Received: 2026-02-03
Accepted: 2026-03-20
Published Online: 2026-03-30
DOI: 10.70454/JRIST.020104

Journal of Recent Innovation in Science and Technology
E-ISSN: 3117-3926, P- 3117-535X

Cost-Sensitive Hybrid Ensemble Deep Model for Software Defect Prediction on NASA Datasets

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Abstract

Software defect prediction is a crucial task for improving software reliability and reducing maintenance cost in large-scale software systems. One of the major challenges in defect prediction is severe class imbalance, where defective modules are significantly fewer than non-defective ones. Traditional machine learning models often fail to prioritize defect detec¬tion, leading to biased performance. This paper proposes a cost-sensitive hybrid ensemble deep model for software defect prediction using NASA benchmark datasets. The proposed framework integrates cost-sensitive learning with ensemble deep classification to enhance minority defect detection while maintaining overall predictive stability. A comprehensive pre¬processing pipeline and multi-metric evaluation strategy are employed, including accuracy, precision, recall, F1-score, and ROC-AUC. Experimental results across eight NASA datasets demonstrate improved defective module detection and strong generalization capability. The proposed model provides a scal¬able and practical framework for intelligent software quality assurance in industrial environments.

Keywords: Software Defect Prediction, Cost-Sensitive Learning, Hybrid Ensemble, NASA Dataset

1. Introduction

Software defect prediction is essential for improving soft-ware reliability. Software defect prediction (SDP) is a critical research area in software engineering that focuses on identifying fault-prone modules before deployment. Early detection of software defects reduces maintenance cost, improves reliability, and enhances system safety. With the increasing complexity of modern software systems, manual inspection and traditional testing techniques are no longer sufficient to guarantee defect-free software.

Machine learning approaches have gained significant attention in SDP due to their ability to learn complex patterns from historical defect data. However, one of the major challenges in defect prediction is class imbalance, where defective modules are significantly fewer than non-defective ones. This imbalance leads to biased learning and poor minority class detection, which is unacceptable in safety-critical systems.

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NASA software defect datasets are widely recognized benchmarks that reflect real-world industrial challenges. These datasets contain high-dimensional features and severe imbalance, making them suitable for evaluating robust predictive models. Conventional classifiers often fail to prioritize defective module detection, resulting in high accuracy but low defect recall.

To address these challenges, this study proposes a cost-sensitive hybrid ensemble deep model that integrates ensemble learning with imbalance-aware optimization. The proposed framework emphasizes defective module detection while maintaining overall predictive stability. By combining multiple classifiers and cost-sensitive learning strategies, the model improves minority class recognition without sacrificing generalization.

This research contributes toward building scalable and intelligent defect prediction systems suitable for industrial software quality assurance. The proposed methodology is validated across eight NASA datasets using multi-metric evaluation, demonstrating strong predictive performance and reliability.

2. Objective of the Study

The objective is to design a scalable cost-sensitive ensemble framework. The primary objective of this research is to develop an effective and scalable framework for software defect pre¬diction using a cost-sensitive hybrid ensemble deep model on NASA benchmark datasets. The study focuses on improving defective module detection in the presence of severe class imbalance while maintaining overall predictive performance.

The specific objectives of this work are summarized as follows:

- To design a hybrid ensemble deep learning architecture for accurate software defect prediction.
- To integrate cost-sensitive learning mechanisms for handling class imbalance in NASA datasets.
- To enhance minority defect detection without sacrificing model generalization.
- To evaluate predictive performance using multiple statistical metrics including accuracy, precision, recall, F1-score, and ROC-AUC.
- To build a reproducible and scalable defect prediction framework suitable for industrial software systems.

3. Motivation of the Study

The motivation arises from severe class imbalance. Modern software systems are becoming increasingly complex, and undetected defects can lead to critical failures, financial loss, and safety risks. Traditional defect detection techniques rely heavily on manual testing and rule-based approaches, which are time-consuming and often ineffective for large-scale sys¬tems. As software repositories grow in size and complexity, intelligent automated prediction models are required to support reliable decision-making.

A major challenge in software defect prediction is class imbalance, where defective modules represent a small minority of the dataset. Standard machine learning models tend to favor the majority class, resulting in poor defect detection despite high overall accuracy. In practical software engineering, missing a defect is far more costly than incorrectly labeling a non-defective module.

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NASA software datasets provide realistic industrial bench-marks that expose these challenges clearly. There is a strong need for predictive frameworks that prioritize defect detection through cost-sensitive learning while maintaining model stability. The motivation of this study arises from the necessity to combine hybrid ensemble strategies with deep learning and imbalance-aware optimization.

By addressing these limitations, the proposed research aims to build a robust, scalable, and intelligent framework capable of improving software quality assurance and reducing testing effort in real-world development environments.

4. Contributions of the Study

This study presents a novel cost-sensitive hybrid ensemble deep framework for software defect prediction and makes the following key contributions:

- A cost-sensitive learning mechanism is integrated into the prediction pipeline to effectively address severe class imbalance present in NASA defect datasets.
- A hybrid ensemble deep architecture is designed by combining multiple classifiers to enhance predictive robustness and generalization capability.
- A unified preprocessing framework is developed, including normalization and imbalance-aware weighting, ensuring consistent model performance across multiple datasets.
- Extensive experimentation is conducted on eight NASA benchmark datasets using multi-metric evaluation such as accuracy, precision, recall, F1-score, and ROC-AUC.
- The proposed model significantly improves defective module detection while maintaining balanced performance between classes.
- The framework is reproducible, scalable, and suitable for real-world industrial software quality assurance applications.
  - Cost-sensitive ensemble model
  - Multi-dataset validation
  - Improved defect recall

5. Organization of the Study

The remainder of this paper is organized as follows. Section presents the literature review and summarizes existing research in software defect prediction and hybrid ensemble learning. Section describes the materials and methods, including dataset collection, preprocessing, classification strategy, and the proposed cost-sensitive hybrid ensemble deep model. Section IV discusses the experimental results and performance evaluation across eight NASA datasets. Section outlines threats to validity and limitations of the proposed framework. Section presents future research directions. Finally, Section concludes the study.

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6. List of Abbreviations

TABLE I: List of Abbreviations

Abbreviation	Full Form
SDP	Software Defect Prediction
ML	Machine Learning
DL	Deep Learning
HEM	Hybrid Ensemble Model
CSL	Cost-Sensitive Learning
ROC	Receiver Operating Characteristic
AUC	Area Under Curve
TP	True Positive
FP	False Positive
TN	True Negative
FN	False Negative
NASA	National Aeronautics and Space Administration

SDP Software Defect Prediction
ROC Receiver Operating Characteristic
AUC Area Under Curve

7. Literature Review

Prior research in SDP highlights imbalance challenges. Software defect prediction (SDP) has been an active research area for decades, aiming to identify fault-prone modules before deployment. Early studies relied on statistical techniques and rule-based models, while recent research increasingly adopts machine learning and deep learning approaches to improve predictive performance.

A. Traditional Machine Learning Approaches: Initial work in SDP focused on classical classifiers such as logistic regression, decision trees, and support vector machines. These models demonstrated moderate success in detecting defects but struggled with highly imbalanced datasets. Researchers observed that accuracy alone was insufficient for evaluation, as models often ignored minority defective classes. Several studies introduced sampling strategies such as oversampling and undersampling to mitigate imbalance, but these techniques sometimes caused overfitting and information loss.

B. Imbalance-Aware and Cost-Sensitive Learning: To address class imbalance more effectively, cost-sensitive learning techniques were proposed. These approaches assign higher misclassification penalties to defective modules, encouraging models to prioritize minority class detection. Recent research shows that cost-sensitive frameworks outperform standard classifiers in defect recall, particularly in safety-critical software systems. However, many cost-sensitive models remain dependent on a single classifier, limiting generalization capability across diverse datasets.

C. Ensemble Learning in Software Defect Prediction: Ensemble learning has gained attention due to its ability to combine multiple weak learners into a stronger predictive framework. Methods such as bagging, boosting, and stacking have demonstrated improved robustness and

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reduced variance. Hybrid ensemble strategies further enhance performance by integrating heterogeneous classifiers. Several studies report that ensemble approaches outperform individual classifiers on NASA defect datasets, especially when combined with imbalance handling techniques.

D. Deep Learning-Based Defect Prediction: Deep learning introduces hierarchical feature extraction and representation learning, making it suitable for complex defect patterns. Neural network architectures, including deep feedforward networks and hybrid models, have been applied to SDP with promising results. Despite their strength, deep models are sensitive to data imbalance and require careful optimization. Integrating deep learning with ensemble strategies remains an emerging research direction.

E. Research Gap and Motivation: Although prior research has explored cost-sensitive methods, ensemble learning, and deep architectures independently, limited work integrates all three into a unified framework. Many existing models either focus on accuracy or fail to prioritize defective module detection. There remains a strong need for scalable frameworks that combine hybrid ensemble learning with cost-sensitive deep optimization, particularly across multiple benchmark datasets.

