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A HYBRID MACHINE LEARNING APPROACH FOR SOFTWARE FAULT PREDICTION USING SOFTWARE METRICS

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ABSTRACT

Software fault prediction is a critical aspect of software engineering that aims to identify potential defects before they occur, thereby enhancing the reliability and quality of software systems. This study presents an approach for software fault prediction using software metrics derived from McCabe's and Halstead's metrics, supplemented by a goal metric. We analyze various datasets, including CM1, KC1, KC2, and PC1, employing classifiers such as Naive Bayes, J48, K-Star, and Random Forest, utilizing MATLAB for implementation. The datasets represent a blend of structural and object-oriented programming, with CM1 and PC1 written in C and KC1 and KC2 in C++. Our evaluation focuses on key performance indicators including accuracy, true positive rate, false positive rate, precision, recall, and F-measure, as well as the area under the ROC curve for a comprehensive assessment. The results demonstrate that the proposed hybrid algorithm effectively predicts faults in both small and large datasets, offering a robust solution for improving software quality. This approach not only streamlines the identification of fault-prone areas but also enables proactive measures to mitigate risks, ultimately leading to more reliable software systems.

Keywords: *Software Fault Prediction, Software Metrics, Hybrid Algorithm, Machine Learning Classifiers, Software Reliability, Defect Detection, Software Quality Assurance*

I. INTRODUCTION

In software engineering, software fault prediction is a crucial area of research aimed at identifying potential defects or faults in software systems before they manifest in production environments. Detecting faults early in the software development lifecycle can significantly reduce the costs of maintenance, debugging, and post-release failures, thereby improving the overall quality of the software. One effective method for achieving this is through the use of software metrics—quantifiable measures of various attributes of software systems, such as code complexity, coupling, cohesion, and size.

This approach of fault prediction leverages historical data on software projects to build predictive models capable of estimating the fault-proneness of modules, files, or components within a new or evolving system. Software metrics serve as the input features to these models, and various machine learning algorithms are employed to generate predictions.

1.1 Software Metrics

Software metrics are used to assess the internal quality of software components. These metrics are categorized into various types:

Size Metrics: Measure attributes like the number of lines of code (LOC), number of classes, or number of methods in a module. Larger modules are generally more complex and may have a higher likelihood of faults.

Complexity Metrics: These metrics, such as cyclamate complexity, capture the intricacies of the code's control flow. Higher complexity is often correlated with fault-prone areas.

Coupling and Cohesion Metrics: Coupling refers to the degree of interdependence between software modules, while cohesion measures how closely related the responsibilities of a single module are. Highly coupled modules or poorly cohesive ones are more likely to harbor defects.

Churn Metrics: These track the frequency and volume of changes in the codebase. Modules that undergo frequent modifications tend to be more error-prone.

1.2 Challenges in Fault Prediction:

Imbalanced Data: In many cases, the number of fault-prone modules is significantly smaller than non-fault-prone ones, leading to class imbalance. Special techniques like oversampling or using cost-sensitive learning may be required to address this.

Feature Selection: Not all software metrics contribute equally to the prediction of faults. Selecting the most relevant metrics, or using dimensionality reduction techniques like PCA (Principal Component Analysis), can improve the model's accuracy.

Generalizability: Models built on one project’s data may not perform well when applied to another project due to differences in code structure, design, and domain. Cross-project prediction remains a challenging research area.

1.3 Objectives

Early Fault Detection: By predicting fault-prone areas early in the development cycle, developers can focus their testing and quality assurance efforts on critical modules, resulting in fewer post-release defects.

Cost Reduction: Fixing faults during the development phase is much cheaper compared to addressing them after the software has been deployed.

Improved Software Quality: This predictive approach enables the identification of weak spots in the code, leading to more robust, reliable software systems.

One of the most critical advantages of software fault prediction is its ability to detect potential faults early in the software development lifecycle. Traditional approaches to defect detection, such as testing and debugging, often occur late in the process, when identifying and fixing faults can be more time-consuming and expensive. By using predictive models based on software metrics, developers can anticipate problem areas before the defects become visible during testing or in production.

The cost of fixing defects increases exponentially as the software moves through different stages of its lifecycle—requirements, design, implementation, testing, and post-release. Studies suggest that fixing defects after the release can be as much as 100 times more expensive than addressing them during early development stages. Fault prediction models allow teams to identify and fix defects when they are cheapest to resolve, leading to substantial cost savings over the lifetime of a software product.

