Automated Software Vulnerability Detection Using CodeBERT and Convolutional Neural Network

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Keywords: Source Code, Vulnerability Detection, CodeBERT, Centrality Analysis, Convolutional Neural Network.

Abstract: As software programs continue to grow in size and complexity, the prevalence of software vulnerabilities has emerged as a significant security threat. Detecting these vulnerabilities has become a major concern due to the potential security risks they pose. Though Deep Learning (DL) approaches have shown promising results, previous studies have encountered challenges in simultaneously maintaining detection accuracy and scalability. In response to this challenge, our research proposes a method of automated software Vulnerability detection using CodeBERT and Convolutional Neural Network called VulBertCNN. The aim is to achieve both accuracy and scalability when identifying vulnerabilities in source code. This approach utilizes pre-trained codebert embedding model in graphical analysis of source code and then applies complex network analysis theory to convert a function's source code into an image taking into account both syntactic and semantic information. Subsequently, a text convolutional neural network is employed to detect vulnerabilities from the generated images of code. In comparison to three existing CNN based methods TokenCNN, VulCNN and ASVD, our experimental results demonstrate a noteworthy improvement in accuracy from 78.6% to 95.7% and F1 measure increasing from 62.6% to 89% which is a significant increase of 21.7% and 26.3%. This underscores the effectiveness of our approach in detecting vulnerabilities in large-scale source code. Hence, developers can employ these findings to promptly apply effective patches on vulnerable functions.

1 INTRODUCTION

Software vulnerabilities pose an increasing risk to software systems making them susceptible to attacks and potential damage, thereby raising security concerns (Alves et al., 2016). In 2023, the *Open Source Security and Risk Analysis* (OSSRA) conducted a comprehensive study involving 1703 codebases with audit data. The findings indicated that 76% of the codes were open source. Moreover, 48% of the codebases exhibited high-risk vulnerabilities and 84% of these vulnerabilities were associated with open source security flaws. Consequently, to enhance the security of software it is crucial to employ advanced methods for detecting vulnerabilities on a large scale.

Recently, several approaches for vulnerability detection using Deep Learning (DL) have emerged falling into two categories: the *text-based* approach (Li et al., 2018; Zou et al., 2019) and the *graph-based* approach (Zhou et al., 2019; Cheng et al., 2021). Prior studies (Li et al., 2018; Zou et al., 2019; Mim et al., 2023a) focusing on text-based identification of source code vulnerabilities applied static program analysis or natural language processing. However, these approaches often fall short in disregarding the semantics of the source code. To address these limitations, program analysis is employed to represent source code semantics as a graph. Graph analysis methods such as Graph Neural Networks (GNN), are then applied to identify vulnerabilities. While these graph-based approaches excel at vulnerability identification but their scalability is challenging, especially when compared to text-based approaches. Text-based approaches, lacking the ability to capture inter-dependencies between different lines of source code, result in lower accuracy. On the other hand, graph-based methods achieve high accuracy but struggle with scalability in complex scenarios with many nodes in a graph representing statements in the program's source code. The most recent vulnerability detection system, VulCNN (Wu et al., 2022) and ASVD (Mim et al., 2023b), attempts to combine both text-based and graph-based approaches to gather syntactic and semantic data from source code. However,

Mim, R., Satter, A., Ahammed, T. and Sakib, K.
Automated Software Vulnerability Detection Using CodeBERT and Convolutional Neural Network.
DOI: 10.5220/0012707900003687

In *Proceedings of the 19th International Conference on Evaluation of Novel Approaches to Software Engineering (ENASE 2024)*, pages 156-167
ISBN: 978-989-758-696-5; ISSN: 2184-4895

VulCNN's scalability has improved compared to eight state-of-the-art vulnerability detectors. Still, its detection performance is deemed unsatisfactory as it leverages Sent2Vec (Moghadasi and Zhuang, 2020) embedding in source code which struggles in capturing intricate code context and misinterpret code semantics. VulCNN only considers three network centralities (Freeman et al., 2002) (degree centrality, katz centrality, and closeness centrality) for calculating the importance of each line of source code. The impact of incorporating other centrality measures such as eigenvector centrality and betweenness centrality in vulnerability detection has not been explored yet. But these centralities might have a greater impact on vulnerability detection combining with DL based approaches which accounts for the overall effect of a node or statement in source code and detects vulnerability.

