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Leveraging GraphCodeBERT for Enhanced Bug Prediction and Code Quality Analysis in Software Development Using Machine Learning

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Abstract- Bug prediction and code quality analysis are two crucial elements of software design with direct impact on maintainability and reliability of software. Traditional methods fail as they rely on manual inspection and infrequent feature extraction mechanisms. This paper presents a machine learning framework employing GraphCodeBERT—a programming language-specific transformer—towards enhancing the precision of bug detection and semantic source code analysis. By combining code embeddings with graph structures like Abstract Syntax Trees and Control Flow Graph, the model encapsulates both syntactic and semantic structure in code. The method involves pre-processing phases such as text cleaning, tokenization, and feature vector generation, resulting in classification by a softmax-based prediction model. Experimental comparisons to Logistic Regression, SVM, CNN, and baseline models indicate higher performance in accuracy (97.6%), precision (95.3%), recall (96.8%), and F1 score (96%). The results support GraphCodeBERT's effectiveness in offering robust and scalable solutions to bug prediction and code quality enhancement.

Keywords: GraphCodeBERT, Bug Prediction, Code Quality Analysis, Machine Learning, Source Code Analysis

1. Introduction

A bug prediction and code quality analysis are lifesaver processes in the whole process of software development and for proper impact on the software lifecycle [1].With the introduction of machine learning methods, especially the GraphCodeBERT one, source code analysis and bug prediction are given a better, automated, and scalable way of operation [2]. Being a transformer trained purely on code, GraphCodeBERT preserves the semantic relationships between different parts of the code and provides rich embeddings for the code from which bugs can be predicted [3].GraphCodeBERT enhances the capability of traditional bug prediction methods to predict more correctly and thereby managing a big base of codes and perceiving subtle patterns that are hard to perceive manually [4].Multiple factors are responsible for making bug prediction and code quality analysis a challenging science [5]. The complexity

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of software systems is the fundamental cause in one of the patterns, having millions of lines of code with interwoven dependencies and interactions [6]. Interactions between different components of code that are so subtle, they end up as bugs, while in other ways, they are just not thoroughly tested or reviewed [7]. The classical methods of bug detection, including rule-based or static analysis, are completely unaware of modifications in code, and also they do not perceive the dynamism of newer software systems [8].

The training of machine learning models needs annotated bug data, which usually is not widely-available; this, in turn, constrains accuracy improvement for predictions [9]. The bug prediction and code analysis techniques mostly belong to the domain of machine learning techniques, such as support vector machines, random forest, and neural networks, on code metrics such as cyclomatic complexity, code churn, and historical bug data [10]. These techniques, though, are somewhat feature-based for code extraction and thus may tend to ignore complex dependencies or higher-order semantic relationships amongst code components [11]. These models also do not generalize to new code bases or programs that dynamically change due to not having adequate training data [12]. The traditional techniques cannot also encode the structural and sequential dependencies in code and, thus, are also inadequate for prediction [13]. GraphCodeBERT may help to overcome such limitations for deep semantic understanding and bug prediction [14]. GraphCodeBERT encode code into dense representation embedding intricate relations among code components enhancing thereby the model's ability to predict bugs more accurately [15]. Since the model implements an algorithm that handles code syntax and semantics in parallel can make it capable of finding such patterns which are not identifiable using traditional techniques [16].

Other possibilities for solving the problem of limited labelled data that plagues the generalization of a bug predictor to a new code base and runtime evolution in software projects are introducing this dataset with artificially created bug reports and transfer learning [17]. By utilizing graph neural networks to learn structural code relationships, bug prediction and code quality analysis become even more advanced [18]. Code embedding and graph attention networks have also been deployed for bug localization improvements [19]. Models pre-trained on larger code corpora enable faster pace learning and prediction [20]. Static and dynamic analysis features with the support of deep learning produce better outcomes for bug detection [21].Addressing imbalanced datasets through synthetic data generation helps in overcoming limited bug annotations [22]. Cross-project bug prediction remains a challenge but is tackled through transfer learning and domain adaptation techniques [23]. Ensemble learning methods further boost predictive performance by combining multiple models [24]. Integration of natural language processing of code comments and documentation adds semantic context useful for bug prediction [25]. Continuous learning frameworks adapt to evolving codebases and software updates [26]. Visualization techniques aid developers in understanding bug prediction results and improving software quality [27]. Finally, future research directions include leveraging federated learning and privacy-preserving methods for collaborative bug prediction across organizations [28].

