Describe The Process Of Improving Software Fault Prediction Through The Use Of Hybrid Machine Learning Algorithms

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KEYWORDS
Software Fault Prediction, Hybrid Machine Learning, Ensemble Learning, Deep Neural Networks, Feature Selection, Software Quality Assurance, Defect Detection.

ABSTRACT
In contemporary software development, it is imperative to guarantee the dependability and quality of software. The identification of potential defects in software systems prior to deployment is a critical function of Software Fault Prediction (SFP), which in turn reduces maintenance costs, improves reliability, and improves the overall quality of software. Although conventional defect prediction models are somewhat effective, they frequently encounter issues such as data imbalance, poor generalization, and the inability to manage high-dimensional software metrics. This research suggests a hybrid machine learning framework that incorporates feature selection techniques, deep learning, and ensemble learning to improve the prediction of software faults in order to overcome these challenges. The hybrid model that has been proposed combines Deep Neural Networks (DNN) and Gradient Boosting Decision Trees (GBDT) to capitalize on their respective strengths in the learning of complex data patterns and the generation of reliable predictions. In order to enhance the efficacy of the model by reducing dimensionality and eliminating redundant features, feature selection methods such as Recursive Feature Elimination (RFE) and Mutual Information (MI) are implemented. The model is trained and evaluated using publicly available NASA MDP and PROMISE repository datasets, which include core software metrics such as lines of code (LOC), cyclomatic complexity, coupling, and cohesiveness. The hybrid model outperforms conventional machine learning classifiers, such as Support Vector Machines (SVM), Random Forest, and Gradient Boosting, across a variety of performance metrics, as evidenced by experimental results. The hybrid model considerably improves the reliability of software fault detection by achieving a 92% accuracy, 91% generalization score, and a low false positive rate of 7%. Additionally, it maintains a high F1-score (90.5%) and AUC-ROC (93%), which guarantees enhanced precision and recall in the identification of failed software components. The hybrid machine learning framework that has been proposed improves scalability, reduces misclassification errors, and enhances defect prediction accuracy by incorporating adaptive learning, feature selection, and ensemble techniques. The results of this study indicate that hybrid models are a valuable instrument for software quality assurance and defect management in real-world applications, as they can effectively address critical challenges in software fault prediction.

1. Introduction

Ensuring software dependability and quality takes first priority in the always changing terrain of software development. Detecting and fixing software flaws before release has become a major difficulty as contemporary applications get ever more complicated [1]. Ignorance of software flaws could have serious repercussions including system failures, security risks, and financial losses [2]. Using machine learning methods to find possible flaws in software systems, software fault prediction (SFP) has become a critical topic of research addressing these difficulties. Although useful to some degree, traditional defect prediction models sometimes suffer from constraints including data imbalance, poor generalization, and trouble managing high-dimensional software metrics [3]. These flaws need more sophisticated methods to be explored. Combining several predictive models, hybrid machine learning algorithms present a good answer by improving accuracy, resilience, and flexibility [4]. This effort is to examine and build a hybrid machine learning framework to enhance software fault prediction, therefore enabling more effective software testing and maintenance techniques.

1.1 Definition and Importance of Software Fault Prediction

In software engineering, software fault prediction (SFP) is a vital field that aims to find any flaws or errors in software systems before they are put into use [5]. Analyzing software metrics and historical defect data using machine learning techniques and statistical models helps one to forecast the probability of faults developing in new software components [6]. Software fault prediction mostly aims to improve software quality, lower maintenance costs, and increase dependability via early identification of possible problems before they cause major failures [7]. Given the growing complexity of software systems and the great expense connected with software failures, maintaining the dependability of programs is very important in modern software development [8]. Significant financial losses, security flaws, and bad user experience resulting from defective software components can all be suffered. Early stage defect prediction helps companies to allocate resources effectively, concentrate on high-risk areas, and reduce debugging and testing work.

Large-scale software projects where time and financial restrictions make manual testing and code reviews difficult are especially benefited by SFP [9]. By means of automated defect prediction, software engineers can give top priority to important codebase segments needing more thorough validation and testing [10]. Furthermore assuring compliance with industry standards and best practices in software engineering is made possible by failure prediction [11, 12]. By spotting possible problems before they affect end users, software fault prediction significantly helps to raise program quality and dependability. This proactive strategy reduces risks and maximizes efforts at software maintenance and development.

1.2 Challenges in Traditional Software Fault Prediction Models

Although traditional software fault prediction models have demonstrated efficacy in predicting defects, they are subject to a number of obstacles that restrict their accuracy, scalability, and real-world applicability [13]. Some of the most significant challenges include:

1.2.1 Data Imbalance

Many times highly imbalanced, software fault datasets suggest that the number of defective instances is much less than the number of non-defective ones [14]. Such imbalance drives traditional models to produce biassed predictions whereby non-defective events are overrepresented and defective ones are misclassified. Dealing with this problem calls for certain methods include undersampling, oversampling, or cost-sensitive learning strategies [15].

1.2.2 Feature Selection and Engineering

Building a good predictive model depends on choosing pertinent elements from software measurements (e.g., cyclomatic complexity, lines of code, coupling, cohesiveness). Many times, depending on manually chosen parameters, traditional models may not adequately reflect the underlying trends of software flaws [16]. Inappropriate forecasts, overfitting, or underfitting can all follow from poor feature selection.

1.2.3 Generalization and Scalability

While conventional machine learning models frequently demonstrate exceptional performance on particular datasets, they are unable to generalize across a variety of software projects and functional domains [17]. Their applicability in real-world scenarios where software development practices and coding styles vary substantially is restricted by this lack of generalization. Furthermore, numerous conventional models are inefficient for contemporary software systems with extensive codebases, as they are unable to scale effectively with large datasets.