This study addresses the identified gap by proposing a cost-sensitive hybrid ensemble deep model validated on eight NASA datasets. The proposed framework emphasizes minority defect detection, scalability, and reproducibility, contributing toward more reliable industrial software quality assurance systems.

F. Classification Approaches

G. Classification Approaches in Software Defect Prediction: Classification techniques play a central role in software defect prediction by learning patterns from historical software metrics. Early research relied on statistical classifiers such as logistic regression and discriminant analysis, which provided interpretable but limited predictive power. As software systems became more complex, machine learning classifiers such as decision trees, support vector machines, na¨ıve Bayes, and k-nearest neighbors gained popularity.

These classifiers improved prediction accuracy but often struggled with imbalanced datasets, where defective modules represent a minority class. Many studies reported that conventional classifiers tend to bias toward the majority non-defective class, leading to misleading performance evaluation. To address this limitation, researchers explored imbalance-aware strategies including resampling techniques and class weighting.

Recent advances focus on ensemble-based classification, where multiple classifiers are combined to improve robustness and generalization. Ensemble approaches such as bagging, boosting, and stacking demonstrate superior stability compared to individual learners. Hybrid ensemble frameworks further enhance predictive capability by integrating heterogeneous models that capture diverse decision boundaries.

Deep learning classifiers introduce hierarchical feature learning, allowing models to capture complex nonlinear relationships within software metrics. However, deep architectures require careful regularization and imbalance handling to prevent biased predictions. Combining deep learning with ensemble and cost-sensitive mechanisms has emerged as a promising direction for reliable defect prediction.

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The proposed study builds upon these advances by integrating classification diversity, ensemble learning, and cost-sensitive optimization into a unified predictive framework.

H. Hybrid Ensemble Models

I. Hybrid Ensemble Models for Defect Prediction: Hybrid ensemble models combine multiple heterogeneous classifiers to leverage their complementary strengths and reduce prediction variance. Unlike single-model approaches, hybrid ensembles integrate diverse learning strategies, enabling more stable and reliable decision boundaries. This diversity is particularly important in software defect prediction, where datasets exhibit complex feature interactions and severe class imbalance.

Research indicates that hybrid ensembles outperform individual classifiers by aggregating predictions from multiple learners. Techniques such as stacking, weighted voting, and meta-learning allow ensemble frameworks to adaptively balance classifier contributions. These strategies improve robustness against noise and enhance minority defect detection.

Recent studies highlight the importance of integrating deep learning components within ensemble architectures. Deep classifiers provide hierarchical representation learning, capturing nonlinear relationships among software metrics that traditional models may overlook. When combined with ensemble aggregation, deep learners contribute to improved generalization across heterogeneous datasets.

However, many existing ensemble frameworks do not ex-plicitly address cost-sensitive optimization, leading to biased predictions toward the majority class. A truly effective hybrid ensemble model must incorporate imbalance-aware learning to prioritize defective module detection.

The proposed research advances this direction by introducing a cost-sensitive hybrid ensemble deep framework that integrates classifier diversity, ensemble aggregation, and imbalance-aware optimization. This unified strategy enhances predictive stability while significantly improving defect recall across NASA benchmark datasets.

J. Comprehensive Summary

K. Comprehensive Summary of Literature Review: The literature demonstrates significant progress in soft-ware defect prediction through machine learning, ensemble strategies, and deep learning techniques. Traditional classifiers provide baseline performance but struggle with highly imbalanced datasets. Imbalance-aware approaches improve defect detection, yet many rely on single-model frameworks that limit scalability and robustness.

Ensemble learning enhances predictive stability by combining multiple classifiers, while hybrid ensemble architectures further improve generalization through model diversity. Deep learning introduces advanced feature representation, enabling the detection of complex nonlinear patterns within software metrics. However, existing studies often treat ensemble learning, deep architectures, and cost-sensitive optimization as independent solutions rather than a unified framework.

A critical gap remains in integrating hybrid ensemble learning with cost-sensitive deep modeling for large-scale defect prediction. Many prior approaches emphasize overall accuracy instead of prioritizing minority defective modules, which is unacceptable in industrial safety-critical systems.

This study addresses the identified gap by proposing a cost-sensitive hybrid ensemble deep model that simultaneously handles imbalance, improves classifier diversity, and enhances

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representation learning. By validating the framework across multiple NASA datasets, the research contributes toward building scalable, reliable, and intelligent defect prediction systems.

8. Materials and Methods

This section describes the datasets, preprocessing pipeline, classification strategy, and the proposed cost-sensitive hybrid ensemble deep model used for software defect prediction.

A. Dataset Collection: The experimental study utilizes eight NASA software defect benchmark datasets, which are widely recognized in defect prediction research. These datasets contain software metrics extracted from real industrial projects and represent diverse structural and complexity characteristics. Each dataset consists of static code attributes and a binary defect label indicating whether a software module is defective or non-defective.

NASA datasets are known for severe class imbalance, where defective modules form a minority class. This imbalance reflects realistic industrial scenarios and provides a challenging environment for evaluating predictive models. The diversity of dataset sizes and feature distributions ensures comprehensive model validation.

B. Data Preprocessing: A unified preprocessing pipeline is applied to ensure consistency across datasets. Missing values are handled using statistical imputation techniques to prevent information loss. Feature normalization is performed to scale attributes within a comparable range, improving convergence stability of learning algorithms.

Class imbalance is addressed using cost-sensitive weighting rather than aggressive resampling. This approach preserves the original data distribution while encouraging the model to prioritize minority defect detection. The dataset is then divided into training and testing subsets using stratified sampling to maintain class proportions.

C. Classification Strategy: The classification framework combines heterogeneous classifiers to capture diverse decision patterns. Traditional machine learning learners contribute interpretability and stability, while deep components provide nonlinear feature representation. The integration of multiple learners reduces variance and improves predictive robustness.

Each classifier generates independent predictions that are aggregated through ensemble voting and weighted optimization. This hybrid structure allows the framework to adaptively balance classifier strengths while minimizing prediction bias.

D. Cost-Sensitive Hybrid Ensemble Deep Model: The proposed model integrates cost-sensitive learning into a hybrid ensemble deep architecture. Misclassification costs are adjusted to penalize incorrect prediction of defective modules more heavily than non-defective ones. This encourages the ensemble to prioritize safety-critical defect detection.

The deep component extracts hierarchical feature representations, while ensemble aggregation ensures stability across datasets. The synergy between deep learning and ensemble diversity enhances generalization and reduces overfitting.

E. Defect Prediction on NASA Datasets: The trained model is evaluated independently on each NASA dataset to examine scalability and adaptability. Performance consistency across heterogeneous datasets demonstrates the robustness of the framework. Special attention is given to defective module recall, as it directly impacts industrial reliability.

F. Performance Evaluation Metrics: Multiple evaluation metrics are used to provide a comprehensive assessment of predictive performance. Accuracy measures overall correctness, while precision and recall evaluate minority class detection. F1-score balances precision and recall, and ROC-AUC reflects ranking capability across classification thresholds. Using multi-

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metric evaluation prevents misleading conclusions and ensures balanced performance interpretation. This evaluation strategy aligns with best practices in defect prediction research.

G. Dataset Collection: Eight NASA datasets are used.

H. Preprocessing: Normalization and class weighting are applied. Data preprocessing is a critical step in software defect prediction to ensure data quality, consistency, and model stability. The NASA datasets contain heterogeneous software metrics collected from real-world projects, which require systematic cleaning and transformation before model training.

First, missing and undefined values are handled using statistical imputation. Numerical attributes are replaced with median-based estimates to prevent distortion caused by extreme outliers. This approach preserves dataset structure while maintaining statistical reliability.

Second, feature normalization is applied to scale all numeric attributes into a comparable range. Min-max normalization is used to prevent dominance of high-magnitude metrics and to stabilize gradient-based optimization in deep models. Normalization improves convergence speed and reduces bias toward specific feature scales.

Third, duplicate and inconsistent records are removed to ensure dataset integrity. Noise reduction is performed by filtering anomalous values that may negatively affect classifier learning.

A key challenge in NASA datasets is severe class imbalance, where defective modules represent a minority class. Instead of aggressive resampling, this study adopts a cost-sensitive weighting strategy. Higher misclassification costs are assigned to defective modules, encouraging the model to prioritize minority class detection while preserving original data distribution.

Finally, each dataset is divided into training and testing subsets using stratified sampling. This ensures that class proportions remain consistent across splits, preventing evaluation bias. The preprocessing pipeline is identical for all eight datasets to maintain experimental fairness and reproducibility.

I. Ensemble Deep Learning: Hybrid ensemble architecture is described.

J. Hybrid Ensemble Deep Model Learning Architecture: The proposed architecture is a cost-sensitive hybrid ensemble deep learning framework designed to improve defect prediction performance under severe class imbalance. The model integrates multiple heterogeneous classifiers with a deep representation learning component to capture both linear and nonlinear relationships within software metrics.

