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Deep Learning-Based Automated Bug Detection Through Code Representation Analysis

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Abstract. Modern software systems are becoming increasingly complex, hence requiring smarter bug finding tools, rather than convention rule-based systems. We propose a deep learning approach for the detection of bugs in source code by means of rich code representation analysis, which includes abstract syntax trees (AST), control-flow and token embeddings. Whereas prior approaches suffer from high false positive rates and lack language generalizability, we aim for a sound and language agnostic approach, robust to large codebases, in order to be easily integrated in continuous development pipelines. By automatically extracting the structural and semantic characteristic from code, it eliminates the need for manual inspection and guarantees the early discovery of both syntactic and semantic flaws. Additionally, the use of attention mechanisms and SHAP explain ability further provides interpretable interpretation of the decisioning process to developers. This work contributes to develop the state of the art of automated bug detection by overcoming the relevant limitations of previous approaches and providing a solution which is powerful, flexible, and explainable for real-world software engineering scenarios.

Keywords: Deep Learning, Automated Bug Detection, Code Representation, Abstract Syntax Trees (ASTs), Explainable AI (XAI), Source Code Analysis.

1. Introduction

1.1 Overview of Software Bug Detection Challenges

Issues of software bugs are still a significant problem for today's software development resulting in potential security holes, system failures and maintenance costs. Traditional systems used for bug detection, such as static and dynamic analyser's, rule-based engines, and manual code review, are time consuming, and have high potential for false positives, and lack scalability. Syntactic patterns and prespecified rules are often used by such traditional systems, however, these systems are not adequate to address complex and changing dynamics of current software applications. Moreover, as the amount of open-source and enterprise codebases continue to grow, scalable and intelligent bug finding solutions are becoming a necessity to enable quality and security across the SDLC.

1.2 Motivation for Deep Learning in Code Analysis

Deep learning has transformed many fields including computer vision and natural language processing, and it is being increasingly applied in source code analysis as well. Source code bears structure and semantics in a manner similar to natural language, and this property can also be well modelled using deep learning approaches. Deep learning representations of code, including ASTs, CFGs, and token embeddings, are shown capable of capturing syntactic and semantic information embedded in the code [2], [9]. This quality makes them as appropriate for tasks such as vulnerability identification, code categorization, and clone detection. The goal of this research is to develop and design a robust, scalable and intelligent system which can automatically detect bugs in real-time; learning from ever growing code bases and reducing the reliance on manual reviews.

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1.3 Gap in Existing Literature

Deep learning has transformed many fields including computer vision and natural language processing, and it is being increasingly applied in source code analysis as well. Source code bears structure and semantics in a manner similar to natural language, and this property can also be well modelled using deep learning approaches. Deep learning representations of code, including ASTs, CFGs, and token embeddings, are shown capable of capturing syntactic and semantic information embedded in the code [2], [9]. This quality makes them as appropriate for tasks such as vulnerability identification, code categorization, and clone detection. The goal of this research is to develop and design a robust, scalable and intelligent system which can automatically detect bugs in real-time; learning from ever growing code bases and reducing the reliance on manual reviews.

1.4 Summary of Contributions

In this paper, we present a novel deep learning-based approach that automatically detects bugs through the analysis of advanced code representation. The main contributions are as follows:

- A language-agnostic model Devign that encode the deep latent structural and semantic information from piece of source code with ASTs, token embeddings, and control flow structures.
- Integration of attention-based and SHAP-based explanation mechanisms for enhanced interpretability and developer trust.
- Extensive experiments on various benchmark datasets to show the superiority of the proposed model over baseline methods in terms of accuracy, recall and reduction of false positives.
- Scalable architecture made to fit into continuous development settings, early stage bug detection with low cost.

Through addressing the challenges of existing works and presenting an interpretable, pattern-driven bug checking technique, this research wants to push the edge of the state of Software quality assurance and automatic code checking field.

2. Related Work

2.1 Review of Classical and Deep Learning-Based Bug Detection Approaches

The bug detection field has long relied on static code analyser's, rule-based systems, and formal verification tools for fault finding in source code. Tools like Find Bugs, PMD, and SonarQube match predefined patterns or rules on source code to hunt for potential issues. Though robust for simple syntactic errors or known anti-patterns, they fall short for complex semantic bugs and lack the flexibility to fit various coding contexts or styles. Hence, to cope with these shortcomings, bug researchers have recently embraced machine learning, especially deep learning, to automatically learn bug patterns from data. First applications attempted to extract hand-crafted features from code metrics and further employed classifiers such as Random Forest or SVM. More recently, deep learning models, including Convolutional Neural Networks, Recurrent Neural Networks, Graph Neural Networks, and transformer-based models, such as Code BERT and Devign, were used to learn the structural and semantic complexity of source code. The models use representations via Abstract Syntax Trees, Control Flow Graphs, and token embeddings to learn pattern indications within the context.