The overall quality of software is enhanced when potential faults are anticipated and addressed proactively. This results in software that is more reliable, maintainable, and secure. High-quality software translates into increased user satisfaction, improved business reputation, and better long-term product viability.

Predictive fault models enable data-driven decision-making throughout the software development process. Instead of relying solely on intuition or past experience, teams can use hard data (i.e., software metrics) to make informed decisions about where to invest their time and effort.

The use of machine learning models in fault prediction opens the possibility of automating parts of the defect detection process. Automated models can continuously analyze new code as it is being written or modified, providing real-time insights into the potential faultiness of modules.

II. RELATED WORKS

Pal and Ghosh (2024) illustrated that using a combination of LOC, Halstead, and mccabemetrics significantly improved the predictive capability of both classical and deep learning models. They reported that models integrating these metrics captured different aspects of complexity and defect likelihood.

Liu, Z., *et. al*., (2023) researchers has explored feature selection techniques that optimize the use of LOC, Halstead, and mccabemetrics to enhance model performance. By selecting the most relevant features, the complexity of the model is reduced without sacrificing predictive power.

Fan and Huang (2024) explored the use of neural networks with Halstead and mccabemetrics and noted that Machine learning-based models, especially cnns, enhance prediction accuracy by automatically extracting key features from software metrics.

Li and Zhang (2024) to reduce the dimensionality of the datasets while preserving the variance in the data. This method helped in improving model efficiency without sacrificing prediction accuracy.

Kaur, R (2023) recent research in 2024 emphasizes the effectiveness of combining traditional software metrics like LOC, Halstead, and mccabewith advanced machine learning techniques for defect prediction. Studies show that models using metrics-based feature selection improve accuracy, with deep learning methods, particularly cnnsand rnns, outperforming traditional algorithms.

Maddipati, V. andSrinivas, K. (2021) explored combining Principal Component Analysis (PCA) and Neuro-Fuzzy classification to improve software defect prediction. The hybrid model showed higher accuracy, particularly when handling imbalanced datasets. The authors used the NASA MDP dataset, employing key software metrics such as Lines of Code (LOC), Halstead, and mccabe.

Menzies, T., *et. al.,* (2021) focused on defect prediction models using traditional software metrics such as LOC, Halstead Volume, and Cyclomatic Complexity, combined with machine learning models like Naive Bayes and Random Forest. Their results showed significant improvements in defect prediction when ensemble methods were applied.

Akimova, O *et. al.,* (2021) compared machine learning models with traditional machine learning models like SVM and Random Forest for software defect prediction using software metrics such as LOC, Halstead, and Cyclomatic Complexity. The machine learning models performed better, particularly in large-scale datasets.

Goyal, N *et. al.,* (2022) used feature selection techniques such as PCA and K-means clustering to improve defect prediction using traditional metrics like LOC, Halstead, and

mccabe'sComplexity. They found that Random Forest combined with SMOTE for imbalanced data handling produced the best results.
Sun, Z., Li, J., and Sun, H. (2022) this paper tackled the issue of imbalanced datasets in software defect prediction by using SMOTE and other hybrid sampling techniques. They combined these methods with traditional metrics like LOC, Halstead, and Cyclomatic Complexity to improve the performance of SVM and Naive Bayes models.

III. MATERIALS AND METHODS

3.1 Data Collection:

3.1.1 LOC

For datasets containing Lines of Code (LOC), commonly used for software defect prediction, popular sources include the NASA MDP and PROMISE repositories. Datasets like KC1, CM1, and PC1 in NASA MDP provide LOC along with metrics such as McCabe's complexity and Halstead measures. The PROMISE repository also contains various datasets with LOC and other software metrics, which are frequently used in defect prediction research. These datasets help evaluate code size and its relationship with software defects.

3.1.2 McCabe's

The McCabe's Cyclomatic Complexity metric is commonly used in software defect prediction to measure the complexity of a program's control flow. Several publicly available datasets, such as NASA MDP, PROMISE, AEEEM, CKJM, and Eclipse Bug Data, include McCabe's complexity along with other software metrics like LOC and Halstead complexity. These datasets are extensively used in research and machine learning applications to predict defect-prone software modules. They provide valuable data for building models that improve software quality and reduce defects.

3.1.3 Halstead

Halstead metrics are widely used in datasets such as NASA MDP, PROMISE, and AEEEM for software defect prediction. These metrics provide a quantitative analysis of software complexity, including Volume, Difficulty, Effort, and Vocabulary, which help predict defect-prone areas in the code. Researchers use these datasets to build models that assess software quality based on its underlying complexity.