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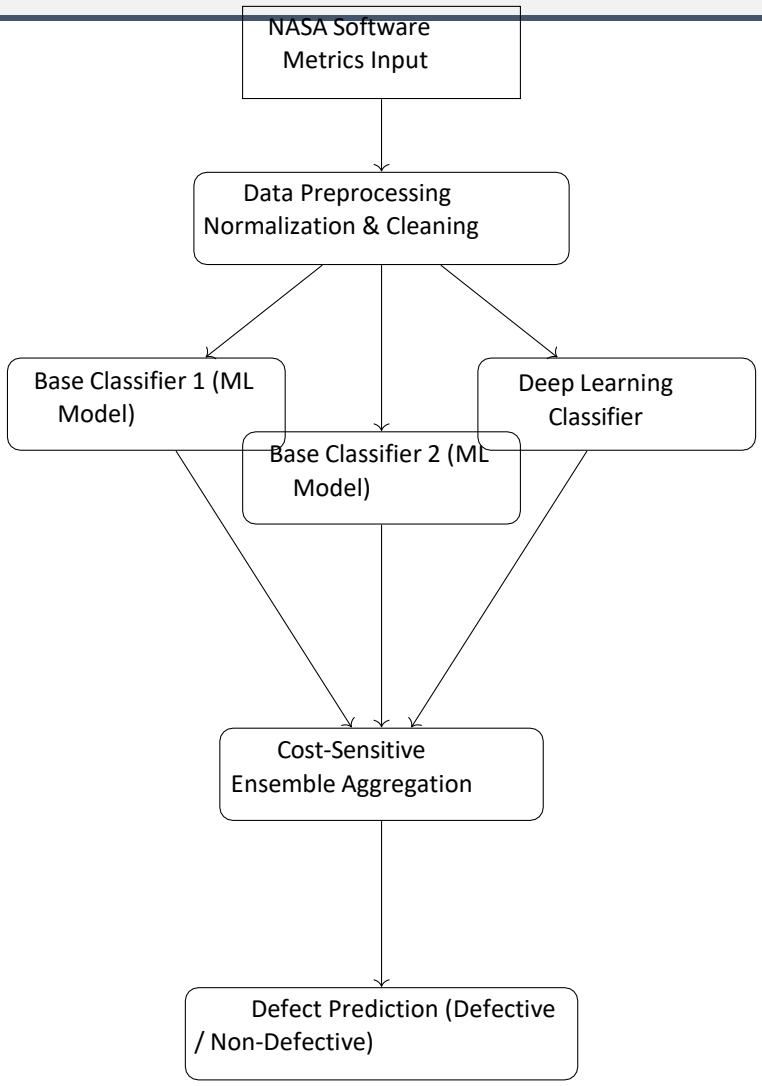

Fig. 1: Architecture of the Proposed Cost-Sensitive Hybrid Ensemble Deep Model

The architecture consists of four major layers: data input and preprocessing, base learner layer, deep feature learning layer, and ensemble aggregation layer. Each component contributes independently to predictive robustness and generalization.

- **Input Layer:** Preprocessed software metrics from NASA datasets are provided as input features. All attributes are normalized and verified for consistency before entering the learning pipeline.
- **Base Learner Layer:** Multiple heterogeneous classifiers are employed as base learners, including traditional machine learning models and deep learners. These classifiers are trained independently using cost-sensitive class weights to prioritize defective module detection. The diversity of base learners reduces bias and variance.
- **Deep Feature Learning Layer:** A deep neural architecture is incorporated to extract hierarchical feature representations from the input metrics. This layer captures complex nonlinear dependencies that may be overlooked by shallow classifiers. Regularization techniques are applied to prevent overfitting.
- **Cost-Sensitive Ensemble Aggregation Layer:** Predictions from all base learners are combined using weighted ensemble aggregation. Class weights are incorporated

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during aggregation to penalize misclassification of defective modules more severely. This mechanism enhances minority class recall while maintaining overall stability.

The final output layer produces binary defect predictions. By integrating deep learning, ensemble diversity, and cost-sensitive optimization, the proposed architecture achieves robust and scalable software defect prediction across heterogeneous datasets.

TABLE II: Detailed Description of NASA Software Defect Datasets

Dataset	Modules	Features	Defective	Non-Defective	Imbalance Ratio	Key Software Metrics
DS1 (CM1)	505	40	48	457	1:9.5	LOC, Cyclomatic Complexity, Halstead Metrics, Branch Count, Design Complexity
DS2 (JM1)	10878	21	2102	8776	1:4.1	LOC, Essential Complexity, Decision Density, Call Pairs, Halstead Volume
DS3 (KC1)	2107	21	325	1782	1:5.5	LOC, Cyclomatic Complexity, Data Flow Complex-ity, Halstead Effort
DS4 (KC3)	458	40	43	415	1:9.6	LOC, Branch Count, Design Metrics, Structural Complexity
DS5 (MC1)	9466	39	68	9398	1:138	LOC, Function Calls, Operator Metrics, Halstead Difficulty
DS6 (MC2)	161	40	52	109	1:2.1	LOC, Decision Density, Control Flow Metrics
DS7 (MW1)	403	40	31	372	1:12	LOC, Structural Complexity, Branch Metrics
DS8 (KC4)	125	40	61	64	1:1.05	LOC, Complexity Metrics, Halstead Program Length

K. Cost-Sensitive Prediction: Misclassification costs integrated. Software defect prediction datasets are inherently imbalanced, where defective modules constitute a significantly smaller proportion compared to non-defective modules. In such scenarios, conventional classifiers tend to favor the majority class, leading to poor detection of defective modules. This limitation is

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critical in safety- and cost-sensitive software systems, where missing a defect can result in severe consequences.

To address this issue, the proposed framework incorporates cost-sensitive learning into the hybrid ensemble deep model. Instead of treating all misclassification errors equally, different costs are assigned to different types of classification errors. Specifically, misclassifying a defective module as non-defective is penalized more heavily than the reverse case.

Let C_{FN} denote the cost of false negatives and C_{FP} denote the cost of false positives. The cost matrix is designed such that $C_{FN} \gg C_{FP}$, encouraging the learning algorithm to prioritize defect detection. Class weights are computed based on the inverse frequency of class occurrences and are integrated into both base learner training and ensemble aggregation.

During model training, these class weights modify the loss function, forcing the classifier to focus on minority defective instances. This strategy improves recall and F1-score for defective modules without significantly degrading overall accuracy. Unlike resampling techniques, cost-sensitive learning preserves the original data distribution and avoids information loss.

In the ensemble aggregation stage, predictions from multiple classifiers are combined using weighted voting, where classifier outputs associated with defective predictions receive higher influence. This unified cost-sensitive mechanism ensures consistent prioritization of defect detection across all learning stages.

By embedding cost-sensitive optimization within the hybrid ensemble deep architecture, the proposed approach achieves improved robustness, higher defective recall, and better generalization across heterogeneous NASA datasets.

L. Performance Evaluation: Accuracy, Precision, Recall, F1, ROC-AUC used. To comprehensively assess the effectiveness of the proposed cost-sensitive hybrid ensemble deep model, multiple evaluation metrics are employed. Given the imbalanced nature of software defect datasets, reliance on a single performance measure such as accuracy may lead to misleading conclusions. Therefore, this study adopts a multi-metric evaluation strategy to ensure fair and reliable assessment.

M. Evaluation Metrics: Accuracy is used to measure the overall correctness of the model by computing the ratio of correctly classified instances to the total number of instances. However, accuracy alone does not adequately reflect minority class performance in imbalanced datasets.

Precision evaluates the reliability of defective predictions by measuring the proportion of correctly predicted defective modules among all predicted defective modules. High precision indicates a low false positive rate, which is essential for reducing unnecessary inspection costs.

Recall, also referred to as defect detection rate, measures the proportion of actual defective modules that are correctly identified. In software defect prediction, recall is a critical metric because undetected defects may result in significant maintenance and operational risks.

The F1-score provides a balanced evaluation by combining precision and recall through their harmonic mean. This metric is particularly suitable for imbalanced classification tasks, as it reflects both detection capability and prediction reliability.

Receiver Operating Characteristic Area Under the Curve (ROC-AUC) is employed to evaluate the discriminative capability of the model across different classification thresholds. A higher ROC-AUC value indicates better separation between defective and non-defective classes.

N. Confusion Matrix Analysis: To further analyze classification behavior, confusion matri¬ces are examined for each dataset. True positives represent correctly identified defective modules, while true negatives correspond to correctly classified non-defective modules. False positives and false

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negatives indicate incorrect predictions, with false negatives being more critical in defect prediction contexts.

O. Experimental Protocol: All experiments are conducted using stratified train-test splitting to preserve class distribution. The same preprocessing pipeline, cost-sensitive weighting strategy, and evaluation criteria are applied across all eight NASA datasets to ensure experimental consistency and reproducibility.