To address these issues, we propose an enhanced automated **Vul**nerability detection method using Code**BERT** and **C**onvolutional **N**eural **N**etwork called VulBertCNN. which uses CodeBERT (Feng et al., 2020) embedding model leveraging the advantages of large-scale pre-training which captures both syntactic and semantic information of source code. Our method comprises of three phases. First, using the source code as input, we create a Program Dependency Graph (PDG) containing data flow and control flow information. In the second phase, CodeBERT embedding is applied to each node of the generated PDG. In the third phase, we utilize different combinations of five centralities on each node, with each centrality corresponding to a channel, to create an image. Finally, a Convolutional Neural Network (CNN) (Krizhevsky et al., 2017) model is trained on the produced images to identify functions as either vulnerable or non-vulnerable.

To ensure the model's effectiveness in large-scale vulnerability scanning we explored pre-trained CodeBERT embedding model with various centrality combinations and we applied the proposed model on two benchmark dataset SARD and Big-Vul (Fan et al., 2020) containing a total of 40,584 and 188,770 functions. Results reveal its outperformance over the state-of-the-art vulnerability detectors in terms of accuracy and F1 measure by 21.7% and 26.3%.

In summary, the contributions of this paper are as follows.

- We analyzed the shortcomings of three recent vulnerability detection approaches TokenCNN, VulCNN and ASVD in doing syntactic and semantic analysis along with selection of node centrality in generating images from source code by CNN. Then we proposed the efficient combination of node centralities to generate images.
- We utilize the language model to develop a technique for representing vulnerable source code to detect software vulnerabilities. In contrast to previous studies (Wu et al., 2022; Mim et al., 2023b) that employed the Sent2Vec embedding method, we incorporate the CodeBERT embedding model. Furthermore, we design a more efficient Convolutional Neural Network (CNN) model by integrating five centralities. This design aims to reduce computational overhead while enhancing the overall detection performance.
- Our experimental results indicate that VulBertCNN outperforms the state-of-the-art methods (Russell et al., 2018; Wu et al., 2022; Mim et al., 2023b) on two benchmark datasets SARD and BigVul (Fan et al., 2020) significantly in terms of accuracy and F1 measure.

Paper Organization. The remainder of this paper is structured as follows. Section 2 gives an overview of previous studies on vulnerability detection and presents the motivation for our improvements. Section 3 introduces the technical route of VulBertCNN. Section 4 presents the experimental setup and results analysis. Section 5 demonstrates the threats to validity of our work. Section 6 includes future research directions and concludes this paper.

2 RELATED WORK

This section focuses on researches that are conducted to detect vulnerabilities. Vulnerability detection techniques vary in their degree of automation, typically falling into three main categories: manual, semi-automatic, and full-automatic methods. Manual techniques rely on human experts to create vulnerability patterns, but they may not cover all potential vulnerabilities, resulting in lower detection efficiency in real world scenarios for tools like Checkmarx, FlawFinder and RATS. Semi automatic techniques (Shankar et al., 2001; Yamaguchi et al., 2015; Shar et al., 2014) involve human experts extracting specific features, such as API symbols (Yamaguchi et al., 2012) and subtrees, import and function calls (Neuhaus et al., 2007) which are then fed into traditional machine learning models to identify vulnerabilities. In contrast, full-automatic techniques (Cheng et al., 2021; Duan et al., 2019; Li et al., 2021; Lin et al., 2017) leverage deep learning to automatically extract features and generate vulnerability patterns without the need for manual expert input. Deep learning based techniques (Cheng et al., 2021; Zhou et al., 2019; Russell et al., 2018; Li et al., 2018; Zou et al., 2019) can be further categorized into text-based approaches and graph-based approaches.

