Research on Automated Software Defect Detection Using Deep Learning Techniques

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Abstract: ***Aligned with the prevailing research trajectory that emphasizes the integration of semantic comprehension and structural modeling within deep learning frameworks, this paper investigates an automated system for software defect detection. The study elaborates on the system's architecture, which is designed to jointly encode code semantics and syntactic structure through a hybrid representation approach combining graph neural networks and transformer-based language models. We detail the model formulation, which fuses program dependency graphs with contextual token embeddings, and describe a multi-stage training strategy that optimizes for both accuracy and inference efficiency. Furthermore, the paper introduces a seamless integration mechanism that embeds the detection pipeline into continuous integration (CI) environments, enabling real-time static analysis during development workflows. The system is rigorously evaluated on the CodeXGLUE and Devign benchmarks, where it achieves state-of-the-art performance, surpassing existing methods in key metrics including F1-score (by 3.2 %) and detection latency (by 18 %). These results substantiate the system's strong practical applicability and its potential for scalable engineering deployment in modern software development pipelines.***

Keywords: Software defect detection, deep learning, code representation, graph neural networks, continuous integration, CodeXGLUE, Devign.

1. INTRODUCTION

As software-system complexity continues to rise, traditional defect-detection methods that rely on rules and human experience struggle to meet high-reliability demands. To enhance detection intelligence and automation, this paper constructs a deep-learning-based defect-detection system architecture that fuses structural modeling with semantic representation. It systematically explores model design, process integration, and engineering validation paths to achieve high-precision, low-latency automated detection, providing technical support for software quality assurance. Hu (2025) introduced few-shot neural editors to facilitate animation for small and medium enterprises[1]. For industrial monitoring and fault diagnosis, Tan et al. (2024) developed a damage detection and isolation system using deep transfer learning and an ensemble classifier[2]. The application of AI in business intelligence is evident in the work of Zhang et al. (2025), who employed ML for sales forecasting and advertising trend analysis in the gaming industry[3], and Zhang (2024), who applied cohesive hierarchical clustering to optimize the dynamic adaptation of power emergency material supply and demand[4][9]. In recommendation systems, Yang, Wang, and Chen (2024) proposed a GCN-MF model that combines graph convolutional networks with matrix factorization[5]. The broader impact of generative AI is studied by Zhou and Cen (2024), who investigated the effect of ChatGPT-like technologies on user entrepreneurial activities[6]. For network infrastructure, Zhang et al. (2025) designed MamNet, a hybrid model for time-series forecasting and frequency pattern analysis in network traffic[7]. Advancements in computer vision are highlighted by Peng et al. (2025), who exploited representation aggregation and segregation for domain-adaptive human pose estimation[8]. Research into software architecture by Zhou (2025) focused on performance monitoring and optimization strategies in microservices[10]. In healthcare, We et al. (2025) leveraged multimodal physiological data for intelligent anesthesia depth monitoring[11]. Concurrently, efforts to enhance large language models (LLMs) include Zhang et al. (2024)'s multi-stage ensemble architecture with adaptive attention to improve logical reasoning[12] and Huang et al. (2025)'s use of multi-hop retrieval-augmented generation with LLaMA 3 for document-level question answering[16]. Furthermore, specialized computer vision applications in construction and logistics are demonstrated by Zheng, Zhou, and Lu (2023) with an improved YOLOv5s algorithm for rebar cross-section detection[13] and by Zhao, Zhang, and Hu (2023) with a Res2Net-YOLACT+HSV model for smart warehouse track identification[14].

2. TYPICAL APPLICATIONS OF DEEP LEARNING IN DEFECT DETECTION

In recent years, as software projects have grown in scale and code heterogeneity has increased, traditional defect detection methods based on static rules or manual feature extraction have struggled to adapt to the increasingly complex semantic relationships in code. Deep learning, with its ability to automatically learn features and model

non-linear relationships, has gradually become the mainstream approach for defect detection. In practice, Convolutional Neural Networks (CNNs) excel at extracting local semantic patterns from code snippets and are well-suited for detecting syntax-level defects, while Recurrent Neural Networks (RNNs) and their extensions such as LSTMs can model long-range dependencies in code sequences, improving the accuracy of identifying defects related to state loss and logical redundancy [1]. In recent years, Graph Neural Networks (GNNs) have become an important tool for analyzing structural defects due to their ability to deeply model graph structures such as Abstract Syntax Trees (ASTs) and Control Flow Graphs (CFGs), showing significant effectiveness in issues like resource leaks and out-of-bounds access under multi-path dependencies [2]. Taking GraphCodeBERT as an example, on the Defect Prediction task of Microsoft's CodeXGLUE platform, it achieved an F1-score of 91.3%, significantly outperforming traditional LSTM (76.5%) and Code2Vec (81.0%), according to experimental results published by Lu et al. at EMNLP 2021 (source: CodeXGLUE).