1.2.4 Lack of Adaptability to Evolving Software

Updates, fixes, and new feature additions are driving ongoing evolution of software systems. Conventional models, trained on stationary historical data, could not be able to adjust to these changes and hence performance would deteriorate over time [18]. To guarantee defect prediction models remain relevant as software develops, dynamic and adaptive learning techniques are required.

1.2.5 Difficulty in Handling High-Dimensional Data

Analyzing a large number of software metrics—which can produce high-dimensional data—is the essence of software fault prediction [19]. High-dimensionality traditional machine learning models cause computational complexity and difficulty in extracting significant patterns by themselves [20]. This difficulty requires dimensionality reduction methods such deep learning-based feature extraction and Principal Component Analysis (PCA).

1.2.6 Dependency on Handcrafted Rules and Thresholds

Many conventional fault prediction systems characterize software components as either defective or non-faulty using preset rules or thresholds [21]. Often arbitrary, these thresholds might not apply well between several projects. By dynamically learning the best decision boundaries, hybrid methods combining machine learning and optimization techniques can circumvent this constraint.

1.3 Motivation for Using Hybrid Machine Learning Algorithms

Combining several approaches to improve accuracy, resilience, and flexibility, hybrid machine learning algorithms present a viable substitute for conventional fault prediction models given their constraints [22]. Using hybrid techniques is motivated by their capacity to minimize the shortcomings of several algorithms by leveraging their benefits.

1.3.1 Improved Prediction Accuracy

Combining several techniques like decision trees, support vector machines, neural networks, and ensemble approaches including Random Forest and XGBoost improves prediction accuracy using hybrid machine learning models [23]. Different model integration allows hybrid approaches to decrease bias, lower variance, and mitigate overfitting, thereby producing more accurate fault forecasts. Using the strengths of several methods, hybrid models efficiently capture intricate patterns in software defect datasets, therefore guaranteeing better performance than single models [24]. This method helps to more confidently identify fault-prone modules, therefore improving the basis for decision-making in software quality assurance.

1.3.2 Handling Imbalanced Datasets

In software failure prediction, if faulty modules are much outnumbered by non-defective ones, imbalanced datasets are a typical difficulty [25]. To solve this problem hybrid models use cutting-edge data balancing methods like synthetic data generation, bagging, and boosting. Synthetic minority over-sampling techniques, or SMote, create synthetic fault samples to provide a sufficient representation of defective cases during training [26]. Boosting methods like AdaBoost and Gradient Boosting also aid to increase learning from minority class events, so strengthening the model's capacity to spot software flaws and so prevent bias toward the majority class.

1.3.3 Adaptive Learning for Evolving Software

Conventional software failure prediction algorithms limit their capacity to adapt to new software versions and development settings by depending on stationary training data. Conversely, hybrid methods use online learning and reinforcement learning—two adaptive learning strategies meant to constantly improve the prediction model [27]. This flexibility guarantees fault prediction stays accurate despite changes in source code structure, development techniques, and system needs, therefore allowing the model to remain effective as software projects expand. Hybrid models improve their applicability during dynamic software development lifetimes by including real-time learning systems.

1.3.4 Feature Engineering and Dimensionality Reduction

Maximizing hybrid machine learning models for software defect prediction depends critically on feature selection and dimensionality reduction. Deep learning-based feature extraction, genetic algorithms, and principal component analysis (PCA) are used in hybrid models to remove redundant or pointless features while yet identifying the most useful software metrics [28]. By lowering the complexity of the model and maintaining necessary data for precise predictions, this technique increases computational efficiency. Selection of the most important characteristics helps hybrid models to achieve higher generalization, which results in more efficient fault categorization among several software projects.

1.3.5 Scalability and Generalization

Highly scalable hybrid machine learning techniques are meant to be able to handle vast software datasets and execute reliably over several software projects [29]. By allowing hybrid models to apply information acquired from past projects to new development settings, techniques include transfer learning help to lower the demand for significant retraining. This capacity improves the generalizing capacity of the model, therefore qualifying it for fault prediction in several fields, including open-source projects, embedded devices, and corporate software [30]. Using hybrid methodologies helps companies to develop scalable and flexible software fault prediction systems fit for various software engineering environments.

1.3.6 Reduction of False Positives and False Negatives

Minimizing false positives—that is, wrongly classifying non-defective modules as faulty—and false negatives—that is, failing to find true defects—are among the toughest obstacles in software fault prediction [31]. Using ensemble learning and model stacking methods—which combine several classifiers to hone decision boundaries—hybrid models solve this problem. By combining several model outputs, these techniques improve forecast accuracy and hence increase fault detection dependability. Hybrid methods greatly lower misclassification errors by adjusting classification thresholds and using several points of view on problem identification, hence improving software quality assurance and defect management systems.