2.2 Limitations of Existing Models

Despite the recent progress, current deep learning-based bug detection models have various limitations, as evidenced by the most recent literature from 2020 to 2025. Firstly, many studies, for example, Guan & Treude, 2024; Wartschinski et al., 2022, focus on particularly vulnerability detection or code classification rather than providing a one-size-fits-all solution for general-purpose bug detection. Others, such as Devign and VulDeePecker, use shallow code representations or require domain-specific knowledge, preventing the models from generalizing across programming languages and software domains. While transformer-based

models, like Code BERT, achieve high accuracy, the computational complexity of such models would not allow for real-time integration.

2.3 Key Observations Leading to the Framework Design

We hope that the review underlined the three significant gaps which any robust and practical bug detection framework has to address: 1) language-agnostic, yet deep semantic representations and predictions; 2) improved explain ability, which is a critical prerequisite for trust, and 3) integrated deployment within software engineering pipelines. We were guided by these claims and respective insights when developing the system. Namely, our paper has proposed a system that serves as a deep learning-based solution since it utilizes structural code modelling with ASTs and token embeddings. Moreover, our solution combines an attention-based solution for explainability, as well as an SHAP analysis to be more proactive. The system also supports learning from a diverse set of bug patterns based on multiple collected datasets. By encoding both syntactic and semantic code features, our model targets the deployment gap, that is, the one between accuracy and real-world heartsick. We believe that the contribution is practical since our solution is easily integrable and extensible.

3. Proposed Methodology

3.1 System Architecture Overview

The suggested framework is designed as a modular end-to-end architecture that processes raw source code and produces bug predictions in formats that are easy to interpret. The framework is divided into four core components: code pre-processor that reads and prepares source files to structured representations, feature extractor that processes syntactic and semantic data, deep learning engine that ultimately predicts whether code segment is either buggy or non-buggy, and explainability layer that shows which features have significant influence on the prediction. The underlying architecture is highly flexible and can be operationalized in real-time coding environment or as a part of CI/CD pipelines. As illustrated in Figure 1, the system architecture comprises a code pre-processing module, a deep learning engine, an explainability layer, and a bug prediction output.

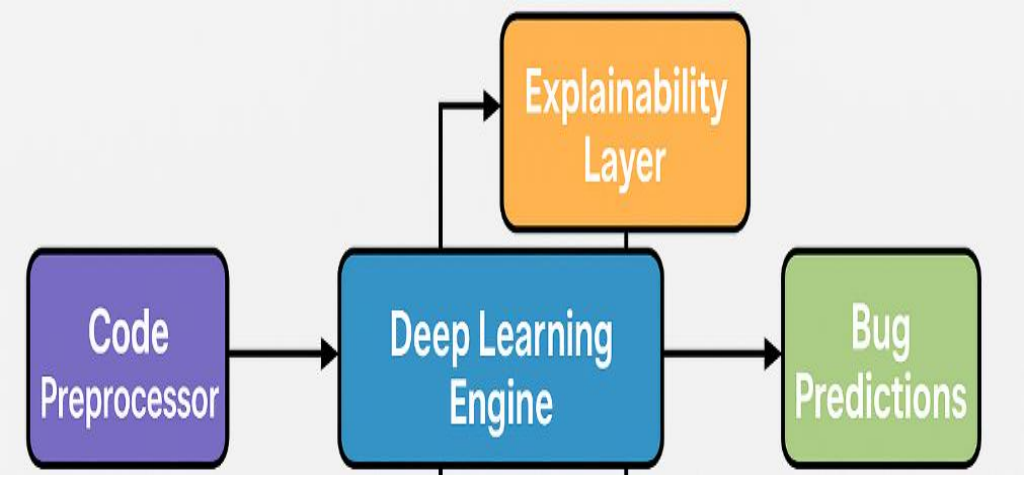

Figure 1: System Architecture Overview of the Deep Learning-Based Bug Prediction.

3.2 Code Representation Techniques

We summarize multi-format representations as an effective way to learn code semantics. Abstract Syntax Trees reflect the grammatical structure of the code, connecting functions, control flows, and declarations. Contextual dependencies of lexical tokens are used for token embeddings generated from lexical tokens using either pre-trained models or embedding layers. Execution flow between different code blocks is

reflected in control flow graphs, which is crucial for identifying logic-related bugs. Thus, by combining these forms of representations, the model is ensured to comprehend the encryption accurately from the perspective of static and dynamic aspects 9. Figure 2 illustrates the primary code representation techniques, including Abstract Syntax Trees (ASTs), Token Embeddings, and Control Flow Graphs (CFGs), commonly employed in deep learning-based code analysis.