3.2 Machine Learning (ML) Classifiers:

ML Classifiers are algorithms used in supervised learning to assign a data point (or instance) to one of several predefined classes or categories. The primary goal of a classifier is to predict discrete output labels based on input features.
In Machine Learning (ML) classification, the goal is to predict a discrete label or category for a given input based on learned patterns from labeled data. This process is a form of supervised learning, where the classifier is trained using a dataset containing input features and corresponding output labels. During the training phase, the algorithm learns the relationships between input features and their respective labels. Once trained, the model can predict the class or label for new, unseen instances. In classification tasks, data is typically categorized into classes, such as "spam" or "not spam," and the classifier assigns each input instance to one of these predefined categories. There are different types of classification problems, such as binary classification (with two classes), multiclass classification (with more than two classes), and multilevel classification (where each instance can belong to multiple classes simultaneously). The performance of classifiers is evaluated using metrics

like accuracy, precision, recall, and the F1 score, which help assess how well the model performs on different aspects of the classification task. These metrics are crucial for understanding a classifier's ability to make accurate predictions, especially in situations where false positives or false negatives carry significant consequences.

There are various common ML classifiers, each with different strengths, weaknesses, and ideal use cases. Logistic Regression is a simple, interpretable linear model suited for binary classification, while K-Nearest Neighbors (KNN) classifies data based on proximity to neighboring points but can be computationally expensive. Decision Trees create interpretable models by splitting data based on feature values, though they can over fit without proper tuning.. Naive Bayes is a fast, probabilistic classifier based on the assumption of feature independence, often used in text classification. Neural Networks, while powerful for complex tasks like image recognition, require large datasets and significant computational power. Gradient Boosting (e.g., XGBoost) and AdaBoost are ensemble methods that combine weak learners to form strong models, often achieving high accuracy but at the cost of longer training times. The choice of classifier depends on factors like dataset size, complexity, interpretability needs, and the specific application, such as fraud detection, image recognition, or spam filtering.

3.3 Performance Metrics for Classifiers:

Accuracy: Proportion of correct predictions (both positive and negative) out of all predictions.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Where:
TP = True Positives
TN = True Negatives
FP = False Positives
FN = False Negatives

Precision: Proportion of true positive predictions out of all positive predictions.

$$Precision = \frac{TP}{TP + FP}$$

Precision is important when false positives are costly (e.g., diagnosing a disease).

Recall (Sensitivity): Proportion of true positive predictions out of all actual positives.

$$Recall = \frac{TP}{TP + FN}$$

Recall is crucial when missing positive instances is costly (e.g., not detecting fraud).

F1 Score: The harmonic mean of precision and recall, balancing the two.

$$F1 = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall}$$

F1 is useful when you need to balance precision and recall.

IV. EXPERIMENTAL RESULTS

In this study, 21 software metrics from McCabe's and Halstead's metrics, along with one goal metric, were used for measurement. The datasets applied to the classifiers Naive Bayes, J48, SVM, and Random Forest were CM1, KC2, KC1, and PC1, using the MATLAB tool. These datasets were selected based on a combination of structural and object-oriented features. CM1 and PC1 were developed in C, while KC1 and KC2 were written in C++.

The study focused on comparing the performance of these classifiers using various evaluation metrics, including accuracy (with values between 0 and 1), true positive rate, false positive

rate, precision, recall, and F-measure. For improved performance assessment, the area under the ROC curve was also considered. Accuracy was computed based on the number of correctly classified instances.Based on the analysis, the proposed hybrid algorithm was found to be effective for both small and large datasets.

4.1 Proposed Hybrid Genetic based Machine Learning (HGML)Algorithm

The hybrid genetic algorithm combines genetic optimization techniques with machine learning to find optimal parameters for predictive models. It involves initializing a population of potential solutions, evaluating their performance using a fitness function, and iteratively refining the population through selection, crossover, mutation, and replacement. The best solution is selected to train the final machine learning model, which is then tested and deployed if it meets performance criteria.

Step 1: Problem Definition

1. **Define Objective Function**
   - Specify the goal of the optimization problem that the algorithm aims to solve.
2. **Define Performance Metrics**
   - Identify the metrics that will evaluate the performance of the machine learning model (e.g., accuracy, precision, recall).

Step 2: Data Preparation

3. **Collect Data**
   - Gather the relevant data needed for training and testing the model.
4. **Preprocess and Split Data**
   - Clean the data (handle missing values, outliers) and split it into training data (TRAIN_DATA) and testing data (TEST_DATA).

