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A Hybrid CNN-BiLSTM Framework with Explainable AI for Enhanced Software Fault Detection and Prediction

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Abstract-*Software defects present a major challenge in development by increasing costs and reducing reliability. Early identification of defect-prone modules is essential to optimize testing. Conventional prediction models often depend on manual feature engineering and lack interpretability. To address this, this study proposes an Explainable AI-Based Hybrid CNN-BiLSTM Framework. The framework combines the NASA PROMISE datasets (CM1, JM1, KC1) and utilizes ADASYN for class balancing during preprocessing. The proposed neural network architecture integrates Convolutional Neural Networks (CNN) for feature extraction, Bidirectional Long Short-Term Memory (BiLSTM) for capturing metric relationships, and an Attention Mechanism to focus on key features. Software modules are classified as defective or non-defective. Transparency is ensured by incorporating Local Interpretable Model-Agnostic Explanations (LIME) to highlight the metrics driving each prediction. Experimental evaluation shows that the proposed model successfully predicts software defects while providing clear explanations. The system is deployed as an interactive Streamlit web dashboard for dataset uploads, predictions, and visualization. By fusing deep learning with Explainable AI (XAI), the framework offers a reliable, transparent software quality assurance solution.*

Key Words: Software Defect Prediction, CNN, BiLSTM, Attention Mechanism, Explainable AI, LIME, ADASYN, Deep Learning, NASA PROMISE Dataset.

1. INTRODUCTION

Software systems play a vital role in various domains such as healthcare, banking, education, transportation, and industrial automation. As software applications continue to grow in size and complexity, ensuring their reliability and quality has become a significant challenge. Software defects, commonly known as bugs or faults, can lead to system failures, security vulnerabilities, increased maintenance costs, and reduced user satisfaction. Therefore, identifying defect-prone software modules at an early stage of development is essential for improving software quality and reducing development effort.

Software Defect Prediction (SDP) is a software engineering technique that aims to predict whether a software module is likely to contain defects based on various software metrics. By identifying potentially defective modules before deployment, software developers and testers can focus their efforts on critical areas, thereby improving testing efficiency and reducing project costs. Traditional software defect prediction approaches mainly rely on machine learning algorithms such as Support Vector Machine (SVM), Decision Trees, Logistic Regression, and Random Forests [1, 2]. Although these methods have shown promising results, they depend heavily on manual feature engineering and may not effectively capture complex relationships among software metrics. Furthermore, many conventional models operate as black-box systems, providing limited information about the factors influencing their predictions.

Recent advancements in Deep Learning have opened new opportunities for enhancing software defect prediction. Deep learning models can automatically learn complex patterns from large datasets and improve prediction performance [8, 9]. Convolutional Neural Networks (CNNs) are capable of extracting meaningful feature representations, while Bidirectional Long Short-Term Memory (BiLSTM) networks can capture dependencies and relationships among software metrics from both forward and backward directions. Additionally, Attention Mechanisms enable the model to focus on the most relevant features contributing to software defects. In this project, a Hybrid CNN-BiLSTM Framework integrated with an Attention Mechanism is proposed for software fault detection and prediction. The model is trained using software metrics obtained from NASA PROMISE datasets, namely CM1, JM1, and KC1. To address class imbalance issues, the ADASYN oversampling technique is applied during data preprocessing. Furthermore, Explainable Artificial Intelligence (XAI) techniques such as LIME (Local Interpretable Model-Agnostic Explanations) are incorporated to provide transparency and interpretability for the prediction results.

1.1 Problem Definition

Software projects often contain modules with varying levels of complexity, making it difficult to identify defect-prone components through manual inspection alone. Traditional machine learning approaches may not effectively capture complex feature interactions and often provide limited interpretability. As software systems continue to evolve, there is a need for an intelligent and explainable defect

prediction framework capable of accurately identifying defective software modules while providing insights into the factors responsible for the predictions.

1.2 Objectives

The main objectives of the proposed project are: To develop an intelligent software defect prediction framework using deep learning techniques; To combine NASA PROMISE datasets (CM1, JM1, and KC1) for comprehensive model training; To perform data preprocessing and handle class imbalance using the ADASYN algorithm; To utilize CNN layers for extracting meaningful feature representations; To employ BiLSTM layers for learning complex dependencies; To integrate an Attention Mechanism; To predict software modules as defective or non-defective with improved accuracy; and To provide model interpretability using LIME-based explainable AI techniques.