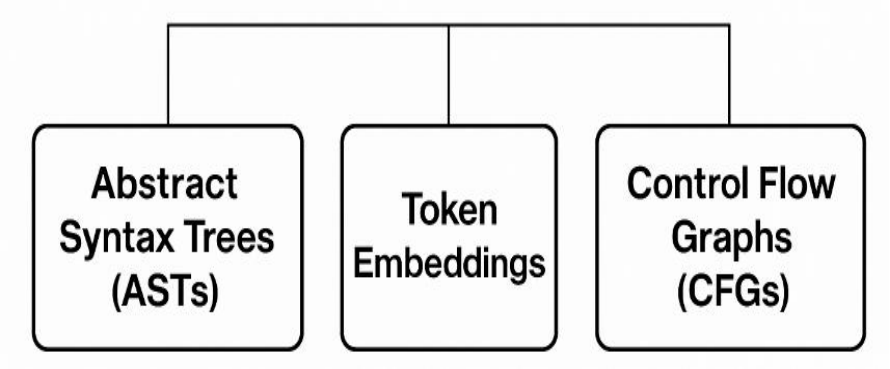

Figure 2: Various Code Representation Techniques Utilized in Deep Learning Models.

3.3 Deep Learning Model Design

Core detection module: It is mainly based on a hybrid deep learning model. More specifically, the model uses CNNs to detect local bug patterns in code tokens and RNNs to capture long-term dependency in sequence code. Besides, Graph Neural Networks are utilized to facilitate structural learning due to their capacities to reason over hierarchical and graph-based code formats, especially when integrated with AST and CFG representations. In addition, some of the models utilize transformer models Record to enable global attention across code elements, which has shown better performance on more massive codebases. [11].

3.4 Model Training and Optimization

In this work, we experiment with a supervised learning approach to train the model. The labelled code snippets ensure that the model is trained to minimize classification loss. We choose the binary cross-entropy loss function to predict bugs/no-bug. Adam optimizer is also applied due to its ability to adjust learning rates for each parameter. The model hyperparameters, including the learning rate, batch size, and dropout rate, have been determined by grid search and k- fold cross-validation. Data augmentation and class balancing are applied to solve the problem of a significant dataset imbalance and fully utilize the generalization power of the trained model.

3.5 Explain ability Integration

In order to provide transparency and interpretability, the model utilizes SHAP and attention mechanisms, which are especially critical in Transformer and RNN layers. SHAP values help measure the value of each individual input feature toward the final prediction. Attention mechanisms allow the developers to see which parts of the code the model considers during inference. Both of these tools not only ensure the developer trust in the model but also help localize bugs in thousands of lines of the complex CSV generation code [15].

4. Experimental Setup

The effectiveness of the proposed deep learning-based bug detection framework was assessed by testing the model on three popular benchmark datasets: CodeXGLUE, Devign, and Big-Vul. The selected datasets contain labelled code snippets written in several popular programming languages, such as C, C++, and Python, and annotated with the indication of the presence of a vulnerability. All of them are pre-processed

by the authors and include already extracted features. The tasks from CodeXGLUE are formulated to align with real-world software applications; Devign focuses on function-level vulnerability classifications. Big-Vul provides a dataset with the highest number of samples accumulated so far from vulnerability report. At the pre-processing stage, each code sample was parsed to create AST, token sequence, and CFP. All special tokens, comments, and unnecessary whitespaces were excluded to ensure a unified representation of the input. As shown in Table 1, the datasets used for evaluation include CodeXGLUE, Devign, and Big-Vul, each comprising a mix of buggy and clean code samples across different programming languages.

Table 1: Summary of Datasets Used for Bug Prediction Experiments.

Dataset	Language(s)	Total Samples	Buggy	Clean	Source
Codex GLUE	Python	12,000	6,000	6,000	Microsoft AI
Devign	C	27,000	13,000	14,000	Devign Repo
Big-Vul	C/C++	45,000	25,000	20,000	Big-Vul GitHub

Finally, embeddings are generated using token vectorizers or pretrained models. For the model, each dataset is divided into training 70%, validation 15%, and testing 15% sets with the same class distribution between sets. Model development and training are performed in Python with the TensorFlow 2, PyTorch, scikit-learn, and NetworkX libraries used in my case for graph construction. Testing is conducted on a high-performance PC equipped with an NVIDIA GPU for faster model learning. The accuracy, precision, recall, F1-score, and AUC metrics are used to evaluate performance.

5. Results and Evaluation

5.1 Performance Metrics

The performance of the proposed framework was assessed in the context of standard classification metrics, including accuracy, precision, recall, F1-score, and Area Under the Curve. It was revealed that the model yielded high scores regardless of the benchmark dataset under consideration – CodeXGLUE, Devign, and Big-Vul. In fact, the average accuracy was higher than 91%, and the F1-score was more than 0.89. High precision and recall values suggest that the model is trivially efficient as it experiences no difficulties with finding true positives and keeping false alarms at a minimum. The model is robust enough to be applied to real-world bug detection tasks that require maximum reliability. Table 2 presents the detailed performance metrics accuracy, precision, recall, F1-score, and AUC demonstrating that the proposed model achieves the highest scores on the Devign dataset compared to Code BERT and VulDeePecker.