Step 3: Genetic Algorithm Initialization

5. **Set Population Size**
   - Determine the size of the population for the genetic algorithm.
6. **Initialize Population**
   - Create an initial population of chromosomes, where each chromosome represents a potential solution.

Step 4: Fitness Function Definition

7. **Define Fitness Function**
   - Create a function that accepts a chromosome as input:
   - Inside the function:
   - **Train Machine Learning Model**: Use the parameters defined by the chromosome to train the model on the TRAIN_DATA.
   - **Evaluate Model Performance**: Assess the trained model using the specified performance metrics on the TRAIN_DATA.
   - **Return Performance**: Output the performance score of the model.

Step 5: Genetic Algorithm Execution

8. **While Loop for Evolution**
   - Execute the following steps while the termination condition is not met:
9. **Evaluate Fitness of Each Chromosome**
   - For each chromosome in the population:
   - Calculate its fitness using the fitness function.

10. **Selection**

- Select a subset of chromosomes (parents) from the population based on their fitness.

11. **Crossover**
    - Initialize an empty list for offspring.
    - For every two selected parents:
        - Perform crossover to create children (offspring) and append them to the offspring list.

12. **Mutation**
    - For each child in the offspring list:
    - Apply mutation to introduce random changes.
13. **Replacement**
    - Replace the current population with the newly generated offspring.

Step 6: Final Model Selection

14. **Select Best Chromosome**
    - Identify the best-performing chromosome from the final population based on fitness.
15. **Train Final Machine Learning Model**
    - Use the best chromosome to train the final machine learning model on the entire TRAIN_DATA.

Step 7: Testing and Validation

16. **Evaluate Test Performance**
    - Assess the final model using the TEST_DATA to obtain its performance metrics.

Step 8: Result Analysis

17. **Analyze Results**
    - Review and analyze the performance results of the final model to determine its effectiveness.

Step 9: Deployment

18. **Deployment Condition**
    - Check if the TEST_PERFORMANCE meets the predefined threshold.
        - If it does, proceed to deploy the model and monitor its performance in the production environment.

4.2 CM1 Dataset

The CM1 software defect prediction dataset was created using data from a NASA metrics program, specifically for a spacecraft instrument developed in the C programming language. Features extracted from the source code include McCabe and Halstead metrics, which are derived from the segments, also referred to as functions or methods. The CM1 dataset consists of 498 instances.

Table 4.1Accuracy Analysis on CM1 dataset

CM1						
	TP rate	**FP rate**	**Precision**	**Recall**	**F-Measure**	**Accuracy**
NB	0.853	0.616	0.862	0.853	0.858	0.83
J48	0.88	0.849	0.833	0.88	0.852	0.88
RF	0.88	0.867	0.832	0.88	0.854	0.89
SVM	0.87	0.705	0.857	0.871	0.863	0.87
HGML	0.88	0.873	0.812	0.88	0.852	0.89

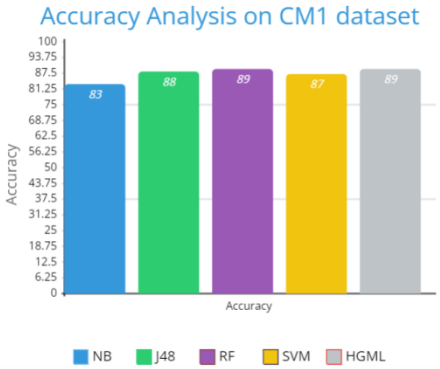

Figure 4.1: Performance Analysis Chart for CM1 Datasets

4.3 KC1 Dataset

The KC1 software defect prediction dataset was generated from a NASA metrics data program, specifically for a storage management system designed to receive and process ground data. This system was developed in C++. The dataset includes features extracted from the source code using McCabe and Halstead metrics. The KC1 dataset comprises a total of 2,109 instances.