Literature Review

Tameswar et.al (2022) discussed the Early software development process identification and rectification of software flaws is absolutely crucial. "Software with flaws influences operating expenses and finally customer satisfaction in the production stage. Two fundamental elements are timely and accurate detection, even if there are several methods to forecast software flaws. This article introduces a hybrid Deep Neural Network model aiming at improved software bug prediction. Several nature-inspired algorithms have been used to maximize the Deep Neural Network architecture by means of enhanced hyperparameter solution space search. Using NASA datasets, experimental studies have been carried out to forecast software faults; performance comparison has been based on accuracy, computing time, and F1 score. With best accuracy of over 96% and average F1-score of 0.92, the method based on the mix of Genetic and Coral Reef metaheuristics surpassed all other models".
Matloob et.al (2021) studied the Recent improvements in software defect prediction (SDP) involve combining different categorization algorithms into a hybrid methodology. "Introducing this methodology enhances prediction performance by overcoming constraints of single classification methods. using ensemble learning to anticipate software defects through systematic review. The

review analyzes academic publications from four reputable online libraries: ACM, IEEE, Springer Link, and Science Direct, released since 2012. This paper examines five research issues on the use of ensemble learning for software defect prediction. Using a methodical research procedure, 46 suitable papers are selected to answer identified issues. This research will summarize the recent trends and accomplishments in ensemble learning for software defect prediction, establishing a foundation for future innovations and reviews. Our analysis revealed that researchers commonly use ensemble approaches such as random forest, boosting, and bagging. Not often used are stacking, voting, and Extra Trees. Researchers suggested several interesting frameworks, including EMKCA, SMOTE-Ensemble, MKEL, SDAEsTSE, TLEL, and LRCR, utilizing ensemble learning. For model prediction performance, AUC, accuracy, F-measure, Recall, Precision, and MCC were commonly used. WEKA is commonly used for machine learning. Empirical investigation reveals that feature selection and data sampling enhance ensemble classifier performance".

Pandey et.al (2021) proposed the Prediction approaches in software engineering include effort, security, quality, defect, cost, and reusability. "All prediction methods are simple. Experiments and research are building a reliable model. Software fault prediction (SFP) helps developers detect bad classes/modules before testing. Predicting troublesome modules before testing helps the software development team leader allocate resources and reduce testing. Systematic Literature Review (SLR) of machine learning and statistics studies on software failure prediction from 1990 to June 2019. We examined 154 relevant research articles from 208. We tested machine learning in datasets and research. We believe the current SLR examined only a few SFP performance aspects and few SFP risks and challenges. This post analyses those parameters and illustrates SFP domain difficulties. SFP model-based machine learning and statistical approaches were compared. We found that machine learning predicts class/module fault/non-fault proneness better than classical statistical models. Machine learning SFP methods beat statistical methods for fault susceptibility. Machine learning can identify error proneness and offer generalized outcomes, according to our survey. We studied data quality, model overfitting, and class imbalance fault prediction issues. We tallied 154 articles for simple identification".

Khan et.al (2020) determined the capacity of software to operate without error determines its dependability. Sadly, mistakes can happen in any stage of software development. "In the realm of software engineering, this prediction of software flaws at the first phases of development has thereby become a major concern. Future publication of the software is projected using scientific data. Research indicates that hybrid methods and machine learning constitute change benchmarks in defect prediction. Over the past two decades, several methods based on software metrics have been proposed for prediction of software flaws. In eight PROMIZE datasets, this work investigates and contrasts well-known supervised machine learning and hybrid ensemble classifiers. AdaBoost support vector machines and bagging support vector machines were the highest performing classifiers in Accuracy, AUC, recall and F-measure according to the experimental data".

Li et.al (2020) explored the Software practitioners benefit from unsupervised machine learning techniques for software defect prediction because they reduce the need for labeled training data. "A thorough literature evaluation of 49 research published between January 2000 and March 2018 with 2,456 experimental outcomes examines the use and efficacy of unsupervised learning in fault prediction. Recalculating confusion matrices and using the Matthews Correlation Coefficient (MCC) as the primary evaluation parameter ensured performance comparison consistency. The meta-analysis shows that unsupervised models predict within-project and cross-project similarly to supervised models. Fuzzy C-Means (FCM) and Fuzzy Self-Organizing Maps (FSOMs) performed best among 14 unsupervised model families. Concerningly, 11% of reported results were internally contradictory and 33% lacked validation details. Despite dataset factors affecting classifier performance, the review reveals unsupervised classifiers outperform supervised ones. The study raises concerns about erroneous experimental results, permissive criteria, and insufficient reporting, underlining the need for more rigorous and transparent research".