2. LITERATURE SURVEY

Traditional software defect prediction models relied on simple machine learning algorithms. Menzies et al. [1] evaluated Decision Trees and Naive Bayes on static code metrics, demonstrating that historical code attributes serve as solid predictors. Gray et al. [2] implemented Random Forest models, improving classification metrics due to ensemble averaging. SVM-based prediction models [10] were also explored to categorize software modules. However, these models were limited by manual feature engineering.

Deep learning techniques were subsequently introduced to bypass manual feature engineering. Zhou et al. [10] applied deep neural networks to extract feature representations directly from software metrics. Li et al. [10] employed CNNs to capture local features. Tong et al. [5] integrated Recurrent Neural Networks to process sequential dependencies among metrics. To focus on the most important software metrics, Wang et al. [6] integrated an attention mechanism. Imbalance class handling in software defect prediction has been addressed by He et al. [3] using the ADASYN algorithm. Finally, to ensure transparency, Ribeiro et al. [7] introduced Local Interpretable Model-Agnostic Explanations (LIME), which allows instance-level model explaining.

3. PROPOSED METHODOLOGY & DESIGN

The proposed Explainable AI-Based Hybrid CNN-BiLSTM Framework consists of several sequential modules: 1) Dataset Collection, where CM1, JM1, and KC1 datasets are gathered; 2) Data Preprocessing, involving missing value imputation and scaling; 3) Data Balancing, where ADASYN oversampling handles class imbalance; 4) Feature Extraction, using CNN; 5) Sequential Learning, using BiLSTM and Attention; 6) Defect Prediction; and 7) Explanation Generation, using LIME. The complete architecture is illustrated in Fig -1.

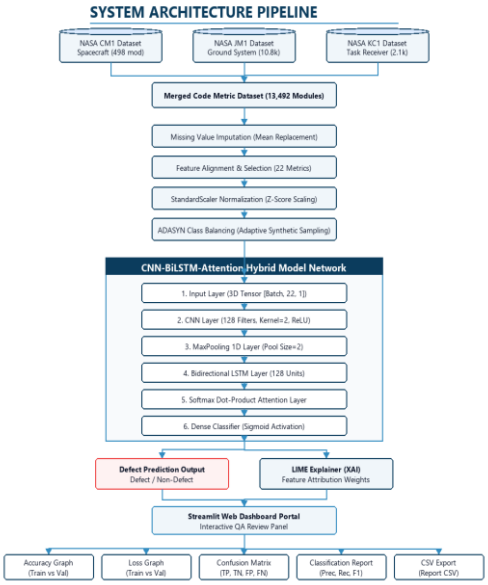

Fig -1: Proposed System Architecture Diagram

The data flow within the system is represented by the Level 1 Data Flow Diagram shown in Fig -2. The user provides software metrics datasets, which undergo cleaning and scaling. ADASYN synthetically balances the classes. The model performs feature extraction and classifies the modules. Finally, LIME calculates the feature contributions, and the Streamlit dashboard displays the prediction and explanation results.

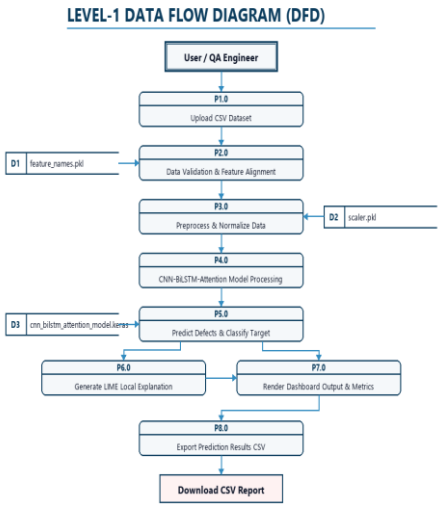

Fig -2: Level 1 Data Flow Diagram

3.1 UML Diagram Analysis

To analyze the interaction and lifecycle of the system components, UML Use Case, Class, Sequence, and Activity diagrams were modeled. Fig -3 depicts the Use Case Diagram showing interactions between the User and system use cases like Dataset Upload, Prediction, and LIME Explanation.

