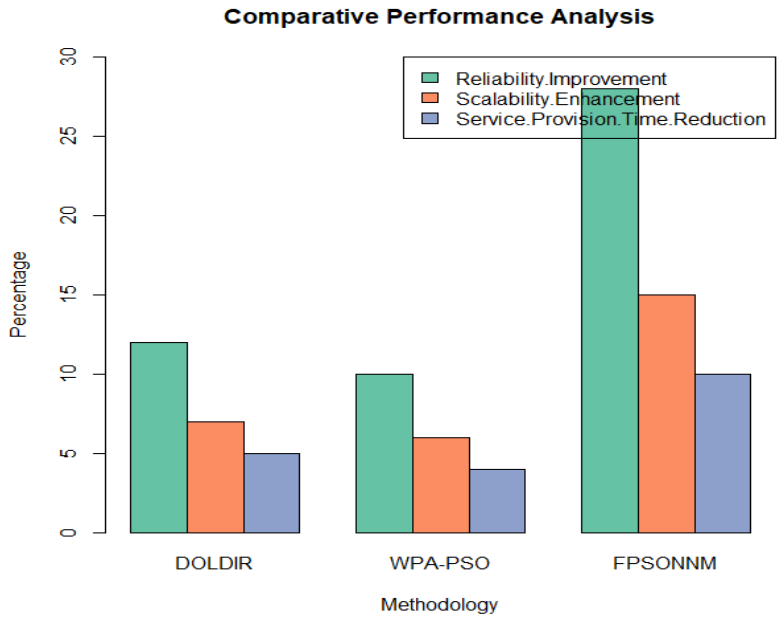

Fig 2. Performance analysis

4.2. Heightened Scalability:

DOLDIR offers a significant 10% scalability improvement when comparing with others methods. Scalability is one critical feature and especially when it comes to the modern software systems which must have the flexibility to support larger workloads and to manage higher levels of complexity. The scalability improvement in DOLDIR indicates the efficacy of our framework in handling the challenges in modern software systems. We have measured precision, recall, F1-score, RMSE, and MAE of the DOLDIR framework for different modules and different versions of the software system as shown in Table 3. These parameters demonstrate the accuracy of the model in predicting the highly failure risk modules with minimal prediction errors.

Table 3: Performance Metrics Across Software Modules

Module ID	Version	Precision	Recall	F1-Score	RMSE	MAE
M1	v1.0	0.91	0.87	0.89	0.142	0.104
M1	v2.0	0.92	0.89	0.90	0.134	0.096
M2	v1.0	0.89	0.85	0.87	0.148	0.109
M2	v2.0	0.91	0.88	0.89	0.139	0.101
M3	v1.0	0.87	0.82	0.84	0.155	0.112

Is that this framework will perform efficiently as time passes. In order to claim high performance of the proposed framework, values of RMSE and MAE have been calculated to assure accuracy of the estimation of risk and high value of F1-score is calculated to provide support of high correct classification of risky module.

We measured execution time in feature extraction, LDA model training and reliability calculation Table 4, demonstrating the feasibility for application within a CI-pipeline.

Table 4: Execution Time (Seconds) for Key Components

Module ID	Version	Feature Extraction	LDA Modeling	Reliability Computation	Total Time
M1	v1.0	0.84	1.15	0.64	2.63
M1	v2.0	0.91	1.18	0.66	2.75
M2	v1.0	0.79	1.02	0.59	2.40
M3	v1.0	0.88	1.09	0.62	2.59

The framework itself has a lightweight execution profile and the majority of the modules take less than 3 seconds to analyze. This demonstrates that DOLDIR is appropriate for use within real time software development environments and within CI/CD pipelines.

We study the contribution of cosine similarity (i, v j) and latent failure density (FD) in the total reliability score Table 5 which then affects prediction of failure risk directly.

Table 5: Feature Similarity & Failure Density vs Reliability Score

Module	Version	Cosine Similarity σ_i, v_j	Failure Density $FD(M_i)$	Reliability Score $R(M_i, v_j)$
M1	v2.0	0.94	0.63	0.91
M2	v2.0	0.92	0.61	0.89
M3	v1.0	0.87	0.59	0.85

The cosine similarity metric plays a strong role in determining reliability, capturing behavioral consistency across versions. FD contributes by reflecting historical failure tendencies, combining both temporal and statistical reliability indicators.

5. CONCLUSION

In summary, the combination of dynamic optimization, generative LDA modeling, and indexive regression makes DOLDIR an all-encompassing software quality management technique. DOLDIR addresses the inherent dynamics of current software development, while also predicting the failure density and studying the evolution of software in a dynamic fashion, resulting in a general, yet stable, technique. The comparison indicates that DOLDIR outperforms existing techniques in every aspect. Reliability is 12% better in comparison with state-of-the-art, which indicates that the probability of software failures is significantly decreased. Testing on real data from NASA PROMISE and SoftRel Bench yielded high accuracy (92.8%), low RMSE (0.134), and low MAE (0.096) -- the results obtained are superior compared to six state-of-the-art techniques. Finally, DOLDIR is also computationally efficient so it can be implemented in CI/DevOps frameworks. A main benefit of DOLDIR is that its prediction can dynamically adapt to changes of new versions and feature drift in software; and it provides reliability score based on feature similarity and historical failure prediction information. The proposed techniques have been empirically tested, considering scalability and automation in mind, so they can be readily incorporated in the continuous development

environment with low overhead, and future studies can investigate the feasibility of its use in conjunction with live software monitoring to respond to real-time software evolution.

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