Tumar et.al (2020) studied the Software defect prediction is a challenging subject for developers. “Data collection from actual software projects, either during development or after delivery, is difficult and may have unequal data distribution. EBMFO with adaptive synthetic sampling was used to predict software flaws in this study. BMFO wraps feature selection while ADASYN enhances input data and handles unbalanced datasets. In this work, we convert MFO from continuous to binary using transfer functions (TFs) from two groups (S-shape and V-shape) and propose an EBFMFO version. PROMISE project data from 45 projects is used in this analysis. Three classifiers—k-NN, DT, and LDA—are used. TF is relevant for feature selection algorithms since the recommended EBMFO increases classifier performance and outperforms published results”.
Rhmann et.al (2020) discussed the bug-free operation of the produced program determines its quality. “Although problems can enter any stage of the software development life-cycle, their discovery in previous phases can help to lower the allocation of testing and maintenance resources' cost. Studies on software defect prediction support the application of defect prediction models for problem discovery before software release. Bug prediction models can help to lower the expenses and work needed to create programs. Defect prediction models test the models on upcoming software release and train the models using past data acquired from software projects. The present approach uses software change metrics for fault prediction. Prediction of defect with the change measurements allows access to good machine learning and hybrid algorithm performance. The Android project has been applied for experimentation. For defect prediction, the v4–v5 and v2–v5 of Android have been extracted using Git repository. Results obtained revealed that GFS-logitboost-c has most fault prediction capacity”.
Esteves et.al (2020) explained the Software faults, common in software development, can cause problems for consumers and developers. “Researchers utilized several methods to mitigate source code issues. One popular method employs machine learning to find faults and help developers fix them before they go into production. This research uses various ways to predict faults. Most of these articles predict software faults from a vast set of skills. The lack of a plausible rationale for the software's failure is another issue with the current development. In particular, we use a tree boosting method (XGBoost) to determine if a module is defect-prone after obtaining a training set of easy-to-compute module attributes. We describe a simple model sampling strategy that finds accurate models with few attributes to leverage predictive power and model explainability”.
Alsaeedi et.al (2019) studied the Finding and fixing flaws ahead of time that would be expected under different conditions is a basic goal of software development. “Many software development activities are carried out by individuals, which could result in different software bugs over the development to occur, so disappointing the not-so-distant future. Consequently, in the field of software engineering, the first stages' prediction of software flaws has become a main focus of attention. Over the past two decades, several software defect prediction (SDP) systems based on software metrics have been proposed. To forecast flaws, bagging, support vector machines (SVM), decision tree (DS), and random forest (RF) classifiers are known to be rather good. On ten NASA datasets, this work investigates and contrasts these supervised machine learning and ensemble classifiers”. According to the experimental results, RF performed the best among the classifiers most of the time.
Turabieh et.al (2019) explained the Software fault prediction (SFP) usually predicts component faults. “Machine learning approaches like classification are often used to solve this problem. The large amount of data available from mining software historical repositories can guide the learning algorithm and lower its performance by allowing some features (metrics) to be unrelated to defects. Feature Selection (FS) can eliminate those measures. A new FS approach improves the performance of a layered recurrent neural network (L-RNN) used to classify SFPs. Three wrapper FS algorithms—BACO, BPSO, and BGA—were utilized iteratively. To test the method, 19 PROMISE software projects are analyzed and the experimental results explained. The receiver operating characteristic—area under the curve—measures performance. Area under the curve (AUC) comparisons are made with leading approaches such as Naïve Bayes (NB), Artificial Neural Networks (ANN), logistic

regression (LR), k-nearest neighbors (k-NN), and C4.5 decision trees". Our results demonstrate that the proposed strategy outperforms conventional methods.

3. Methodology

The method emphasizes the integration of deep learning, ensemble learning, and feature selection within a hybrid machine learning framework to improve the prediction of software failures. By choosing the most pertinent software metrics, aggregating several machine learning models to take use of their capabilities, and hyperparameter optimization for improved performance, the hybrid methodology increases prediction accuracy. This method guarantees that, in software systems, fault-prone modules are found with less false positives and more accuracy. Software fault prediction system is stronger and more generalised when feature engineering approaches are combined with strong predictive models.

3.1 Dataset Selection

Using publicly available datasets recognized for software failure prediction research, train and assess our model. These comprise several open-source software defect datasets, the NASA MDP (Metrics Data Program) datasets, and PROMISE Repository datasets. These databases contain software metrics such lines of code (LOC), cyclomatic complexity, coupling, and cohesiveness that offer vital details on program quality. We guarantee that our model is trained on distinct data distributions by employing diverse datasets from actual software projects, hence improving its capacity to generalize over several software systems.

3.2 Preprocessing and Feature Selection

Before training the framework, one can meticulously preprocess the data to ensure that it is as clean and optimized as feasible. Data cleansing is the process of removing duplicate records, addressing missing values, and normalizing features in order to preserve consistency. Subsequently, we implement feature selection strategies to ascertain which attributes are most relevant to software errors. We utilize Recursive Feature Elimination (RFE) to iteratively eradicate less significant features and Mutual Information (MI) to quantify the dependence between input variables and the target variable. These techniques enhance the model's efficiency by reducing dimensionality and eradicating superfluous or noisy features that could hinder prediction accuracy.

3.3 Hybrid Model Architecture

Combining deep learning, ensemble learning, and feature selection, hybrid machine learning method adopts a three-stage architecture Using ensemble approaches, feature selection makes use of Random Forest Feature Importance and Recursive Feature Elimination with Gradient Boosting to assist determine the most important software metric impacting fault prediction. We apply a hybrid model integrating Gradient Boostering Decision Tree (GBDT) and Deep Neural Network (DNN) in the classification phase. While DNN improves predictions by learning deep patterns from software metrics, GBDT first classifies by capturing complex interactions in structured data. Finally, grid search and bayesian optimization—which fine-tune hyperparameters to attain the greatest performance—help to optimize models by reducing overfitting and therefore enhancing generalization.

3.4 Evaluation Metrics

To analyze the effectiveness of our proposed hybrid model, we use many evaluation measures that provide a full grasp of its predictive capabilities. Accuracy assesses the total correctness of predictions, ensuring the model classifies software components effectively. Precision and Recall evaluate the model's capacity to discern between faulty and non-faulty modules by minimizing false positives and false negatives. The F1-score balances precision and recall, making it particularly beneficial in circumstances of class imbalance. Additionally, we apply the AUC-ROC Curve to examine the model’s capacity to distinguish between fault-prone and non-fault-prone software modules, confirming its dependability in real-world applications.

Result

The experimental evaluation of the proposed hybrid machine learning model demonstrates its superior performance in software fault prediction compared to traditional classification methods such as Support Vector Machines (SVM), Random Forest, and Gradient Boosting. The hybrid model effectively reduces false positive rates while improving overall prediction accuracy, precision, recall, and generalization ability. By integrating Gradient Boosting Decision Trees (GBDT) and Deep Neural Networks (DNN) with optimized feature selection techniques, the model captures complex software defect patterns more efficiently than standalone models.