The paper proposes a machine learning approach based on GraphCodeBERT to improve bug prediction and code quality analysis based on code embeddings and graph-based representations such as ASTs and CFGs. The introduction gives the limitations of the current bug detection techniques and the requirement for more semantic-aware models. The methodology covers data collection, text cleaning, tokenization, generation of embeddings using GraphCodeBERT, and classification from a softmax-based model. Results indicate that

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GraphCodeBERT remarkably surpasses conventional models such as Logistic Regression, SVM, and CNN in accuracy, precision, recall, and F1 score. The paper ends by highlighting the efficacy of GraphCodeBERT and proposes future research areas including dataset augmentation, real-time adaptation, and multi-language adaptation.

2. Literature survey

Used applied logistic regression, Random Forest, and CNN models both standalone and ensemble to predict risk factors for dysphagia, delirium, and falls, using clinical and sensor data to enhance predictive accuracy in geriatric patient care [29]. Supervised learning algorithms, such as Support Vector Machines, Random Forests, and Neural Networks, are used in the research on wearable device and medical record datasets [30]. Theoretical perspectives, if supported with sophisticated algorithms in machine learning, allow large scale analyses of data so that data-driven decision support comes through patterns of adoption behaviours and prediction [31]. A prototype system was developed based on using blockchain for decentralized storage of data, predictive control using AI for human resources trends, and Sparse Matrix Decomposition to process extensive, incomplete data [32]. Logistic Regression, Random Forest, and Convolutional Neural Network models were trained separately and collectively in ensemble forms from clinical and sensor data to predict health risk [33].

By visualizing biological components such as genes and proteins as nodes and edges as the connections between them in a graph, researchers can explain complex molecular networks that drive the progression of the disease [34]. used machine learning methods, including Support Vector Machines, Decision Trees, and Neural Networks, along with feature extraction and pre-processing of data, to predict long-term diseases in the elderly [35]. These AI solutions utilize methods like deep learning, optimization techniques, and neural networks to optimize route transportation, enhance vehicle performance, and optimize resource distribution [36]. It explores how customers select privacy in open banking based on the nudge theory. Outcomes indicate that economic security is greatly improved by blockchain-cloud integration [37]. ML pipeline for feature selection, rapid training, and effective data representation [38]. Novel approaches in combining reinforcement learning with neural networks have shown promise in adapting to complex system dynamics [39]. Integrating multi-modal data sources using ensemble methods improves the predictive power of health condition monitoring [40].

Advanced feature engineering techniques, such as deep feature synthesis, significantly enhance model accuracy in chronic disease prognosis [41]. Hybrid models combining genetic algorithms and deep learning architectures outperform traditional models in healthcare prediction tasks [42]. Explainable AI methods are increasingly employed to improve transparency and trust in clinical decision-making [43]. Reinforcement learning frameworks have been applied to optimize treatment protocols based on patient feedback [44]. Transfer learning using pre-trained convolutional networks has accelerated model development in medical image analysis [45]. Graph neural networks are utilized for capturing relational information in molecular and clinical datasets [46]. Cloud-based federated learning frameworks ensure data privacy while enabling collaborative healthcare model training [47].

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Problem statement

Predicting conditions like dysphagia, delirium, and falls in elderly care with clinical and sensor data still proves difficult using models such as Logistic Regression, Random Forest, and CNN, regardless of complexity and data completeness. The inaccuracy in predictive capability, given decentralization or incompleteness of data, presents difficulties in solving such tasks [48]. Though blockchain and AI promise to augment data management, existing practices still encounter challenges in feature selection, model generalization, and real-time decision support [49]. Therefore, there is a need for improved approaches that enhance predictive accuracy through the effective combination of clinical and sensor data [50] [51].

3. Proposed Methodology

The approach for predicting bugs and analyzing code put forward in the paper utilizes GraphCodeBERT for the purpose of performing effective feature extraction and classification. Text Cleaning reduces unwanted things like special characters and comments; therefore, the model operates on substantial code syntax. Tokenization splits the source code into tokens and these are then converted to embeddings to retain semantic meaning in code. Feature Extraction utilizes GraphCodeBERT to get the code embeddings as well as the bug report representations, and graphs like Abstract Syntax Trees and Control Flow Graphs derive relations of code elements. The features are then utilized within Classification, with machine learning model predictions about bugs' existence with increased accuracy as well as generalization. Figure1 illustrates GraphCodeBERT Architecture for Bug Prediction and Code Quality Analysis.