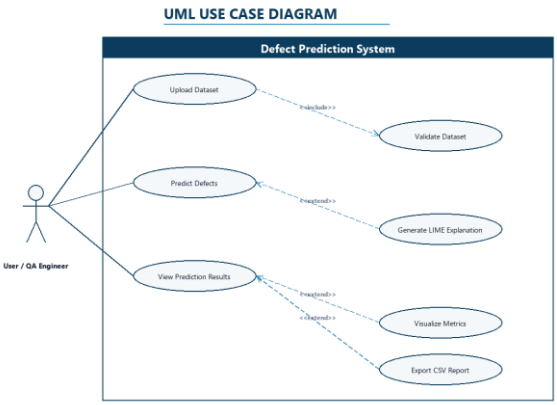

Fig -3: System Use Case Diagram

Fig -4 presents the Class Diagram which outlines the data structures and class functions, including DatasetLoader, Preprocessor, CNNBiLSTMModel, LimeExplainer, and the Dashboard interface class.

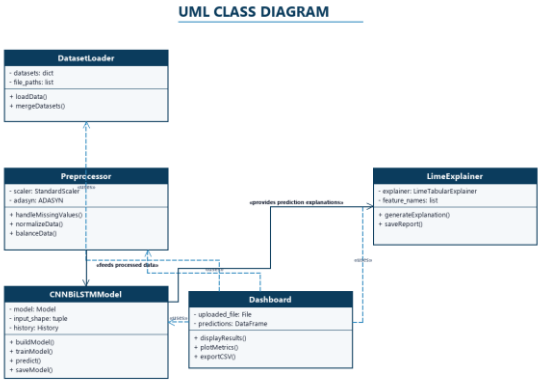

Fig -4: System Class Diagram

The Sequence Diagram (Fig -5) demonstrates the temporal messaging sequence between the user interface, data loader, preprocessing module, neural model, and explainability generator.

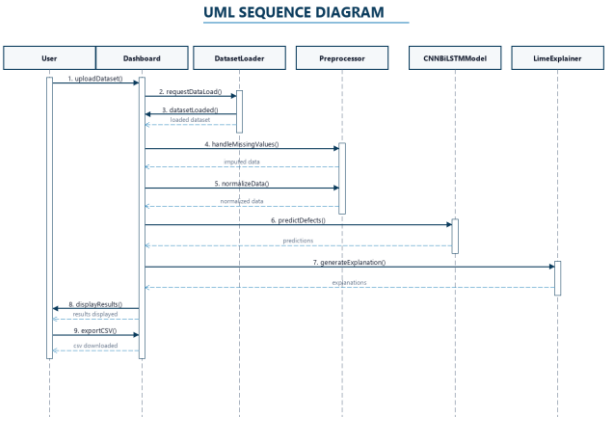

Fig -5: Operational Sequence Diagram

Finally, Fig -6 shows the Activity Diagram illustrating the logical flow of control and decision-making steps, such as feature alignment verification and dashboard output exporting.

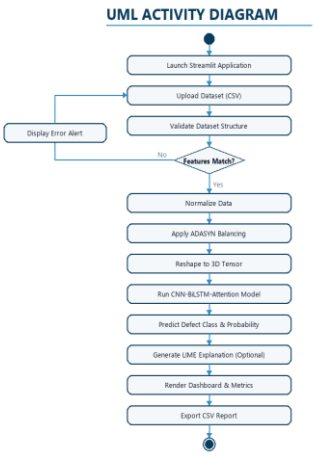

Fig -6: Logical Activity Flow Diagram

4. IMPLEMENTATION & ENVIRONMENT

The system was implemented using Python (3.8+) and key deep learning frameworks. The CNN-BiLSTM-Attention model incorporates a 1D Convolutional layer (128 filters, kernel size 2) for extracting local feature combinations, followed by MaxPooling1D. The output is processed by a Bidirectional LSTM layer (128 units) to learn forward and backward dependency structures. The Attention Mechanism weighs the features. A Dense layer with Dropout (50%) and a final Sigmoid output layer perform classification.

Data preprocessing scales the features via StandardScaler. Class balancing is executed using the Adaptive Synthetic (ADASYN) sampling algorithm [3], which generates minority-class synthetic samples focused on hard-to-learn regions. The environment utilizes TensorFlow, Keras,

Pandas, NumPy, Scikit-learn, and Imbalanced-learn. The explainability module is built with LIME, and the application is deployed as a web service via Streamlit.