2.1 Text Based Approach

The text-based approaches involve treating a program's source code as text and employing natural language processing techniques to identify vulnerabilities. Russell et al. presented a TokenCNN model, which utilizes lexical analysis for obtaining source code tokens and employs a Convolutional Neural Network (CNN) for the detection of vulnerabilities (Russell et al., 2018). Rahman et al. introduced a method-level detection approach that minimizes the search space, determining similarity scores between source code and bug reports. Based on these scores, it ranks methods that are identified as vulnerable (Rahman et al., 2016). Li et al. proposed Vuldeepecker, which gathers code gadgets through program slicing, converts them into vector formats, and utilizes Bidirectional Long Short Term Memory (BLSTM) models for vulnerability detection (Li et al., 2018). Zhou et al. presented an enhanced method called μVulDeePecker, which incorporates code attention integrating control dependence into Vuldeepecker's program processing technique to identify multi-class vulnerabilities (Zou et al., 2019). Mim et al. proposed VFDetector which uses information retrieval based method for detecting vulnerability from source code using vulnerability reports. VFDetector calculates the textual similarity score between vulnerability report's description and source code of a software system. Higher similarity score suggests highly vulnerable software system (Mim et al., 2023a). These text-based approaches suffer from poor detection performance due to their reliance on static analysis of source code neglecting source code semantics and considering the whole source code as plain text.

2.2 Graph Based Approach

To overcome the limitations of text-based approaches, researchers have turned to dynamic program analysis, converting source code semantics into a graph and employing graph analysis for vulnerability detection. Zhou et al. introduced an approach utilizing a graph neural network with a convolutional module to identify vulnerabilities, achieving complete graph-level classification through node pooling (Zhou et al., 2019). Cheng et al. segmented the program dependency graph into subgraphs after distilling program semantics, integrating these subgraphs into a graph neural network to train a vulnerability detector (Cheng et al., 2021). While graph-based approaches prove more effective in identifying vulnerabilities, they suffer from scalability issues compared to text-based strategies. Addressing these, Wu et al. proposed VulCNN, which leverages a program dependency graph (PDG) to extract information from each line of code. Centrality analysis on the PDG quantifies the significance of each node in a specific function, considering three centralities: degree, katz, and closeness. This analysis produces an image capturing graph features from three perspectives. Subsequently, a convolutional neural network (CNN) is trained to detect vulnerabilities (Wu et al., 2022). Though VulCNN address both syntactic and semantic analysis but it's detection performance is not satisfactory.

Text-based vulnerability detection techniques often overlook program semantics, leading to inaccurate results. Conversely, graph-based techniques offer accuracy but face scalability challenges, primarily due to the substantial number of nodes in program graphs. Consequently, there is a need for automated vulnerability detection techniques that strike a balance between accuracy and scalability, considering both aspects simultaneously.

3 PROPOSED METHODOLOGY

This section proposes VulBertCNN (Vulnerability detection with CodeBERT based Convolutional Neural Network) which consists of three major phases: *Graph Generation*, *Feature Extraction* and *Vulnerability Detection* as shown in Figure 1. The details are described in the followings.

3.1 Graph Generation

As shown in Figure 2, this phase initially normalize the source code of a function before performing static analysis to obtain the function's Program Dependency Graph (PDG). Since the goal of VulBertCNN is to concurrently detect vulnerabilities with accuracy and scalability, firstly static analysis is performed to translate the program semantics of source code into a graph representation. Since a function can potentially implement a specific task, hence this phase concentrate on finding vulnerabilities at a more fine grained level (i.e., function-level) due to the coarse granularity of file-level vulnerability detection. The normalization is performed in three steps. A sample function transformation at three normalization steps has been demonstrated in Figure 2. The steps are -

- **Step 1:** Eliminates the comments from the source code because they have no effect on the semantics of the program.