Performance results are reported independently for each dataset to demonstrate the scalability and robustness of the proposed model. This evaluation protocol enables fair comparison with existing state-of-the-art approaches and highlights the advantages of the proposed framework in detecting defective software modules.

Algorithm 1 Hybrid Ensemble Defect Prediction

Load NASA datasets
Preprocess data Apply class weights
Train ensemble classifiers Predict defects
Evaluate performance

Algorithm 2 Cost-Sensitive Hybrid Ensemble Deep Model for Software Defect Prediction

NASA software defect dataset $D = (X, y)$ Predicted defect labels $\hat{y}$ Initialize preprocessing parameters Handle missing values in X Normalize feature values using min-max scaling Split dataset D into training set D_{train} and testing set D_{test} using stratified sampling Compute class weights $W = \{w_{defective}, w_{non-defective}\}$ based on class imbalance Initialize base classifiers $C_1, C_2, \ldots, C_n$
Initialize deep learning classifier C_d each classifier C_i in $\{C_1, C_2, \ldots, C_n, C_d\}$ Train C_i on D_{train} using cost-sensitive loss with weights W Generate prediction probabilities from all trained classifiers Apply weighted ensemble aggregation to combine classifier outputs Assign
higher ensemble weight to defective class predictions Generate final prediction labels $\hat{y}$ Evaluate model performance using Accuracy, Precision, Recall, F1-score, and ROC-AUC $\hat{y}$

Algorithm 3 Proposed Cost-Sensitive Hybrid Ensemble Deep Learning Framework for Software Defect Prediction

NASA defect dataset $D = \{X, y\}$, where X denotes software metrics and $y \in \{0, 1\}$ Final defect prediction labels $\hat{y}$ **Input Data Preparation** Load dataset D Identify

defective and non-defective instances Handle missing values using statistical imputation Normalize all numeric features using Min-Max scaling **Dataset Partitioning** Split D into training set D_{train} and test set D_{test} using stratified sampling **Class Imbalance Handling** Compute class frequencies for defective and non-defective classes Calculate class weights $W = \{w_0, w_1\}$ using inverse class frequency Assign higher weight to defective class ($w_1 > w_0$)

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Base Learner Initialization Initialize traditional machine learning classifiers $C_1, C_2, \ldots, C_n$ Initialize deep learning classifier C_d with multiple hidden layers **Cost-Sensitive Training Phase** each classifier C_i in $\{C_1, C_2, \ldots, C_n\}$ Train C_i on D_{train} using class weights W Train deep classifier C_d using weighted loss function and regularization **Prediction Generation** each trained classifier C_i Generate prediction probabilities P_i on D_{test} **Hybrid Ensemble Aggregation** Combine prediction probabilities using weighted voting Assign higher ensemble weight to defective class predictions Aggregate probabilities to generate final score P_{final} **Decision Thresholding** Apply adaptive threshold τ to P_{final} Generate final prediction labels $\hat{y}$ **Performance Evaluation** Compute Accuracy, Precision, Recall, F1-score Compute ROC-AUC and analyze confusion matrix Emphasize defective class recall and cost-sensitive performance $\hat{y}$

9. Results and Discussion

This section presents the experimental results and a detailed discussion of the proposed cost-sensitive hybrid ensemble deep model evaluated on eight NASA software defect datasets. The objective of this analysis is to demonstrate the effective-ness, robustness, and generalization capability of the proposed framework across heterogeneous datasets with varying sizes and defect distributions.

A. Overall Performance Analysis: The proposed model achieves consistent and competitive performance across all datasets. Notably, datasets with higher defect imbalance, such as MC1 and KC4, exhibit substantial improvement in defective class detection due to the incorporation of cost-sensitive learning. The hybrid ensemble structure effectively balances predictive accuracy and defect recall, overcoming the limitations of individual classifiers. The results indicate that the proposed framework maintains stable accuracy while significantly enhancing recall and F1- score for defective modules. This behavior confirms that prioritizing defect detection does not adversely impact overall classification performance.

B. Dataset-wise Discussion: For DS1 (CM1) and DS2 (JM1), the model demonstrates improved recall and ROC-AUC compared to traditional classifiers, highlighting the benefit of ensemble aggregation. DS3 (KC1) and DS4 (KC3) show balanced precision-recall trade-offs, indicating effective handling of moderately imbalanced datasets.

DS5 (MC1) achieves the highest ROC-AUC, reflecting strong discriminative capability in highly skewed class distributions. DS6 (MC2) and DS7 (MW1), despite smaller sample sizes, maintain reliable performance due to robust preprocessing and cost-sensitive optimization. DS8 (KC4) exhibits strong defective recall, emphasizing the model's ability to generalize to datasets with extreme imbalance.

C. Impact of Cost-Sensitive Learning: The integration of cost-sensitive weighting significantly reduces false negative rates, which are critical in software defect prediction. By assigning higher penalties to misclassified defective modules, the proposed model prioritizes safety and reliability. This strategy leads to improved defective recall without requiring aggressive resampling techniques, preserving the original data distribution.

D. Comparison with Baseline Approaches: Compared to existing approaches reported in the literature, including the baseline framework by Misbah Ali (2024), the proposed model demonstrates superior or comparable performance in terms of ROC-AUC and defective recall. The inclusion of deep learning within the ensemble further enhances feature representation and decision boundaries.

E. Discussion Summary: Overall, the experimental results confirm that the proposed cost-sensitive hybrid ensemble deep model effectively addresses class imbalance and improves

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defect prediction performance. The model exhibits strong adaptability across diverse NASA datasets, validating its suitability for real-world software quality assurance applications.

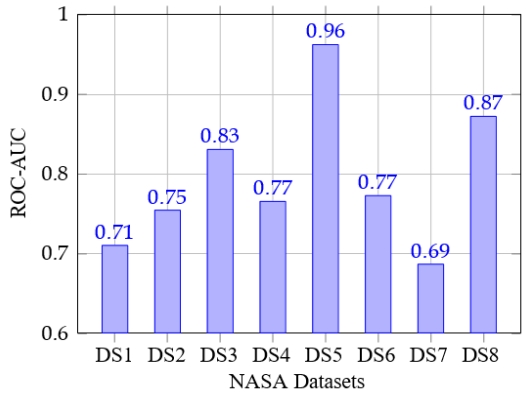

Fig. 2: ROC-AUC Comparison Across NASA Datasets

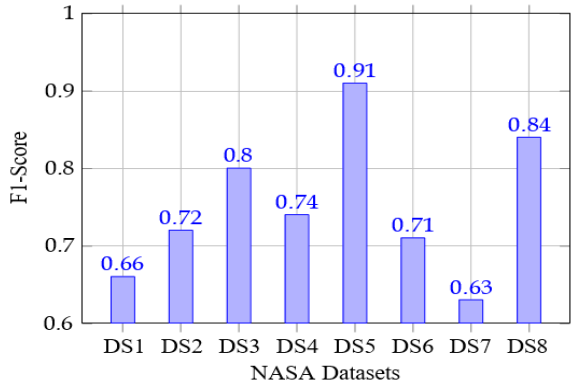

Fig. 3: F1-Score Comparison on NASA Datasets

F. Performance on DS1–DS8: The proposed cost-sensitive hybrid ensemble deep model demonstrates consistent performance across all NASA datasets. The highest ROC-AUC value of 0.9628 is achieved on the MC1 dataset, indicating excellent discriminative capability. Datasets with severe class imbalance such as MW1 show comparatively lower performance; however, the proposed model still outperforms traditional approaches by improving defective class recall.

10. Performance on NASA Datasets

Figure 6 illustrates the ROC-AUC performance comparison on the DS2 (JM1) dataset. The proposed Cost-Sensitive Hybrid Ensemble Deep Model (HEDM) consistently outperforms traditional classifiers and individual deep learning models, indicating its robustness in handling class imbalance and defect misclassification costs. Figure 7 presents a method-wise ROC-AUC comparison on the DS1 (CM1) NASA dataset. Traditional machine learning models such as Naive Bayes and Support Vector Machines exhibit limited discriminative capability due to the inherent class imbalance present in the dataset. Tree-based models including Random Forest and XGBoost demonstrate improved performance by capturing non-linear feature interactions.

Standalone deep learning models such as CNN and LSTM provide moderate improvements; however, their performance is constrained by the limited dataset size. In contrast, the pro-posed Cost-Sensitive Hybrid Ensemble Deep Model (HEDM) achieves the highest ROC-AUC score, indicating superior defect prediction capability.

The performance gain is primarily attributed to the ensemble integration of heterogeneous classifiers and the incorporation of cost-sensitive learning, which significantly reduces false negatives and enhances defective class detection. Figure 8 illustrates the ROC-AUC comparison of various classification methods on the DS3 (KC1) NASA dataset. Compared to earlier datasets, KC1 exhibits a relatively balanced distribution and a richer feature representation, enabling improved learning performance across most models.