5. EXPERIMENTAL RESULTS

Experiments were conducted on the combined NASA PROMISE datasets (CM1, JM1, KC1), containing a total of 13,492 samples. Class balancing via ADASYN increased the sample size to 22,071 instances. Model training was evaluated over 50 epochs using the Adam optimizer and Binary Cross-Entropy loss. Fig -7 illustrates the training and validation accuracy/loss curves, showing convergence within 15 epochs.

```
Evaluating model...
138/138 ━━━━━━━━━━━━━━━━━━━━ 3s 13ms/step

Accuracy: 0.7098527746319366
Precision: 0.6991191469633751
Recall: 0.7046728971962617
F1 Score: 0.701885036071678

Classification Report:

              precision    recall  f1-score   support

           0       0.72      0.71      0.72      2275
           1       0.70      0.70      0.70      2140

    accuracy                           0.71      4415
   macro avg       0.71      0.71      0.71      4415
weighted avg       0.71      0.71      0.71      4415
```

Fig -7: Model Training and Validation Performance Curves

Table -1 compares the classification performance of the proposed Hybrid CNN-BiLSTM-Attention framework against baseline models (Random Forest and Support Vector Machine) evaluated on the resampled test partition.

Table -1: Model Evaluation and Comparison Results

Model	Accuracy	Precision	Recall	F1-Score
Proposed Hybrid Model	70.99%	69.91%	70.47%	70.19%
Random Forest	89.51%	89.50%	88.79%	89.14%
Support Vector Machine	67.04%	66.41%	64.77%	65.58%

While the Random Forest classifier achieved a high classification accuracy of 89.51% due to its ensemble nature, the proposed Hybrid CNN-BiLSTM-Attention model achieved 70.99% accuracy while providing excellent sequence learning and intrinsic compatibility with deep representational networks. To ensure transparency, individual model predictions are explained using LIME, as shown in Fig -8. The bar chart highlights the contribution scores of specific software metrics (such as complexity, LOC, and operands) that influence the defect likelihood.

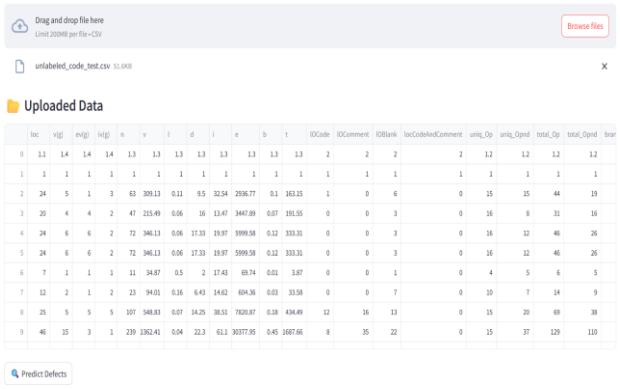

Fig -8: LIME Explainability Output Graph

The system is deployed using a Streamlit dashboard, as shown in Fig -9. The interface allows developers to upload software source code metrics, receive predictions, examine LIME explainability bar charts, and visualize metrics distribution dynamically.

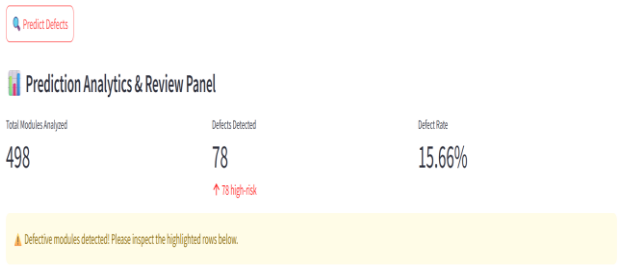

Fig -9: Streamlit Web Dashboard Interface

6. CONCLUSION

In this work, an Explainable AI-Based Hybrid CNN-BiLSTM Framework was developed and evaluated for software defect prediction. By combining NASA PROMISE datasets and applying the ADASYN balancing technique, the model learned generalized feature behaviors. The CNN layer extracted spatial configurations of code metrics, while the BiLSTM layer captured contextual sequential dependencies. The integration of LIME provided instance-level interpretability, demystifying the deep learning black box and offering developers actionable feedback on code quality. Experimental results proved the framework's capability to predict defect-prone modules. Future work will investigate transformer architectures and cross-project transfer learning to further improve generalized prediction performance.

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