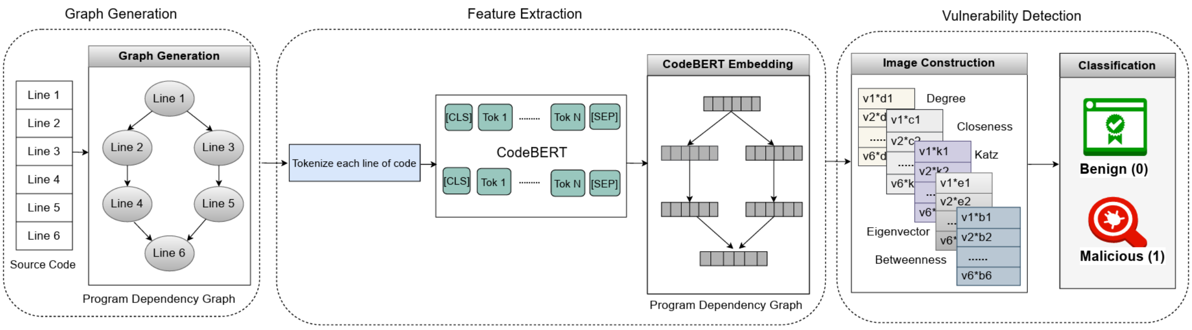


Figure 1: Overview of proposed vulnerability detection system using CodeBERT and Convolutional Neural Network.

- **Step 2:** One-to-one mapping of user-defined variables to symbolic names is performed. For example, the variable named "value" is mapped to symbolic name "VAR1".
- **Step 3:** One-to-one mapping of user-defined functions to symbolic names is performed. Such as the function named "Vulnerable()" is converted to symbolic name "FUN1()".

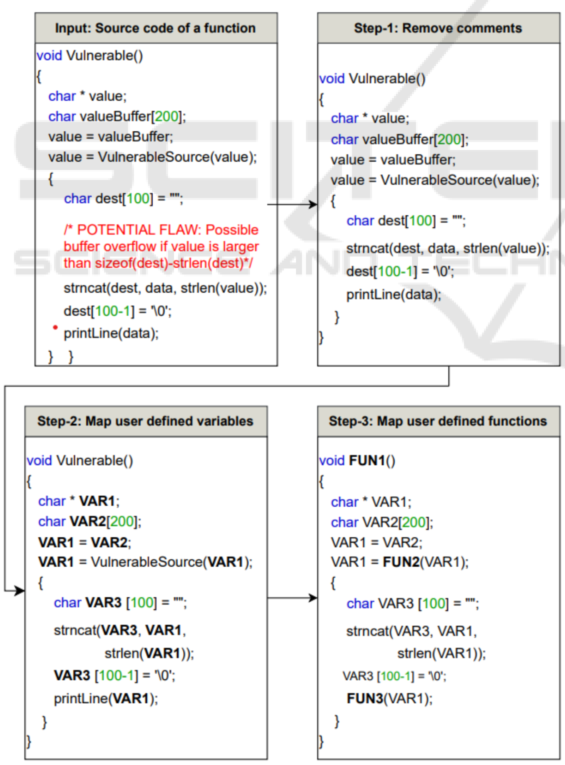


Figure 2: Steps of Source Code Normalization.

After normalization the PDG of the function is then extracted using an open source code analysis tool for C/C++ named Joern (Yamaguchi et al., 2014). Each line of code in the function represents a node in a PDG.