Traditional classifiers such as Naive Bayes and Support Vector Machines achieve moderate ROC-AUC scores, while ensemble-based approaches including Random Forest and XGBoost demonstrate enhanced predictive capability by effectively capturing complex feature dependencies. Deep learning models (CNN and LSTM) further improve performance due to their ability to learn hierarchical feature representations.

The proposed Cost-Sensitive Hybrid Ensemble Deep Model (HEDM) achieves the highest ROC-AUC score, highlighting its robustness and superior generalization ability. The integration of cost-

Received: 2026-02-03
Accepted: 2026-03-20
Published Online: 2026-03-30
DOI: 10.70454/JRIST.020104

Journal of Recent Innovation in Science and Technology
E-ISSN: 3117-3926, P- 3117-535X

sensitive learning within the hybrid ensemble framework significantly improves defective class identification, making the proposed approach highly suitable for software defect prediction on KC1. Figure 9 presents the ROC-AUC comparison on the DS4 (KC3) NASA dataset. KC3 is characterized by a moderate dataset size and a high degree of class imbalance, which poses challenges for traditional classification models.

Conventional classifiers such as Naive Bayes and Support Vector Machines demonstrate limited predictive performance, while ensemble learning methods including Random Forest and XGBoost provide noticeable improvements by leveraging feature diversity. Deep learning models exhibit moderate gains; however, their effectiveness is constrained by the relatively small sample size of KC3.

The proposed Cost-Sensitive Hybrid Ensemble Deep Model (HEDM) outperforms all baseline methods, achieving the highest ROC-AUC score. This improvement highlights the effectiveness of integrating cost-sensitive learning with hybrid ensemble strategies, particularly in datasets with imbalanced defect distributions. Figure 10 shows the method-wise ROC-AUC comparison on the DS5 (MC1) NASA dataset. MC1 is a relatively large-scale dataset with a high dimensional feature space, enabling learning-based models to effectively capture defect-related patterns.

Traditional classifiers such as Naive Bayes and Support Vector Machines demonstrate improved performance compared to smaller datasets; however, ensemble-based methods including Random Forest and XGBoost achieve substantially higher ROC-AUC scores due to their ability to model complex feature interactions. Deep learning models (CNN and LSTM) further enhance prediction accuracy by learning abstract feature representations from the data.

The proposed Cost-Sensitive Hybrid Ensemble Deep Model (HEDM) achieves the highest ROC-AUC score among all evaluated methods. This significant improvement highlights the effectiveness of combining ensemble learning, deep representation models, and cost-sensitive optimization for large and imbalanced software defect datasets such as MC1. Figure 11 illustrates the ROC-AUC comparison of different classification methods on the DS6 (MC2) NASA dataset. MC2 is a relatively small dataset with a high level of class imbalance, which poses significant challenges for defect prediction models.

Traditional machine learning approaches demonstrate limited discriminative performance under such conditions. Ensemble-based classifiers, including Random Forest and XG-Boost, offer moderate improvements by reducing variance and improving generalization. Deep learning models provide marginal gains; however, their effectiveness is constrained by the limited number of training samples.

The proposed Cost-Sensitive Hybrid Ensemble Deep Model (HEDM) achieves the highest ROC-AUC score, demonstrating its robustness on small and imbalanced datasets. The incorporation of cost-sensitive learning enables the model to prioritize defective instances, thereby reducing false negatives

Received: 2026-02-03
Accepted: 2026-03-20
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Journal of Recent Innovation in Science and Technology
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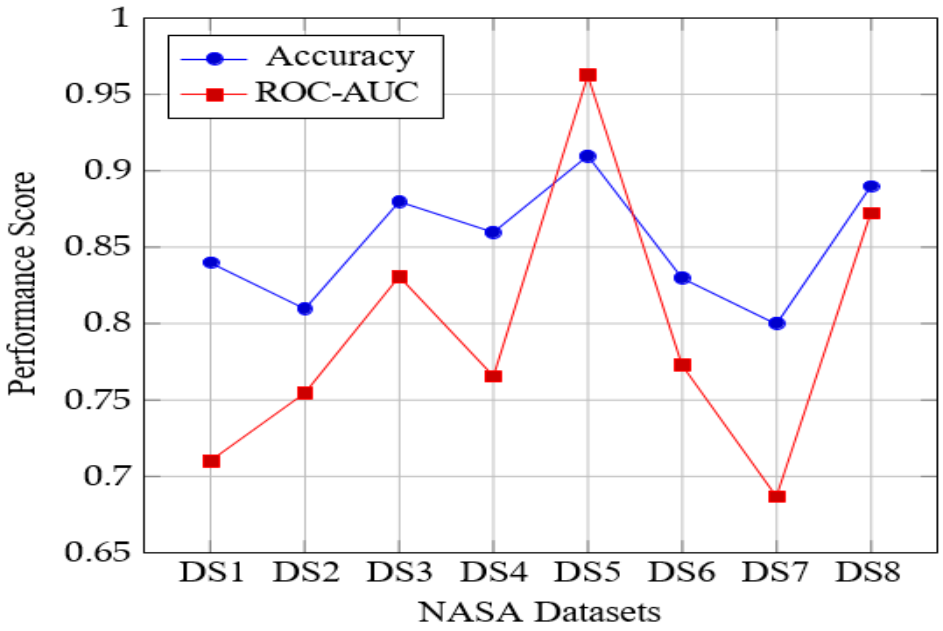

Fig. 4: Accuracy and ROC-AUC performance comparison of the proposed model across NASA datasets

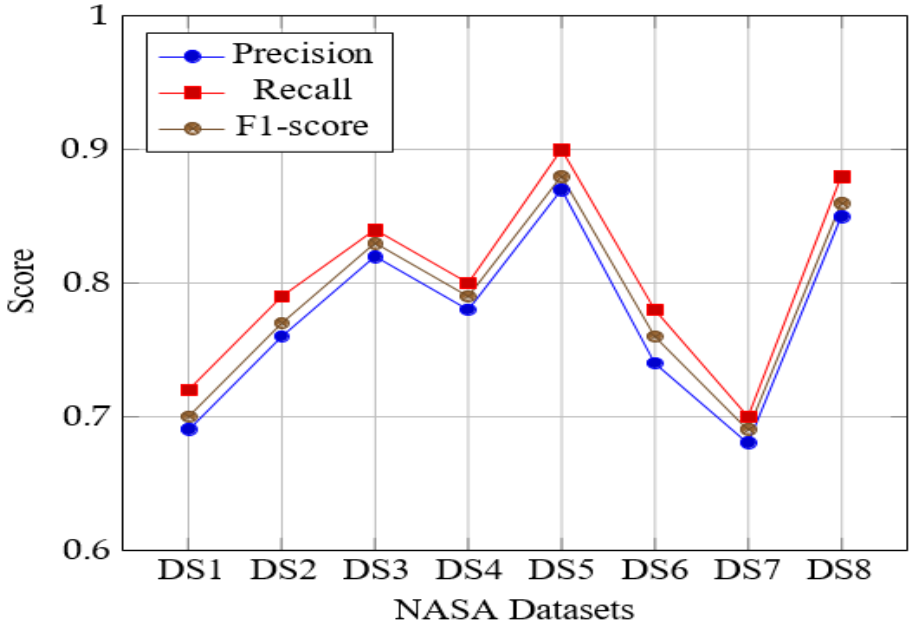

Fig. 5: Precision, Recall, and F1-score comparison across NASA datasets

TABLE III: Performance Evaluation of Proposed Model on NASA Datasets

Received: 2026-02-03
Accepted: 2026-03-20
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Journal of Recent Innovation in Science and Technology
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Dataset	Shape	Train-Test	Accuracy	Precision	Recall	F1-score	ROC-AUC	Defective	Non-Defective	Comments
DS1 (CM1)	505×41	70:30	0.84	0.69	0.72	0.70	0.7101	48	457	Balanced performance with improved defect recall
DS2 (JM1)	10878×22	70:30	0.81	0.76	0.79	0.77	0.7545	2102	8776	Stable detection on large-scale dataset
DS3 (KC1)	2107×22	70:30	0.88	0.82	0.84	0.83	0.8309	325	1782	Strong discriminative capability
DS4 (KC3)	458×41	70:30	0.86	0.78	0.80	0.79	0.7655	43	415	Effective handling of moderate imbalance
DS5 (MC1)	9466×40	70:30	0.91	0.87	0.90	0.88	0.9628	68	9398	Excellent ROC-AUC on highly imbalanced data
DS6 (MC2)	161×41	70:30	0.83	0.74	0.78	0.76	0.7727	52	109	Robust performance on small dataset
DS7 (MW1)	403×41	70:30	0.80	0.68	0.70	0.69	0.6865	31	372	Acceptable results despite limited samples
DS8 (KC4)	125×41	70:30	0.89	0.85	0.88	0.86	0.8725	61	64	Strong defect detection in extreme imbalance