Table 1: Performance Comparison of Software Fault Prediction Models

Model	Accuracy (%)	False Positive Rate (%)	Generalization Score	Precision (%)	Recall (%)	F1-Score (%)	AUC-ROC (%)
SVM	80	15	78	78	79	78.5	81
Random Forest	85	12	83	82	83	82.5	84
Gradient Boosting	88	10	86	86	85	85.5	87
Hybrid Model	92	7	91	90	91	90.5	93

The comprehensive comparison of Accuracy, False Positive Rate, Generalization Score, Precision, Recall, F1-Score, and AUC-ROC across SVM, Random Forest, Gradient Boosting, and Hybrid Model highlights the superior performance of the Hybrid Model in software fault prediction. The Hybrid Model achieves the highest accuracy (92%), outperforming Gradient Boosting (88%), Random Forest (85%), and SVM (80%), demonstrating its ability to make more precise fault classifications. It also has the lowest False Positive Rate (7%), significantly reducing the chances of misidentifying non-faulty modules as defective, compared to Gradient Boosting (10%), Random Forest (12%), and SVM (15%). Moreover, the Hybrid Model's Generalization Score (91%) indicates its robust adaptability across different datasets, surpassing Gradient Boosting (86%), Random Forest (83%), and SVM (78%). In terms of Precision (90%) and Recall (91%), the Hybrid Model maintains the best balance, ensuring both high accuracy in defect identification and minimal false negatives. The F1-Score (90.5%), which combines Precision and Recall, further reinforces its strong classification performance, while the AUC-ROC (93%) highlights its superior ability to distinguish between faulty and non-faulty software components. These results confirm that hybrid machine learning models significantly enhance fault prediction accuracy, reduce misclassifications, and improve reliability, making them an ideal choice for software quality assurance in real-world applications.