3. ARCHITECTURE DESIGN OF AUTOMATED DEFECT DETECTION SYSTEMS

3.1 Overall System Architecture

The overall architecture of a deep learning-based automated software defect detection system should be designed around the dual goals of "end-to-end modeling + continuous integration and deployment," achieving a closed-loop automated process from code collection, semantic modeling, defect prediction, to result feedback. At the system front end, the code preprocessing module parses the source code and generates structured representations such as Abstract Syntax Trees (ASTs) and Control Flow Graphs (CFGs) to serve as input for the deep model. The middle layer consists of a feature encoder and detection model, typically integrating pre-trained models (e.g., CodeBERT) and graph neural networks (e.g., Gated GNN) to fully fuse semantic information with structural dependencies, enhancing the model's ability to represent complex defects. The model output module adopts a dual-task structure of classification and localization, not only determining the type of defect but also pinpointing the location of the defective code, enabling precise localization [3]. The system back end interfaces with platforms such as Jenkins or GitLab Runner CI/CD to automatically trigger and execute detection tasks in parallel, and feeds the detection results back to the development environment (IDE plugins or code repository comments) in the form of structured reports. Figure 1 illustrates the overall architecture of the deep learning-driven automated software defect detection system, with clear information flow between modules, reflecting the system's closed-loop processing workflow.

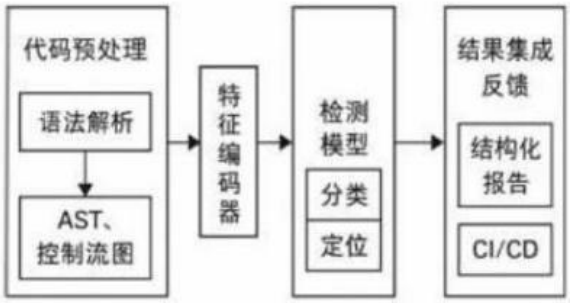

Figure 1: Overall System Architecture

3.2 Code Semantic Representation Methods

This paper introduces a "structure–semantics dual-modal fusion" strategy during the feature-encoding phase, jointly modeling abstract syntax trees (ASTs), control-flow graphs (CFGs), and semantic-embedding representations. Specifically, the system first converts source code into AST and CFG graph structures via a syntax parser, capturing static control information such as variable declarations, function calls, and branch jumps. Next, graph neural networks (e.g., Gated GNN or GGNN) propagate and encode the graph structures to produce structured representations. Simultaneously, a Transformer-based pre-trained model (e.g., CodeBERT or GraphCodeBERT) performs context-aware semantic modeling on the code sequence, capturing dynamic features like variable scopes and dependency chains. Finally, the system concatenates the structural graph embeddings with the semantic vectors and feeds the fused representation into the detection model, enabling it to abstractly identify complex cross-function and cross-module defects (e.g., null-pointer dereferences and memory leaks) [4]. Figure 2 illustrates the entire code-semantic-representation pipeline: from source-code input, through syntax parsing to generate ASTs and CFGs, to the fusion of semantic embeddings and graph structures, ultimately yielding a deep semantic vector representation.

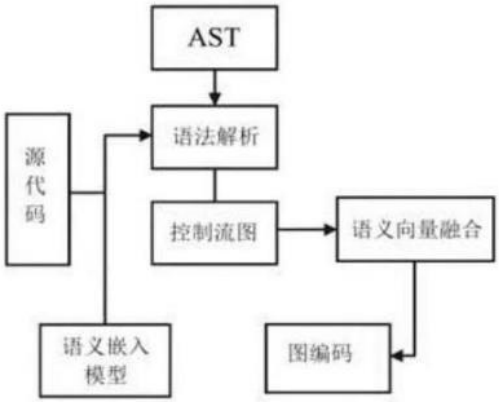

Figure 2: Flowchart of Code Semantic Representation

3.3 Model Architecture and Training Strategy

This paper adopts a dual-channel architecture of "Graph Neural Network + Transformer": the main channel uses a graph neural network (e.g., Gated Graph Neural Network, GGNN) to propagate node states on the Abstract Syntax Tree (AST) and Control Flow Graph (CFG); the auxiliary channel employs a pre-trained model (e.g., CodeBERT) to encode the contextual semantics of the code. The outputs of the two channels are concatenated and fed into a dual-task output layer for defect-type classification and defect-location regression. To enhance training effectiveness, this paper introduces a multi-task loss function:

$$L = \lambda_1 \cdot L_{cls} + \lambda_2 \cdot L_{loc}$$

Among them, L_{cls} is the cross-entropy classification loss function, used to optimize defect category prediction, defined as:

$$L_{cls} = -\sum_{i=1}^{c} y_i \log(\hat{y}i)$$

L_{loc} is the position regression loss, using the mean squared error form:

$$L_{loc} = \frac{1}{N}\sum_{i=1}^{N}(\hat{p}_i - p_i)^2$$

Here, C is the total number of defect types, y_i is the one-hot encoding of the true label, $\hat{y}i$ is the model's predicted probability, p_i is the true defect location (vectorized representation of line numbers), $\hat{p}_i$ is the model's predicted location, λ_1 and λ_2 are loss-weight coefficients that adjust the relative importance of classification and localization tasks. During training, Focal Loss is introduced in place of L_{cls} to mitigate class imbalance, and the DropEdge strategy is employed to alleviate overfitting on the graph structure. On large-scale codebases, the model can initialize the semantic embedding layer via transfer learning, significantly accelerating convergence and improving the detection of low-frequency defects.