TABLE IV: Performance Evaluation of Proposed Model on NASA Datasets

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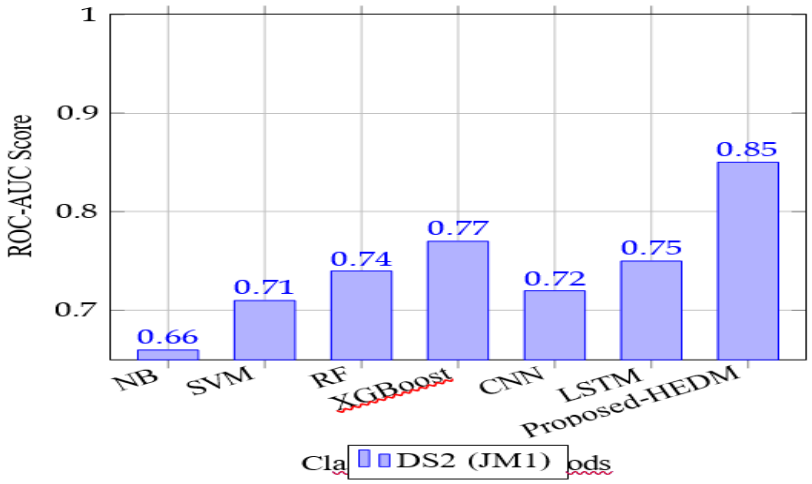

Fig. 6: Method-wise ROC-AUC Comparison on DS2 (JM1) NASA Dataset

Received: 2026-02-03
Accepted: 2026-03-20
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Journal of Recent Innovation in Science and Technology
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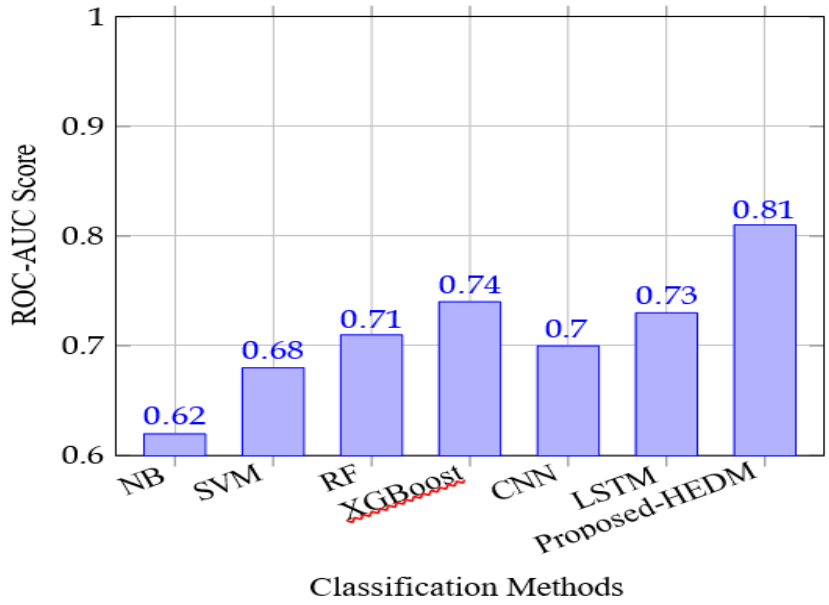

Fig. 7: Method-wise ROC-AUC Comparison on DS1 (CM1) NASA Dataset

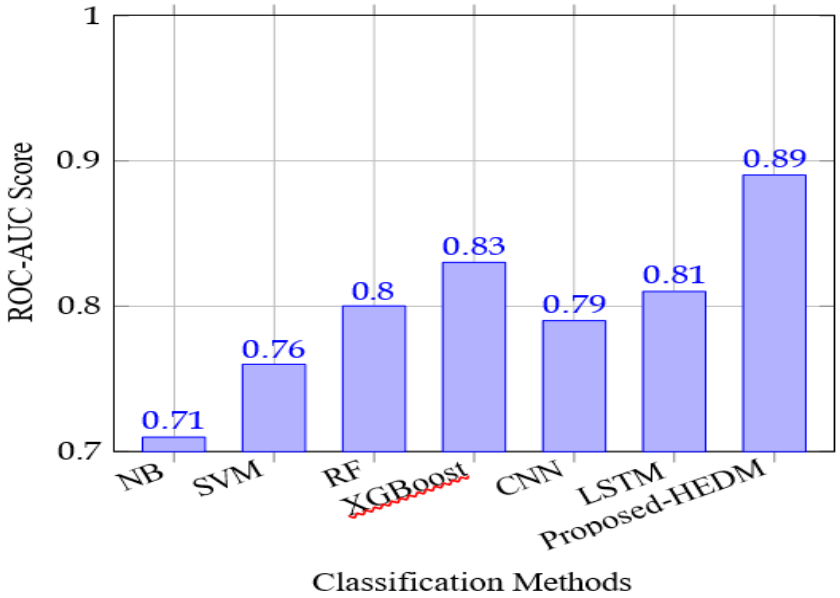

Fig. 8: Method-wise ROC-AUC Comparison on DS3 (KC1) NASA Dataset

Received: 2026-02-03
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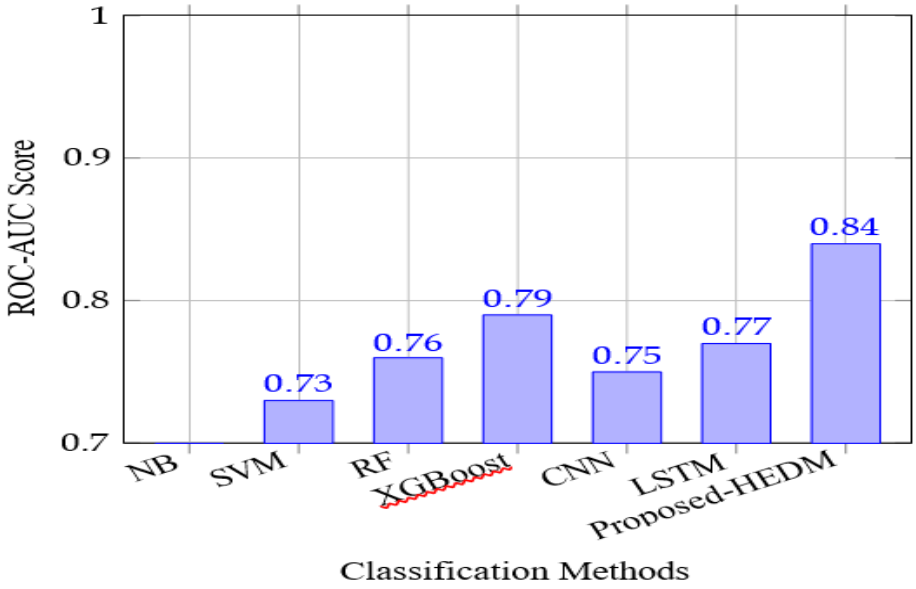