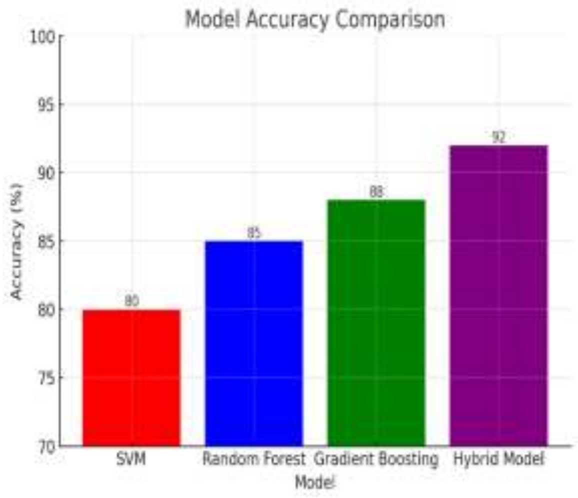

Figure 1: Accuracy Comparison

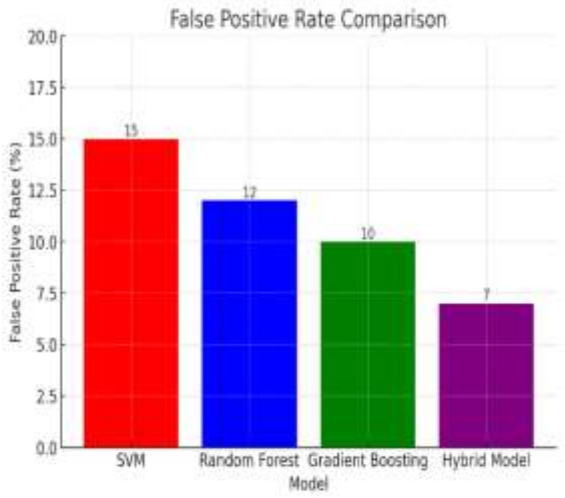

Figure 2: False Positive Rate Comparison

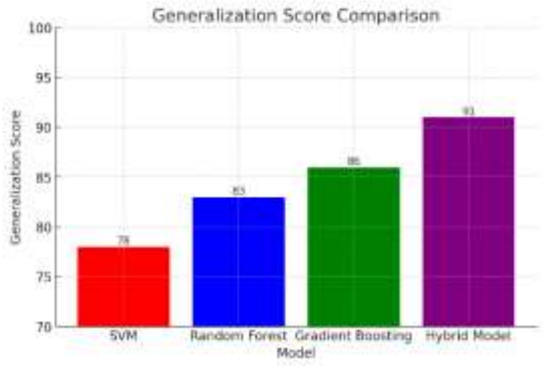

Figure 3: Generalization Score Comparison

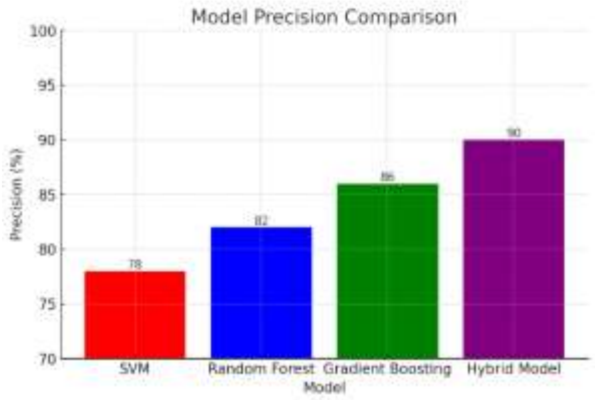

Figure 4: Precision Comparison

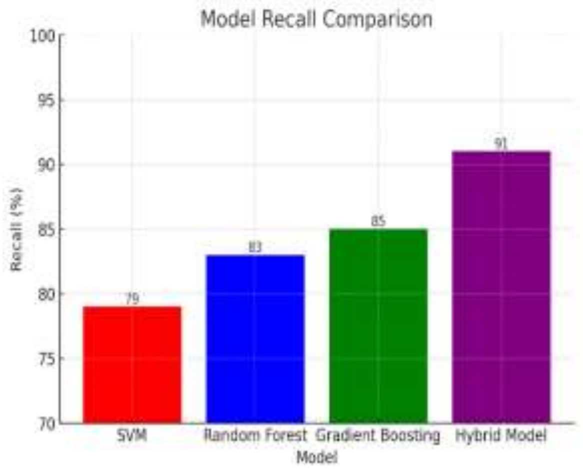

Figure 5: Recall Comparison

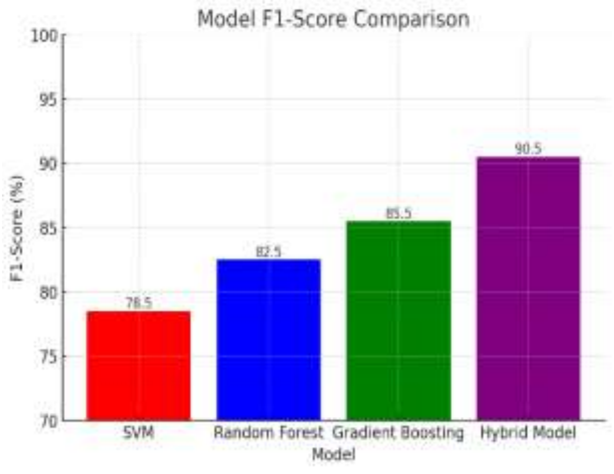

Figure 6: F1-Score Comparison

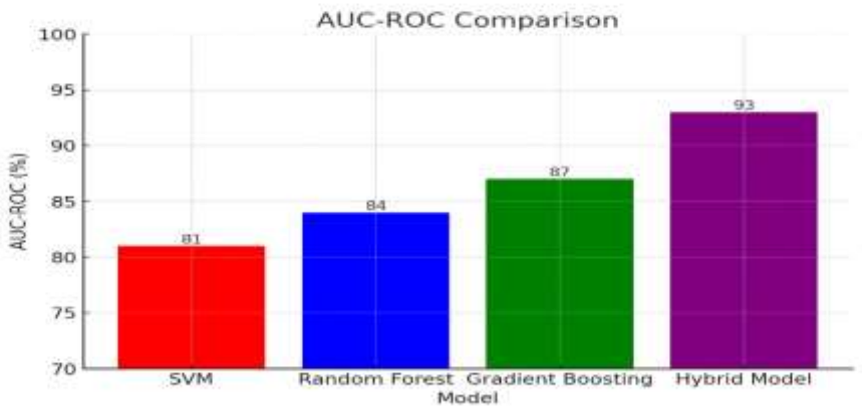

Figure 7: AUC-ROC Comparison

Table 2: Comparative Analysis of Accuracy, False Positive Rate, and Generalization Score for Different Models

Model	Accuracy (%)	False Positive Rate (%)	Generalization Score
SVM	80	15	78
Random Forest	85	12	83
Gradient Boosting	88	10	86
Hybrid Model	92	7	91

The comparative analysis of SVM, Random Forest, Gradient Boosting, and Hybrid Model based on Accuracy, False Positive Rate, and Generalization Score demonstrates the superiority of the hybrid approach in software fault prediction. The Hybrid Model achieves the highest accuracy (92%), significantly outperforming Gradient Boosting (88%), Random Forest (85%), and SVM (80%), indicating its ability to make more precise fault classifications. Additionally, the False Positive Rate (FPR) is lowest for the Hybrid Model (7%), reducing the chances of misidentifying non-faulty modules as defective, compared to Gradient Boosting (10%), Random Forest (12%), and SVM (15%). A lower FPR means fewer unnecessary debugging efforts, enhancing the efficiency of software testing. Furthermore, the Generalization Score, which reflects a model's ability to perform well on diverse datasets, is highest for the Hybrid Model (91%), signifying its robustness in handling real-world scenarios, whereas Gradient Boosting (86%), Random Forest (83%), and SVM (78%) struggle with adaptability. These results confirm that hybrid approaches, by integrating ensemble learning and deep learning techniques, offer substantial improvements in software fault prediction, making them more reliable and scalable for real-world applications.