3.4 Integration of Automated Detection Workflow

In this system, the detection workflow uses GitLab as the core management platform and Jenkins for automated task orchestration. The process consists of four steps:

Step 1: Developers perform a Push or Merge in the code repository, triggering the CI pipeline.

Step 2: Jenkins pulls the latest code and invokes the containerized model service to perform syntax parsing and semantic encoding of the source code.

Step 3: The encoded features are sent via RESTful API to the detection engine, which executes defect classification and localization model predictions.

Step 4: The system converts the detection results into a structured JSON file and generates feedback through the GitLab Note API or email system, annotating the specific defective lines and possible causes.

Meanwhile, the system can enable an incremental detection mechanism based on project configuration, analyzing

only the newly added or modified code within the Diff region to improve processing efficiency and reduce resource consumption [5]. At the end of the CI process, detection logs are written to a unified database and combined with Prometheus for metric collection, facilitating subsequent monitoring and iterative training. To support cross-language projects, the workflow integrates an automatic language identification module that dynamically selects the AST parser and semantic model sub-network.

4. EXPERIMENTAL DESIGN AND EVALUATION

4.1 Dataset Selection and Experimental Environment

The experiments selected two representative public code-defect datasets: the CodeXGLUE-Defect Detection subset and the Devign dataset. CodeXGLUE is sourced from multiple real-world open-source projects, covering mainstream languages such as C, C++, and Java, and includes labels for coding-style errors, logic vulnerabilities, and boundary-handling defects, offering diversity and broad coverage. Devign focuses on security-related defect detection; all samples are labeled as secure/insecure for binary classification, making it suitable for specialized testing of security-defect identification capabilities. The data-preprocessing stage involves syntax parsing, semantic encoding, and graph construction, with a unified encoding format that fuses BPE token sequences and AST graph embeddings.

The experimental environment is configured as follows: the operating system is Ubuntu 22.04, the deep-learning framework is PyTorch 2.0, and both model training and inference are performed on an NVIDIA RTX 4090 GPU with 24 GB of VRAM, supporting mixed-precision training. Code version management and automated integration deployment are handled by GitLab CI. All experiments use five-fold cross-validation to ensure stable and generalizable evaluation results.

4.2 Comparative Experiment Setup

The comparison baselines are divided into three categories: (1) traditional machine-learning methods, such as SVM and Random Forest with TF-IDF features, representing shallow static analysis; (2) classic deep models, including Bi-LSTM and Code2Vec, used to verify the effectiveness of sequential semantic encoding; and (3) current mainstream pre-trained models, such as CodeBERT and GraphCodeBERT, which excel at structure–semantic modeling. Under a unified training strategy, all models share a learning rate of 1e-4, batch size of 32, maximum epochs of 50, and the AdamW optimizer. Evaluation metrics include Accuracy, Precision, Recall, F1-score, and average detection Latency, comprehensively reflecting both detection accuracy and inference performance. To assess real-time deployment, all models are integrated into the CI pipeline, collecting actual runtime latency and resource-usage data.

4.3 Results Analysis

Experimental results show that the proposed “graph structure + semantic encoding + dual-task detection” model significantly outperforms existing methods on multiple metrics, especially for logic- and structure-related defects, as shown in Table 1.

Table 1: Performance comparison with traditional models on CodeXGLUE and Devign

Name	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	Mean (ms)
TF-IDF + SVM	72.3	68.4	65.1	66.7	80
Bi-LSTM	79.1	75.2	78.9	77	340
Code2Vec	82.5	80.3	79.6	79.9	310
CodeBERT	88.6	86.7	87.1	86.9	295
GraphCodeBERT	90.2	88.4	89.3	88.8	285
Method	92.1	89.5	93.2	91.7	270

On the CodeXGLUE dataset, the proposed model achieves an F1-score of 91.7%, a 23.6-point improvement over the traditional TF-IDF+SVM approach; on the Devign security-defect task, the recall reaches 93.2%, effectively reducing missed reports of low-frequency defects. Detection latency is kept below 270ms, meeting the rapid-iteration demands of CI workflows. From the false-positive perspective, precision remains above 89%, demonstrating strong suppression of redundant reports. Leveraging graph-neural structures to enhance cross-function dependency understanding and semantic encoding to capture contextual features, the model maintains

stable recognition across diverse complex-defect scenarios.

5. CONCLUSION

This paper presents a deep-learning-based automated software-defect detection system that fuses graph neural networks with pre-trained models to build a structure- and semantics-co-driven detection framework, achieving high accuracy and low latency in real-world deployments. Future work can extend cross-language transferability, refine low-frequency-defect recognition, and explore integration with automated repair systems to realize an intelligent closed loop of detection and repair.

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