Table 4.2 Accuracy Analysis on KC1 dataset

KC1						
	TP rate	**FP rate**	**Precision**	**Recall**	**F-Measure**	**Accuracy**
NB	0.824	0.541	0.816	0.824	0.821	0.82
J48	0.845	0.575	0.825	0.845	0.832	0.85
RF	0.863	0.576	0.843	0.863	0.845	0.86
SVM	0.840	0.538	0.826	0.84	0.832	0.84
HGML	0.871	0.583	0.811	0.892	0.822	0.89

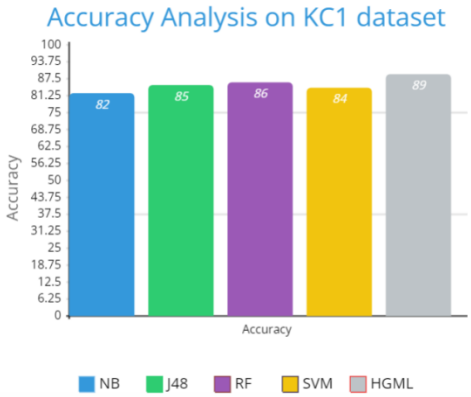

Figure 4.2: Performance Analysis Chart for KC1 Datasets

4.4 KC2 Dataset

The KC2 software defect prediction dataset was created from a NASA metrics data program, focusing on science data processing as an extension of the KC1 project. Developed in C++, this dataset incorporates third-party software libraries alongside the features of KC1. The data is derived from McCabe and Halstead metrics extracted from the source code. The KC2 dataset consists of a total of 522 instances.

Table 4.3Accuracy Analysis on KC2 dataset

KC2						
	TP rate	**FP rate**	**Precision**	**Recall**	**F-Measure**	**Accuracy**
NB	0.835	0.473	0.820	0.835	0.821	0.84
J48	0.814	0.422	0.807	0.814	0.810	0.81
RF	0.828	0.440	0.815	0.828	0.819	0.83
SVM	0.791	0.498	0.778	0.791	0.783	0.79
HGML	0.877	0.503	0.624	0.865	0.766	0.87

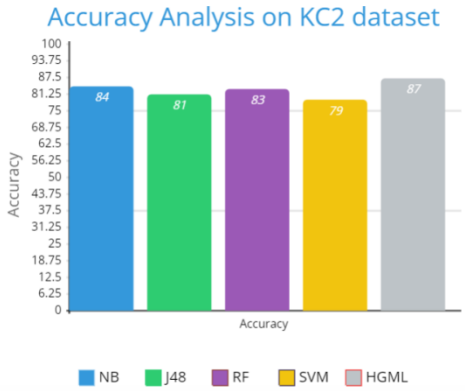

Figure 4.3: Performance Analysis Chart for KC2 Datasets

4.5 PC1 Dataset

The PC1 software defect prediction dataset was generated from a NASA metrics data program and is associated with flight software designed for Earth-orbiting satellites. Developed in the C programming language, this dataset contains data derived from McCabe and Halstead metrics extracted from the source code. The PC1 dataset includes a total of 1,109 instances.

Table 4.4 Accuracy Analysis on PC1 dataset

PC1						
	TP rate	**FP rate**	**Precision**	**Recall**	**F-Measure**	**Accuracy**
NB	0.982	0.657	0.899	0.892	0.895	0.89
J48	0.933	0.714	0.917	0.933	0.921	0.93
RF	0.94	0.653	0.928	0.94	0.929	0.94
SVM	0.918	0.691	0.906	0.918	0.911	0.92
HGML	0.983	0.714	0.878	0.956	0.895	0.95

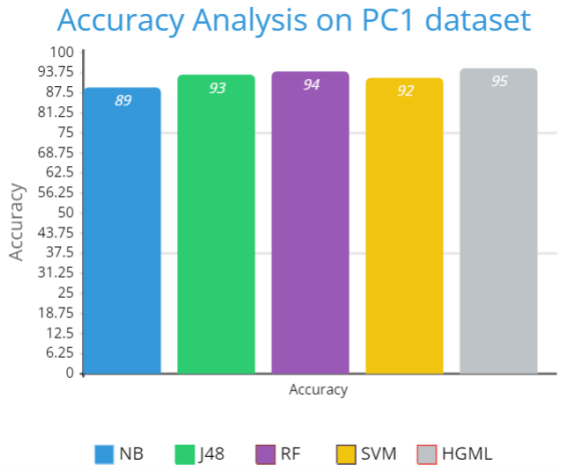

Figure 4.5: Performance Analysis Chart for PC1 Datasets

V. CONCLUSION

The primary objective of this study is to evaluate the performance of various classifiers using different metrics on NASA datasets. The analysis employs measures such as the true positive rate, false positive rate, precision, recall, and F-measures to assess the classifiers' effectiveness. The findings indicate that Naive Bayes is particularly suitable for small datasets, while Random Forest performs better with larger datasets. Future enhancements of this research are intended to apply the same evaluation process to Java-based open-source projects using the same metrics, with plans to extend the analysis to E-Commerce networking projects as well.

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