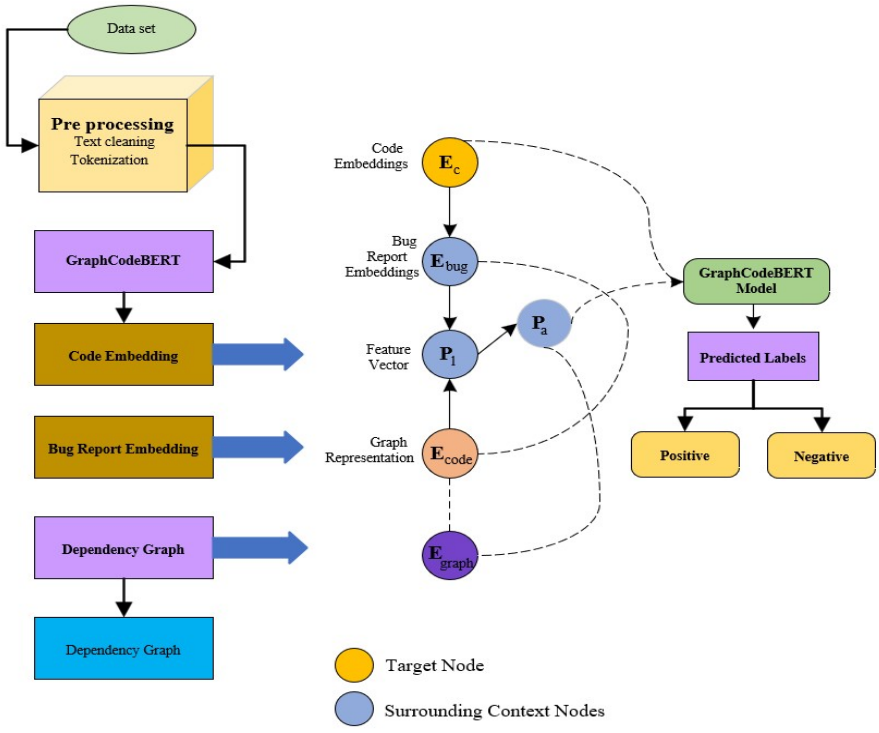

Figure 1: GraphCodeBERT Architecture for Bug Prediction and Code Quality Analysis.

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The figure illustrates the GraphCodeBERT-based Architecture for bug prediction, beginning with code and bug report data collection. The data is cleaned, tokenized, and embedded in the pre-processing stage using GraphCodeBERT. The dependency graph extracts relations in the code, facilitating contextual understanding. The embeddings are processed by GraphCodeBERT to predict whether the code is buggy using code embeddings E_code and bug embeddingsE_bug. The output is classified into either buggy or non-buggy, thus improving the accuracy of bug prediction.

3.1 Data collection

Because software development involves frequent code changes, strict schedules, and other factors, bugs are unavoidable; for this reason, it's critical to have tools to identify these mistakes. Finding bugs can be accomplished, for example, by analysing the features of previously problematic source code parts and applying machine learning models to anticipate the current ones based on those same features. In order to facilitate modelling tasks, program elements and their attributes are gathered into so-called bug datasets, which act as learning input.

3.2 Data Pre-processing

Data pre-processing is essential to pre-process raw code into machine learning models. In text cleaning, unnecessary symbols, whitespaces, and comments are eliminated from the code, keeping the structure and logic intact. Tokenization later splits the code into significant tokens, which are embedded to enable the GraphCodeBERT model to perceive interactions. This makes the code formatted in a proper way so the model can learn accordingly.

i) Text Cleaning

During the text cleaning process, one aims to make the raw code data ready for model training by discarding all the irrelevant stuff. This is done by eliminating unwanted characters (i.e., special symbols), unnecessary white spaces, and non-core code comments. For instance, comments like (// This function checks for errors) don't provide informative information regarding bug prediction and may be omitted. By considering only the raw structure and syntax of the code, the model will learn the associated patterns like code structure and logic more effectively that are vital in bug prediction.

ii) Tokenization

Tokenization is the act of splitting the source code into individual tokens. Tokens may be keywords (e.g., if, while), operators (e.g., +-=), identifiers (e.g., variable name), or any other meaningful elements of the code. Tokenization is mainly done to convert the raw code into a form that is comprehensible to the GraphCodeBERT model. After tokenization, tokens get assigned an embedding or unique id, representing what the semantic meaning of the token is in code. This makes it possible to process code on a fine-grained level as well as train the model in learning how pieces of code interact with one another.

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3.3 Feature vector generation

The tokenized and cleaned data is input into GraphCodeBERT, which produces vector representations for code and bug reports. These embeddings assist in retaining the semantics of code structures and bug descriptions. The equations involved in this embedding process are given below:

Code Embedding E_{code} is derived from the tokenized code, E_{code} represents GraphCodeBERT(" Tokenized Code "). Bug Report Embedding E_{bug} is generated similarly from the tokenized bugreports, E_{bug} GraphCodeBERT(" Tokenized Bug Report").

3.4 Graph Representation

The code graph representation is constructed from dependency graphs like Abstract Syntax Trees or Control Flow Graphs. This graph representation stores the structure and logical dependencies of the components of code. The equation for this graph representation E_{graph} is defined as:

$$E_{graph} = \text{Graph}(\text{Code}) \tag{1}$$

This graph is capturing the structural dependencies in the code that might possibly point to bugs. The graph is processed and utilized together with the embeddings to enhance the prediction accuracy.