3.2 Feature Extraction

In this feature extraction step of our research, we employ CodeBERT (Feng et al., 2020), a pre-trained BERT model that integrates both Natural Language (NL) and Programming Language (PL) encodings creating a comprehensive model suitable for fine-tuning on source code tasks. Trained on an extensive dataset sourced from code repositories and programming documents, CodeBERT demonstrates enhanced effectiveness in software program training and source code analysis. Firstly, each node of program dependency graph which represents a statement of source code in tokenized. Then each tokenized lines of code is given input to pre-trained codeBERT model and output contains contextual vector representation of each token. This phase has two steps : Tokenization and CodeBert Embedding.

Tokenization: During the pre-training phase, input data is constructed by combining two segments using special tokens, [CLS], w1, w2, ..wn, [SEP], where [CLS] serves as a classification token. This input structure involves one segment representing natural language text and the other representing code from a specific programming language. The [CLS] token is a special token placed before the two segments. Following standard text processing in Transformer, natural language text is treated as a sequence of words and divided into WordPieces (Wu et al., 2016), while a code snippet is considered a sequence of tokens. The output of CodeBERT includes contextualized vector representations for each token, encompassing both natural language and code, as well as the representation of [CLS], which serves as a summarized representation.

CodeBert Embedding: In the context of our research, a snippet of source code is extracted as a PDG from graph generation phase. Processing the PDG during this feature extraction phase includes obtaining a comprehensive code representation which is vital for subsequent model construction. We leverage

CodeBert (Feng et al., 2020), designed to extract code features using a transformer-based method, specifically effective for source code-related tasks with self-supervised learning objectives. CodeBert takes a PDG of a single function of source code as the raw input and then processes and splits it into individual statements S_i. Each statement is tokenized using CodeBERT's pretrained BPE tokenizer. After collecting S = $S_1, S_2, ..., S_n$ the entire function is input into CodeBERT, enabling the acquisition of function-level and statement level code representations. This CodeBert embedding converts each sentence into a equivalent vector representation having dimension size 768. Finally an embedded function-level graph with statement level features is extracted from this feature extraction phase.

3.3 Image Construction

After completing CodeBert embedding, each node in the new embedded PDG is substituted with its corresponding embedded vector. In this phase, our goal is to convert the new PDG into an image efficiently taking into account how various lines of code contribute to program semantics.To generate an image of a function from the PDG, it's essential to have information about the connections between the nodes. The weight of each connection is determined by evaluating the node's contributions to program semantics. Treating the PDG as a social network graph, node connection weights are determined using social network centrality analysis. This analysis is employed to evaluate the significance of each node or in other words each line of code. Centrality (Freeman et al., 2002) concepts, originally introduced in social network analysis aim to assess a node's importance within the network. Various fields including biological and transportation networks have successfully applied centrality analysis demonstrating its utility in network assessment. Our paper considers five centrality metrics which are discussed below.

Degree Centrality: Degree centrality for a node is determined by counting both the incoming edges (indegree) and outgoing edges (outdegree), essentially representing the number of links associated with the node. To obtain the standardized value, the highest degree is divided by N-1, where N represents the total number of nodes in the network.

Katz Centrality: It calculates the centrality value of a node by taking into account the centrality of its neighboring nodes. This is determined by summing the number of directly connected nodes and the number of indirectly connected nodes through these immediate neighbors. The Katz centrality of a node 'n' can be expressed as follows:

$$x_n = \alpha \sum_j A_{nj} x_j + \beta \tag{1}$$

In the given expression, A represents the Adjacency Matrix, and α, β and λ stand for the Attenuation Factor, Initial Centrality Controller and Eigenvalues of the graph G respectively. These parameters are instrumental in assigning increased weight to nearby neighbors (via β), while simultaneously applying a penalty to distant links (utilizing α). Notably, α must be smaller than the inverse of the largest eigenvalue of the adjacency matrix to ensure the proper computation of Katz centrality allowing for an accurate measurement by considering the influence of various factors.

$$\alpha < \frac{1}{\lambda_{max}} \tag{2}$$

Closeness Centrality: Closeness centrality measures how close a node is to every other node in the graph. It is computed by averaging the shortest path lengths between the nodes within the graph. A node with a smaller average distance signifies greater closeness to the center of the graph. The average distance is essentially the inverse of the node's proximity centrality among all x-1 accessible nodes.

$$C(x) = \frac{x-1}{\sum_{n=1}^{x-1} d(n,x)} \tag{3}$$

In this equation, where x represents the total number of nodes in the graph and d(n, x) denotes the distance between nodes n and x.