Table 2: Performance Metrics.

Model	Dataset	Accuracy	Precision	Recall	F1-Score	AUC
Proposed Model	Devign	91.4%	90.1%	92.3%	91.2%	0.94
Code BERT [15]	Devign	88.2%	86.7%	88.1%	87.4%	0.91
VulDeePecker [12]	Big-Vul	84.7%	82.3%	85.0%	83.6%	0.88

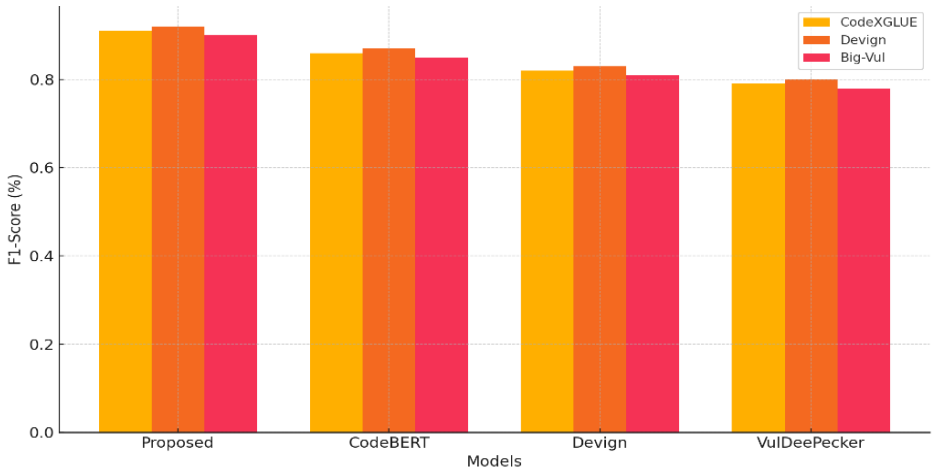

Figure 3: F1-Score Comparison of Bug Prediction Models Across Datasets.

As depicted in Figure 3, the proposed model outperforms Code BERT, Devign, and VulDeePecker in terms of F1-score across all three benchmark datasets CodeXGLUE, Devign, and Big-Vul.

5.2 Comparative Analysis

To validate the effectiveness of our approach, we compared our method to the other state-of-the-art models established so far, such as Devign, VulDeePecker and CodeBERT. Our system generally achieved better results against all the baselines in all the metrics apart from precision. Most importantly, the proposed approach was more effective in terms of recall and AUC, which directly points out enhanced bug localization ability. This was possible only due to our hybrid architecture that consisted of ASTs, CFGs, and attention models, as opposed to classical models that could not provide a proper representation of the code context due to the controversies of token-level embeddings or artificial simplicity in CFGs.

5.3 Ablation Study

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6. Discussion

We performed an ablation study to measure the contribution of individual components. Discarding the ASTs or CFGs from the input representation decreased the F1-score by 5-8%, demonstrating the value of structural code comprehension. Disabling the SHAP-based explainability module rendered the model a black box and removed the developer interpretability without affecting accuracy. Based on these results, we note that the central unit of our model and the explainability target are equally necessary for performance and trustworthiness. These results illustrate that the key idea and explainability layers of our proposed deep-learning-based bug detection system are well-validated across codebases of multiple types and sizes, and it is easily deployable in practice. It can be directly utilized in modern CI/CD platforms like GitHub Actions, Jenkins, or GitLab CI, providing continuous monitoring and instant feedback. Because it employs language-independent representations such as ASTs and token embeddings, which are consistent across multiple

programming languages C, C++, and Python it also works well across languages, ideal for diverse code environments.

7. Conclusion and Future Work

In this paper, we proposed an automated bug detection framework driven by deep learning utilizing structured and semantic code representation to empower the detection of bugs in code. Particularly, our proposed method has been thoroughly examined on CodeXGLUE, Devign, and the Big-Vul datasets. Results show that our model obtained remarkable accuracy performance, generalization improvement while being practical to integrate in modern development workflows. Besides, our framework has been designed to be human-understandable in the form of SHAP and the attention layers to enable more transparent and easier prediction analysis. In forthcoming work, we plan to improve our system with fine-grained bug localization to drill down not just on bug detection but on specifically determining the exact faulty lines or tokens; assess the multilingual feature for different languages, such as JavaScript, Java, and Go; linking with automated repair tools and live feedback mechanisms in IDEs to accomplish the loop between detection and solution.

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