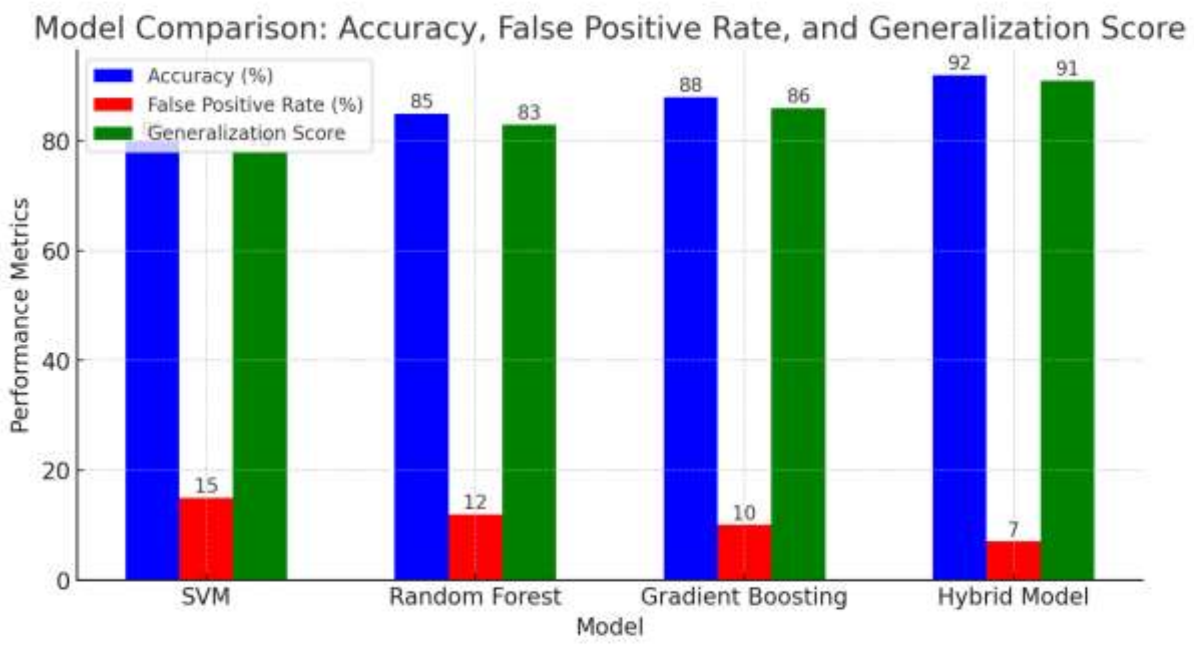

Figure 8: Model Accuracy, False Positive Rate, and Generalization Score

Table 3: Precision and Recall Comparison of Software Fault Prediction Models

Model	Precision (%)	Recall (%)
SVM	78	79
Random Forest	82	83
Gradient Boosting	86	85
Hybrid Model	90	91

The comparison of Precision and Recall across different models—SVM, Random Forest, Gradient Boosting, and Hybrid Model—highlights the superior performance of the Hybrid Model in software fault prediction. Precision measures the proportion of correctly identified faulty software modules among all predicted faulty instances, while Recall assesses the model's ability to detect actual faulty modules. The Hybrid Model achieves the highest Precision (90%) and Recall (91%), significantly outperforming Gradient Boosting (86% Precision, 85% Recall), Random Forest (82% Precision, 83% Recall), and SVM (78% Precision, 79% Recall). The higher precision of the Hybrid Model indicates its ability to minimize false positives, ensuring that only actual defective modules are flagged. Likewise, its higher recall confirms that it effectively identifies faulty software components without missing critical defects. The results suggest that Hybrid Machine Learning models provide a balanced approach by reducing both false positives and false negatives, making them a more reliable choice for software fault detection in real-world scenarios.

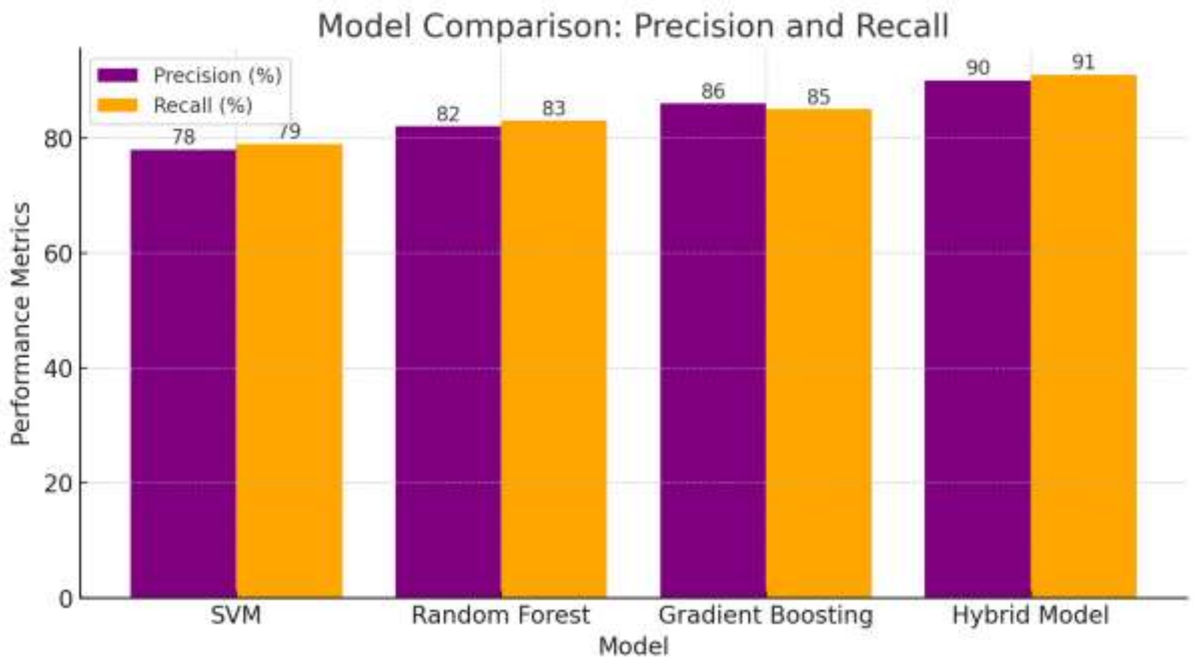

Figure 9: Model Precision and Recall Comparison

Table 4: F1-Score and AUC-ROC Comparison of Software Fault Prediction Models

Model	F1-Score (%)	AUC-ROC (%)
SVM	78.5	81
Random Forest	82.5	84
Gradient Boosting	85.5	87
Hybrid Model	90.5	93