Eigenvector Centrality: Eigenvector centrality assesses a node's overall impact based on the centrality of its neighboring nodes. In accordance with the given definition, the i-th element in the n vector corresponds to the eigenvector centrality of the i node.

$$An = \lambda n \tag{4}$$

Here, the eigenvalue λ is associated with the adjacency matrix A.

Betweenness Centrality: Betweenness centrality calculates the shortest paths for nodes within a graph, representing the overall percentage of total pairs of shortest routes that traverse through a specific node α a. Mathematically, it is expressed as:

$$C_B(a) = \sum_{s,t \in N} \frac{\sigma(s,t|a)}{\sigma(s,t)} \tag{5}$$

In this formula, N signifies the set of nodes, $\sigma(s,t)$ denotes the count of shortest paths between nodes s and t, and $\sigma(s,t|a)$ represents the count of paths passing through node a other than nodes s and t.

$$A_x = \frac{Degree(x)}{N-1} \tag{6}$$

Due to the typical composition of a RGB image with three channels: Red, Green, and Blue, prior studies utilize three different centrality measures: degree centrality, Katz centrality, and closeness centrality. These centrality measures provide insights into the importance of various lines of code within a function from distinct perspectives. By incorporating additional two centrality measures: Betweenness centrality and Eigenvector centrality we can achieve a more comprehensive assessment of each line of code's contribution to the overall program semantics because Eigenvector centrality assesses the importance of a node based on its connections to other highly central nodes, offering insight into critical elements within a PDG. Betweenness centrality identifies nodes that act as key intermediaries, revealing critical pathways for information flow or dependencies between different modules or functions in a program. Both measures provide valuable insights into the structural and functional importance of nodes within a network, aiding in understanding program semantics and dependencies in source code.

In summary, we compute the centrality values for all nodes in the new embedded PDG. Subsequently, we arrange the resulting vectors in accordance with the number of lines of code multiplied by the corresponding centrality measure. These arranged vectors represent the "Degree channel" "Katz channel", "Closeness channel" , "Betweennes channel" and "Eigenvector channel" Additionally, by applying betweenness centrality and eigenvector centrality analysis we obtain two more channels. Ultimately, the combination of these five channels is utilized to generate the final image representation from a source code function.

3.4 Vulnerability Classification

Deep learning algorithms have outperformed previous technologies in various domains, such as speech and image recognition. By utilizing effective hierarchical feature extraction methods and unsupervised or semi-supervised feature learning, deep learning presents the advantage of replacing manual feature acquisition. In the domain of image processing, Convolutional Neural Network (CNN) has gathered significant attention. This is attributed to its ability not only to eliminate the need for manual image preparation but also to enable users to extract features at a level comparable to human capabilities. Following the image generation phase, a function's source code is transformed into an image. To identify vulnerabilities, the initial step involves training a CNN model on an image. While CNN typically utilizes input images of equal size, it encounters variations in the number of lines of code required for each function. Hence, adjustments are necessary.

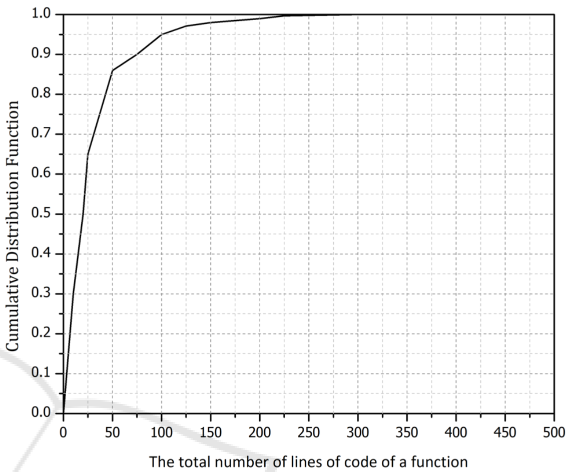


Figure 3: Cumulative Distribution Function of total number of lines of code of a function.