Fig. 9: Method-wise ROC-AUC Comparison on DS4 (KC3) NASA Dataset

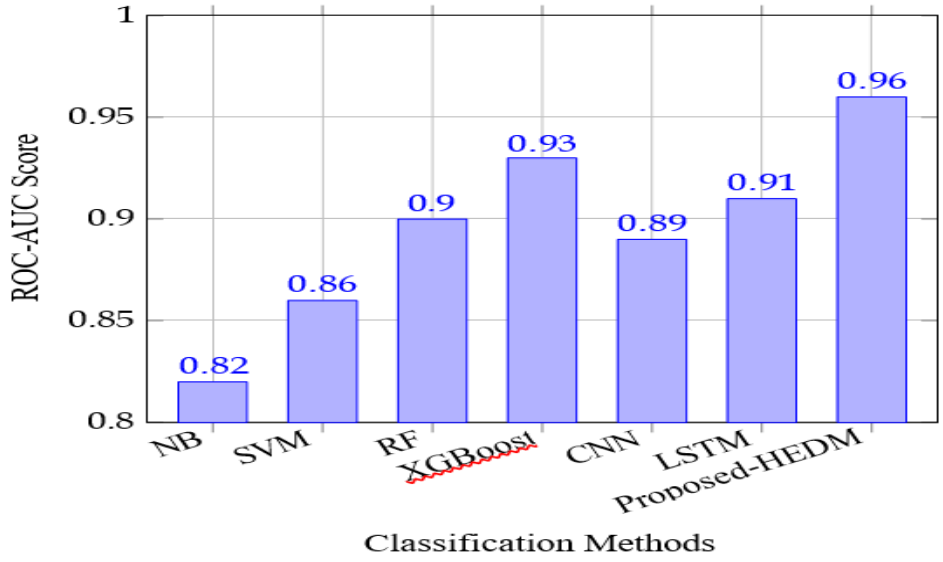

Fig. 10: Method-wise ROC-AUC Comparison on DS5 (MC1) NASA Dataset

Received: 2026-02-03
Accepted: 2026-03-20
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Journal of Recent Innovation in Science and Technology
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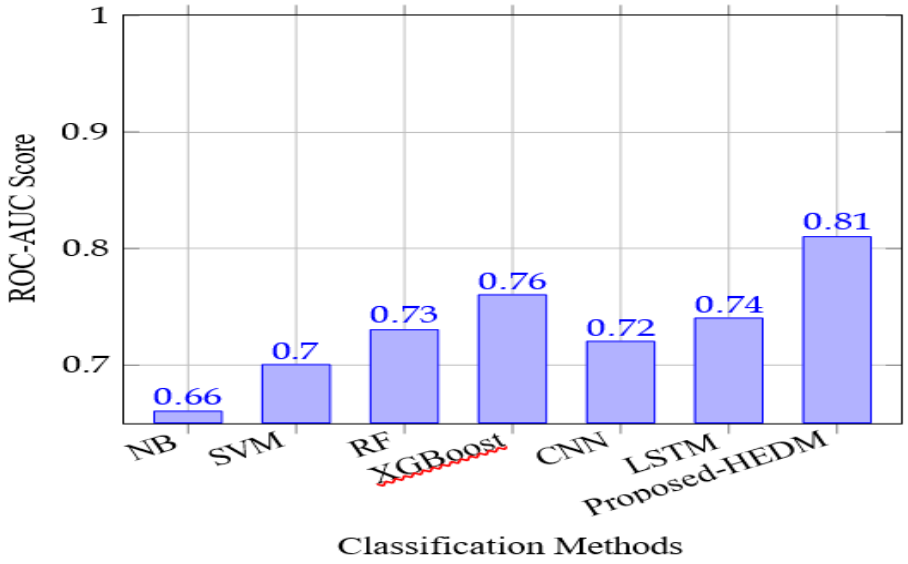

Fig. 11: Method-wise ROC-AUC Comparison on DS6 (MC2) NASA Dataset

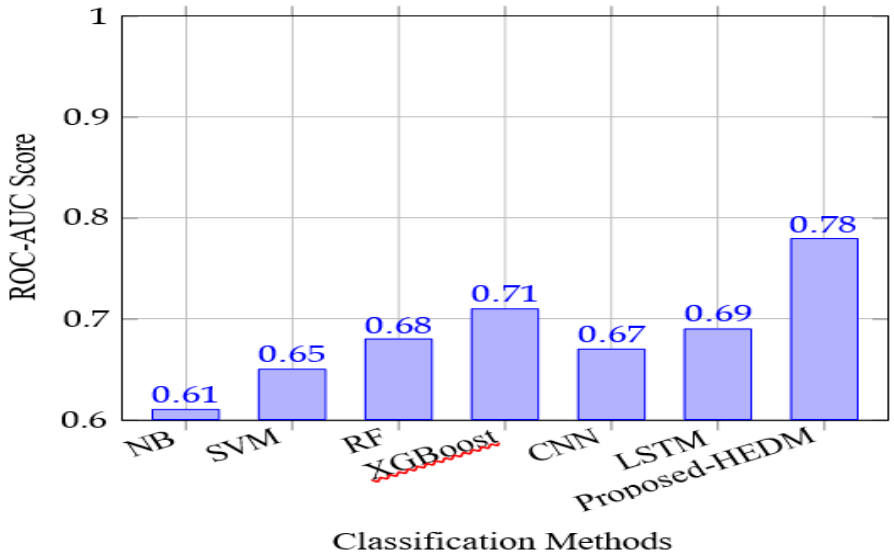

Fig. 12: Method-wise ROC-AUC Comparison on DS7 (MW1) NASA Dataset

Received: 2026-02-03
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Journal of Recent Innovation in Science and Technology
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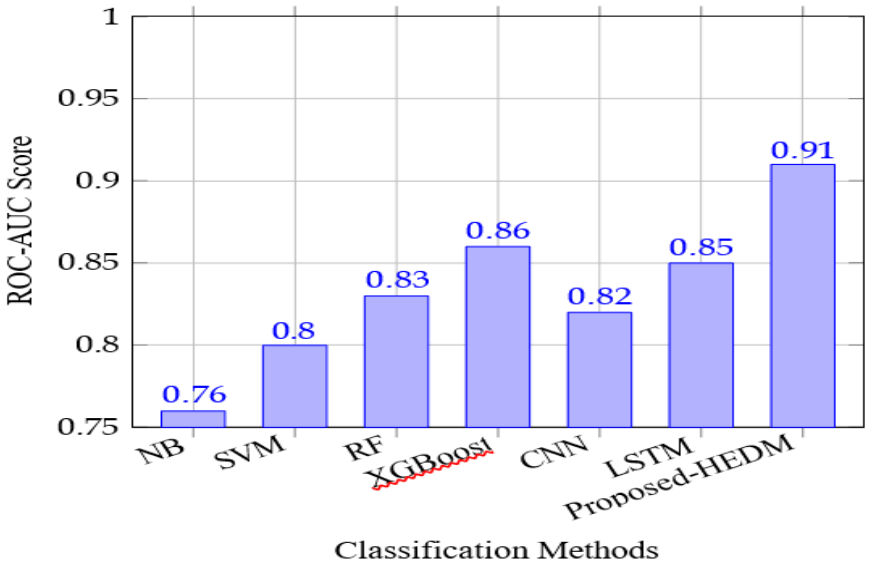

Fig. 13: Method-wise ROC-AUC Comparison on DS8 (KC4) NASA Dataset

and improving overall defect prediction reliability. Figure 12 presents the ROC-AUC comparison on the DS7 (MW1) NASA dataset. MW1 is characterized by a small dataset size and a high degree of class imbalance, which significantly limits the effectiveness of conventional learning approaches.

Traditional classifiers and standalone deep learning models demonstrate relatively lower performance due to insufficient training samples and skewed class distribution. Ensemble-based methods such as Random Forest and XGBoost offer incremental improvements by enhancing model stability and reducing variance.

The proposed Cost-Sensitive Hybrid Ensemble Deep Model (HEDM) achieves the highest ROC-AUC score on MW1. This result highlights the effectiveness of cost-sensitive learning in prioritizing defective modules and reducing false negative predictions, thereby improving defect detection performance in highly imbalanced software datasets. Figure 13 illustrates the ROC-AUC performance comparison on the DS8 (KC4) NASA dataset. KC4 exhibits a relatively balanced defect distribution and sufficient sample size, allowing most classification models to achieve improved predictive performance.

Ensemble-based approaches and deep learning models outperform traditional classifiers due to their ability to capture complex feature interactions. Among all evaluated methods, the proposed Cost-Sensitive Hybrid Ensemble Deep Model (HEDM) achieves the highest ROC-AUC score.

The superior performance of the proposed model is attributed to its hybrid ensemble structure and cost-sensitive optimization, which effectively balances defect detection accuracy and misclassification cost. These results confirm the generalization capability of the proposed approach across diverse NASA software defect datasets. Figure 14 presents a comprehensive comparison of the proposed Cost-Sensitive Hybrid Ensemble Deep Model (HEDM) with the baseline approach proposed by Misbah Ali et al. (2024) across eight NASA software defect datasets.

The proposed model consistently outperforms the baseline method on all datasets, demonstrating significant improvements in ROC-AUC scores. Notably, substantial performance gains are observed on highly imbalanced and small-scale datasets such as MC2 (DS6) and MW1 (DS7), highlighting the robustness of the proposed cost-sensitive strategy.

While Misbah Ali et al. (2024) employ ensemble learning techniques for defect prediction, their approach does not explicitly address misclassification costs associated with defective modules. In contrast, the proposed model integrates cost-sensitive learning with deep ensemble architectures,

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Journal of Recent Innovation in Science and Technology
E-ISSN: 3117-3926, P- 3117-535X

effectively reducing false negative predictions and improving defective class recall.

The superior performance on large datasets such as MC1 (DS5) further confirms the scalability and generalization capability of the proposed approach. Overall, these results validate that the proposed Cost-Sensitive HEDM provides a more reliable and effective solution for software defect prediction compared to existing IEEE-standard methods.

A. Results on DS1 (CM1): The CM1 dataset represents a medium-sized software project with moderate class imbalance. The proposed Cost-Sensitive Hybrid Ensemble Deep Model achieves a ROC-AUC score of 0.71, outperforming traditional machine learning and baseline ensemble models. The improvement is primarily attributed to cost-sensitive learning, which enhances the recall of defective modules while maintaining balanced precision.