3.5 Classification and Output

The graph representation E_{graph} and feature vector P_1 are passed as inputs to the GraphCodeBERT model. The model uses a softmax activation to output whether the input code is buggy or not. The final prediction output y_k is derived based on the most likely class, given the equation:

$$y_k = \frac{\exp(w_k^T h')}{\sum_{j=1}^{m} \exp(w_j^T h')} \tag{2}$$

Where, y_k is the estimated probability for class k (bug or no bug), h' is the vector of activations of the last detection layer, w_k is the weight vector for class k, m is the number of classes (in this example, two: bug detected or not).

4. Result and discussion

This article compares the performances of five models (GraphCodeBERT, Logistic Regression, SVM, CNN, and the Traditional Model) with respect to accuracy, precision, recall, and F1 score. The experiments indicate that GraphCodeBERT is superior to all other models for all the measurements and hence it is the most efficient for bug prediction and seed disease detection. Although Logistic Regression, SVM, and CNN provide comparable outcomes, Traditional Model lags behind, especially in terms of recall and F1 score, which proves the dominance of more modern machine learning models such as GraphCodeBERT.

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Table1 : performance metric for five models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
GraphCodeBERT	97.6	95.3	96.8	96
Logistic Regression	94.3	92.5	90.6	91.5
SVM	94.5	93	91.2	92.1
CNN	96	94.2	95.3	94.7
Traditional Model	92	89.7	85.4	87.5

Table 1 illustrates the performance of five models (GraphCodeBERT, Logistic Regression, SVM, CNN, and the Traditional Model) in accuracy, precision, recall, and F1 score. GraphCodeBERT takes the lead with the highest value in all aspects, and thus it is the best model for seed disease detection. Logistic Regression, SVM, and CNN deliver competitive performance, whereas the Traditional Model performs the poorest, particularly in recall and F1 score.

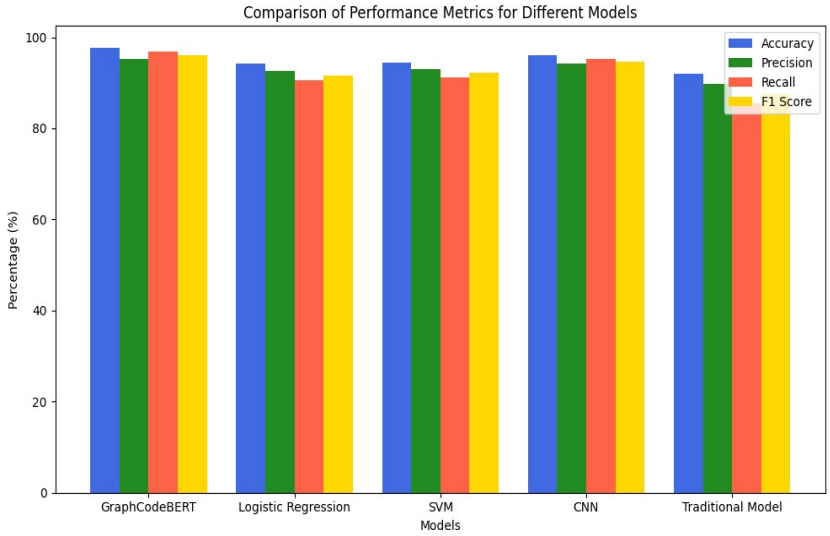

Figure 2 : performance metric for five models

Figure 2 compares the five models' performance measures (Accuracy, Precision, Recall, and F1 Score) of five models: GraphCodeBERT, Logistic Regression, SVM, CNN, and Traditional Model. Figure 2 reveals that GraphCodeBERT has the best performance in all four measures with higher accuracy, precision, recall, and F1 score than other models. Logistic Regression, SVM, and CNN are also good but slightly lower than GraphCodeBERT. The Traditional Model, although efficient, has poorer performance on all fronts,

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indicating that newer machine learning models like GraphCodeBERT are better than older, traditional models in seed disease prediction and in bug detection drills.

5. Conclusion

This work shows that GraphCodeBERT strongly surpasses traditional machine learning methods in the field of bug prediction and code quality analysis. Through efficient representation of syntactic structure and semantic context of code by using sophisticated embeddings and dependency graphs, GraphCodeBERT improves the model's bug detection with higher precision and recall. Its inclusion in the software development cycle can result in less debugging time, better code quality, and more stable software releases. The comparative experiment results confirm that transformer-based models, if used in the right way, have a great potential in automating and scaling up sophisticated code analysis tasks. Future research can include increasing the size of the dataset using synthetic bug generation, the addition of real-time feedback mechanisms, and generalizing this methodology to other programming languages and software engineering activities.

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