To identify vulnerabilities, the initial step involves training a CNN model with images. While CNN typically utilizes equal-sized input images, the varying number of statements in each function within our input dataset necessitates an adjustment. To determine a threshold for fixed-size images, an analysis is conducted to assess the number of lines of code in each function. Figure 3 shows the Cumulative Distribution Function (CDF) of the total number of statements (lines of code) in functions from the input dataset is calculated. It is observed that over 99% of the functions contain fewer than 200 statements. After experimenting with various threshold values (ranging from 40 to 200 statements) for vulnerability detection, a decision is made to set the cutoff at the first 100 statements of a function. This decision is based on considerations of detection accuracy and related runtime overhead. For functions with fewer than 100 statements, zeros are padded at the end of the vectors. In functions with more than 100 statements, the vector's tail is discarded. The input images are typically of sizes 3*100*768, 4*100*768, or 5*100*768, where 3, 4, 5 denote the number of channels, and 786 denotes the dimensions of the embedded vector.

In Figure 4, the input image shape is specified as $5 * 100 * 768$, where 5 represents five dis-

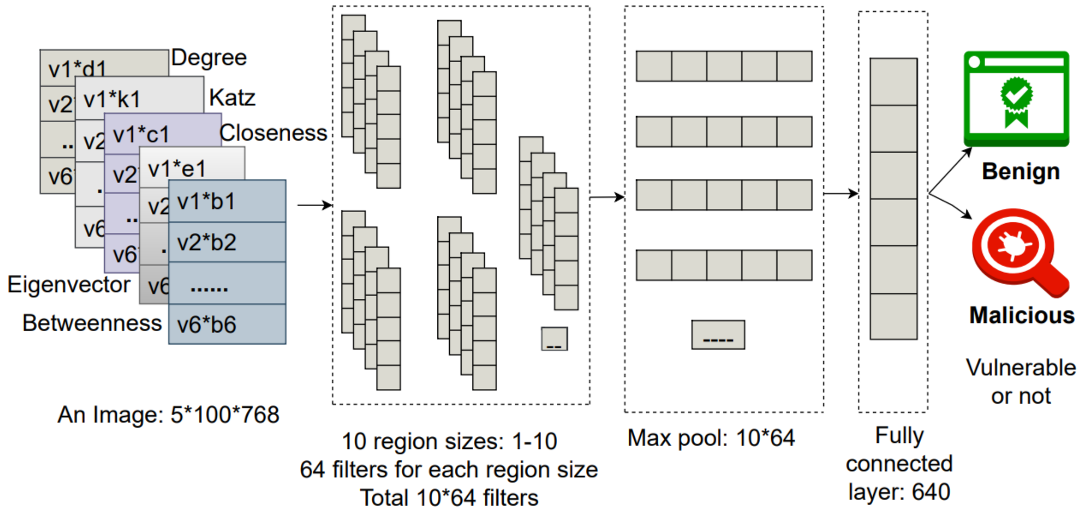


Figure 4: CNN Classification of VulBertCNN.

tinct channels: "degree" (D),"Katz" (K),"Closeness" (C),"Eigenvector" (E), and "Betweenness" (B). These channels are created to incorporate different aspects. Following the generation of fixed-size images, they are utilized for training a CNN model. The CNN model employs various convolution filters, each with a shape of m*768 as depicted in Figure 4. This design allows each filter to independently cover the entire capacity of the CodeBert embedding. The variable m denotes the size of the filter, indicating the number of consecutive sentences to be considered.