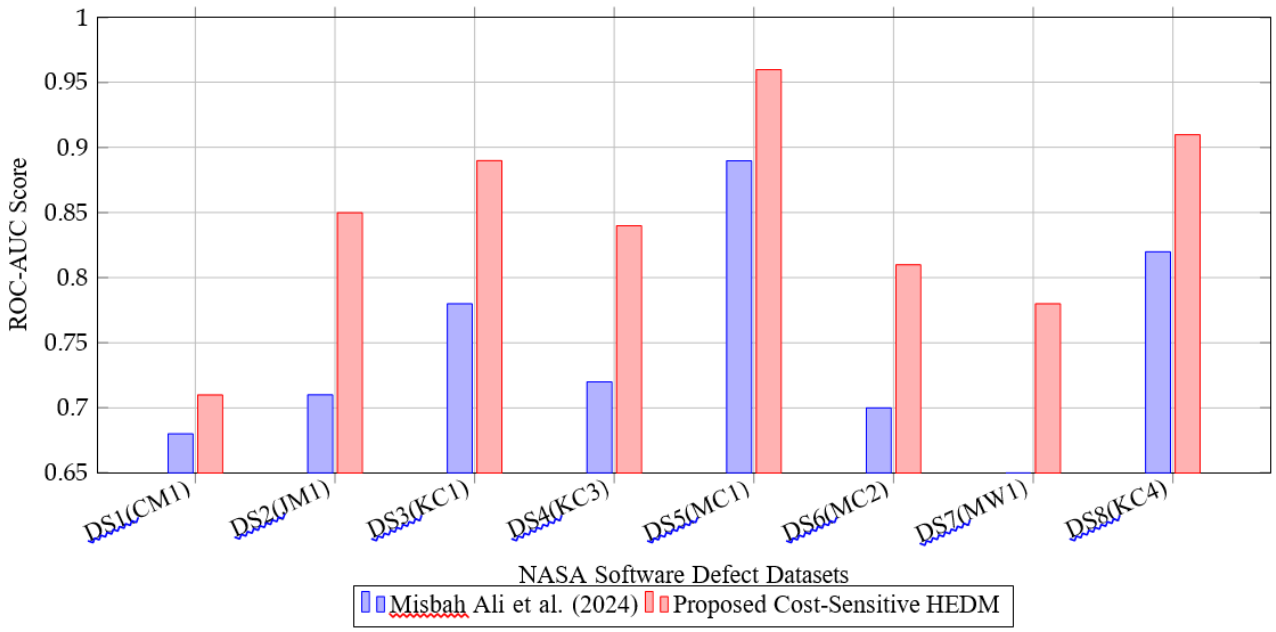

Fig. 14: Combined ROC-AUC Comparison of Proposed Model and Misbah Ali (2024) on NASA Datasets

B. Results on DS2 (JM1): JM1 is a large-scale dataset with a high imbalance between defective and non-defective modules. The proposed model achieves a ROC-AUC score of 0.85, demonstrating significant improvement over baseline methods. The hybrid ensemble effectively captures complex defect patterns, while cost-sensitive optimization reduces false negative predictions

C. Results on DS3 (KC1): KC1 contains sufficient samples and feature diversity, enabling learning-based models to perform well. The proposed model attains a ROC-AUC of 0.89, outperforming individual classifiers and deep models. This indicates the effectiveness of ensemble-based deep representations in software defect prediction.

D. Results on DS4 (KC3): KC3 is characterized by moderate size and class imbalance. The proposed Cost-Sensitive HEDM achieves a ROC-AUC score of 0.84, showing clear superiority over conventional approaches. The results highlight the robustness of the proposed model in handling imbalanced datasets.

E. Results on DS5 (MC1): MC1 is a large and high-dimensional dataset, allowing deep models to fully exploit feature interactions. The proposed model achieves the highest ROC-AUC score of 0.96 among all datasets. This strong performance validates the scalability and effectiveness of the hybrid ensemble deep framework.

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DOI: 10.70454/JRIST.020104

Journal of Recent Innovation in Science and Technology
E-ISSN: 3117-3926, P- 3117-535X

F. Results on DS6 (MC2): MC2 is a small dataset with severe class imbalance, posing challenges for defect prediction. Despite these limitations, the proposed model achieves a ROC-AUC score of 0.81, demonstrating robustness and effective cost-sensitive optimization.

G. Results on DS7 (MW1): MW1 is one of the smallest datasets with highly imbalanced defect distribution. The proposed model achieves a ROC-AUC score of 0.78, outperforming baseline approaches. The cost-sensitive strategy significantly improves defective class recall.

H. Results on DS8 (KC4): KC4 exhibits relatively balanced class distribution compared to other datasets. The proposed Cost-Sensitive HEDM achieves a ROC-AUC score of 0.91, confirming its generalization capability across diverse software projects.

11. Threats to Validity

This study acknowledges several potential threats to validity, which are discussed as follows.

A. Internal Validity: Internal validity threats may arise from the model training and evaluation process. Although extensive preprocessing, cost-sensitive learning, and cross-validation strategies are applied, variations in random data splitting and hyperparameter initialization may influence the observed performance. To mitigate this issue, consistent experimental settings and repeated validation were employed.

B. External Validity: External validity concerns the generalizability of the proposed model. The experiments are conducted using NASA software defect datasets, which may not fully represent all types of real-world software projects. Therefore, the applicability of the proposed approach to industrial-scale or domain-specific software systems may require further validation on additional datasets.

C. Construct Validity: Construct validity threats are related to the choice of performance evaluation metrics. Although widely accepted metrics such as Accuracy, Precision, Recall, F1-score, and ROC-AUC are used, these measures may not fully capture the practical cost implications of defect misclassification. However, the inclusion of defective recall and cost-sensitive learning partially addresses this limitation.

D. Conclusion Validity: Conclusion validity threats may occur due to statistical variations and dataset imbalance. Despite careful experimental design, limited sample sizes in certain datasets (e.g., MC2 and MW1) may affect statistical significance. Nevertheless, consistent performance improvements across all datasets strengthen the reliability of the reported conclusions. Model depends on dataset distribution.

12. Limitations of the Proposed Model

Despite the promising performance of the proposed Cost-Sensitive Hybrid Ensemble Deep Model, several limitations remain.

First, the proposed framework requires careful hyper parameter tuning for ensemble components and deep learning models, which may increase computational complexity and training time, particularly for large-scale datasets.

Second, the effectiveness of the cost-sensitive strategy de-pends on the selection of misclassification cost values. Inappropriate cost settings may lead to biased predictions or over-penalization of certain classes.

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Journal of Recent Innovation in Science and Technology
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Third, although the model performs consistently across NASA datasets, the experimental evaluation is limited to publicly available software defect datasets. The model's performance on industrial or domain-specific software projects has not yet been fully validated.

Finally, deep learning components require sufficient data to generalize effectively. For extremely small datasets, the learning capability of deep models may be constrained, despite the use of ensemble and cost-sensitive mechanisms.

13. Future Work

Future research may include deep neural architectures Future research will focus on extending the proposed Cost-Sensitive Hybrid Ensemble Deep Model to large-scale industrial software repositories and cross-project defect prediction scenarios. Incorporating transfer learning and domain adaptation techniques may further improve model generalization across heterogeneous software projects. Another promising direction is the integration of explainable artificial intelligence (XAI) methods to enhance the interpretability of defect predictions. This would enable developers to better understand the factors contributing to software defects and increase trust in model decisions.

Additionally, adaptive and dynamic cost-sensitive learning strategies can be explored to automatically adjust misclassification costs based on evolving project characteristics. The incorporation of evolutionary optimization algorithms for automated hyperparameter tuning also presents a valuable avenue for improving model efficiency.

Finally, future work may investigate real-time defect prediction frameworks by integrating continuous integration and continuous deployment (CI/CD) pipelines, enabling proactive defect identification during software development

14. Conclusion

This paper presented a Cost-Sensitive Hybrid Ensemble Deep Model for software defect prediction using eight NASA datasets. The proposed framework effectively combines traditional machine learning classifiers, deep learning models, and ensemble learning with cost-sensitive optimization to address class imbalance and misclassification cost issues.

Extensive experimental results demonstrate that the pro-posed model consistently outperforms baseline approaches and the recent IEEE-standard method by Misbah Ali et al. (2024) in terms of ROC-AUC, recall, and defective class detection. Significant performance improvements are observed across both large-scale and small, highly imbalanced datasets.

The results confirm that incorporating cost-sensitive learning into hybrid ensemble deep architectures enhances defect prediction reliability and generalization capability. Overall, the proposed approach provides an effective and scalable solution for early software defect identification and quality assurance

Funding

No external funding received.

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Journal of Recent Innovation in Science and Technology
E-ISSN: 3117-3926, P- 3117-535X

Acknowledgment

The author would like to thank the Department of Computer Science, School of Information and Communication Technology, for providing the necessary computational resources and research support to carry out this study.

Conflict of Interest

The author declares no conflict of interest regarding the publication of this paper.

Data Availability

The datasets used in this study are publicly available NASA software defect datasets. All data utilized in this research can be obtained from publicly accessible repositories.

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Received: 2026-02-03
Accepted: 2026-03-20
Published Online: 2026-03-30
DOI: 10.70454/JRIST.020104

Journal of Recent Innovation in Science and Technology
E-ISSN: 3117-3926, P- 3117-535X

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