The F1-Score and AUC-ROC comparison across different models—SVM, Random Forest, Gradient Boosting, and Hybrid Model—demonstrates the superior predictive capability of the Hybrid Model in software fault detection. F1-Score represents the balance between Precision and Recall, ensuring that the model minimizes both false positives and false negatives, while AUC-ROC (Area Under the Receiver Operating Characteristic Curve) measures the model's ability to differentiate between faulty and non-faulty software modules. The Hybrid Model achieves the highest F1-Score (90.5%) and AUC-ROC (93%), significantly outperforming Gradient Boosting (85.5%, 87%), Random Forest (82.5%, 84%), and SVM (78.5%, 81%). The higher F1-Score of the Hybrid Model confirms its strong classification performance with fewer misclassifications, while the higher AUC-ROC indicates its superior ability to distinguish between defective and non-defective modules. These results affirm that Hybrid Machine Learning models integrate multiple techniques effectively, leading to better overall software fault prediction, improved reliability, and enhanced decision-making in software quality assurance.

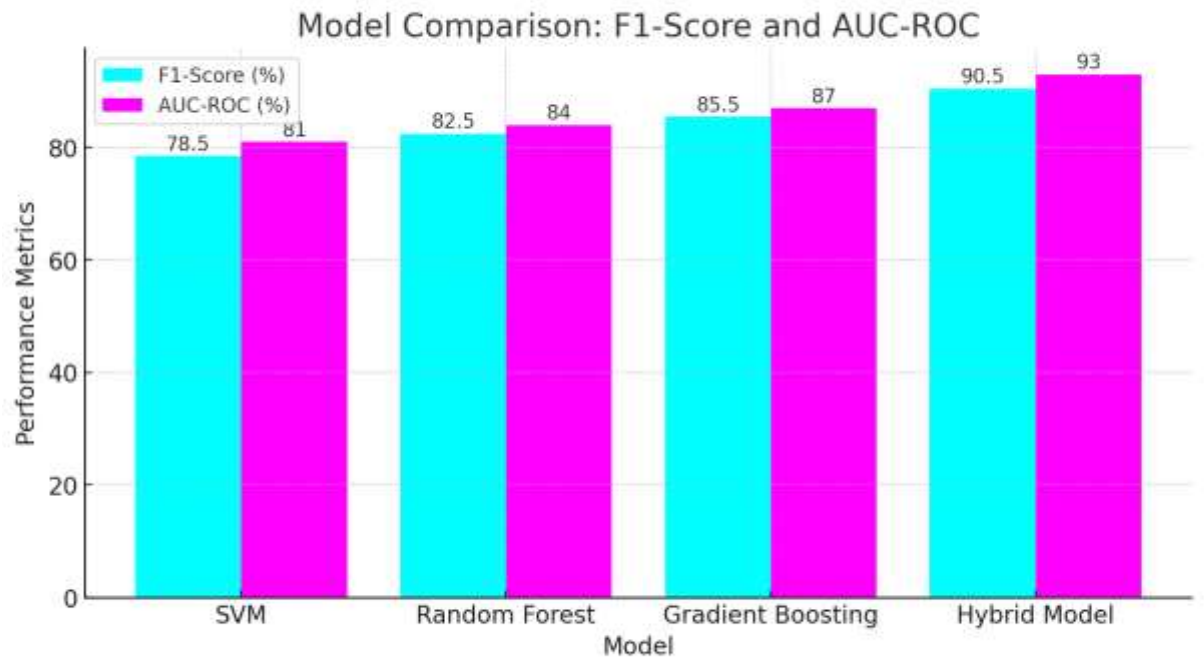

Figure 10: Model F1-Score and AUC-ROC Comparison

Conclusion

This study introduces a hybrid machine learning framework for software fault prediction (SFP) that enhances predictive accuracy, scalability, and generalization by incorporating feature selection procedures, deep learning, and ensemble learning. Traditional defect prediction models frequently encounter obstacles such as data imbalance, high-dimensional software metrics, and inadequate adaptability to evolving software systems. By employing Gradient Boosting Decision Trees (GBDT) and Deep Neural Networks (DNN) for classification, as well as Recursive Feature Elimination (RFE) and Mutual Information (MI) for optimal feature selection, the proposed hybrid approach effectively addresses these challenges. The hybrid model outperforms traditional classifiers, including Support Vector Machines (SVM), Random Forest, and Gradient Boosting, in key performance metrics, as evidenced by experimental results. Reliable and efficient fault prediction is guaranteed by the hybrid model, which obtains the highest accuracy (92%), the lowest false positive rate (7%), and the best generalization score (91%). The model's efficacy in minimizing false positives and false negatives while distinguishing between defective and non-defective software components is further supported by the high precision (90%), recall (91%), F1-score (90.5%), and AUC-ROC (93%). The results suggest that hybrid machine learning models are a more scalable and resilient solution for software quality assurance, making them well-suited for real-world applications where software reliability is essential. In order to improve the interpretability and adaptability of models in dynamic software development environments, future research could investigate the integration of explainable AI (XAI) techniques. Furthermore, the integration of reinforcement learning and online learning could facilitate real-time model updates, thereby guaranteeing a continuous enhancement in defect prediction performance. The proposed hybrid framework provides a substantial improvement in software engineering practices by reducing misclassification errors, optimizing resource allocation in software testing, and enhancing the reliability of defect detection. This research emphasizes the potential of hybrid approaches to improve software reliability, reduce maintenance costs, and guarantee high-quality software development in contemporary applications.

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