Table 1: Hyper-Parameter Settings In VulBertCNN.

Hyper-Parameters	Value
Learning Rate	0.0001
Number of Epochs	100
Batch-Size	64
loss function	Cross Entropy Loss
Activation Function	ReLU
Optimizer	Adam

In our proposed method, we extract features from different parts of the image by employing various filter sizes ranging from 1 to 10, each with 64 feature maps. This process is followed by max pooling and the application of the Rectified Linear Unit (ReLU) (Dahl et al., 2013) activation function across the entire model. The datasets are initially divided based on their original split. However, in cases where the split information is unavailable, we adopt a default split of 80:10:10 for training, validation and testing sets respectively. The hyperparameters utilized in the CNN architecture are detailed in Table 1.

4 EVALUATION AND RESULT ANALYSIS

In this section, we perform experiments to compare the detection accuracy of VulBertCNN with state-of-the-art solutions TokenCNN (Russell et al., 2018), VulCNN (Wu et al., 2022) and ASVD (Mim et al., 2023b). Before delving into the effectiveness of VulBertCNN, we provide details on the implementation specifics.

4.1 Experiment Setup

The proposed method is implemented in Python (version 3.11.5). We conducted experiments using an ASUS TUF Gaming laptop featuring an Intel Core i7-8th generation CPU on a Windows server. The processor in the laptop has six cores, each with a maximum operating frequency of 2.5 GHz.

4.2 Datasets

To evaluate the effectiveness of VulBertCNN, we use two benchmark vulnerability datasets: SARD and Big-Vul (Fan et al., 2020) in alignment with state-of-the-art methods. The datasets were collected from two sources: National Institute of Standards and Technology (NIST) and Common Vulnerability Exposure (CVE) database. The details of the experimental datasets are presented below in Table 2.

SARD: The software assurance reference dataset (SARD) dataset encompasses a significant volume of production, synthetic, and academic security flaws

Table 2: Details of Datasets.

Dataset	Total	Vul	Non-Vul	Vul (%)
SARD	40,584	13,684	26,900	33.71
Big-Vul	188,770	10,670	178,100	5.65

(i.e., bad functions) and non-vulnerable function (i.e., good functions). Our paper concentrates on identifying vulnerabilities specifically in C/C++, thus we exclusively target functions written in C/C++ within SARD. The dataset from SARD comprises 12,300 instances of vulnerable functions and 21,000 instances of non-vulnerable functions. Recognizing the potential lack of realism in synthetic programs within SARD, we supplement our data with another dataset derived from real-world software. For real-world vulnerabilities, we utilize the National Vulnerability Database (NVD) as our primary data source, resulting in 1,384 vulnerable functions from various open-source C/C++ projects. To complement this, we randomly select a subset of non-vulnerable functions from the dataset which contains non-vulnerable functions from diverse open-source projects, ensuring a balanced representation. The ultimate dataset comprises 13,684 functions with vulnerabilities and 26,900 functions without vulnerabilities.

Big-Vul: We utilized the benchmark dataset Big-Vul, created by Fan et al. (Fan et al., 2020). This dataset contains reliable and comprehensive code vulnerabilities directly associated with the publicly accessible CVE database. Notably, the construction of this dataset involved a significant investment of manual resources to ensure its high quality. Additionally, it stands out for its substantial scale, being one of the most extensive vulnerability datasets available. The dataset is compiled from 348 open source Github projects spanning from 2002 to 2019, covering 91 distinct Common Weakness Enumeration (CWE) categories. This comprehensive dataset includes approximately 188,700 C/C++ functions, with 5.6% identified as vulnerable, equivalent to 10,600 vulnerable functions. It offers detailed ground-truth information at the function level, specifying which functions within a codebase are susceptible to vulnerabilities.

4.3 Evaluation Metrics

To effectively evaluate model predictions, we established and defined ground truth values as follows: True Positive (TP) is the number of vulnerable samples correctly detected as vulnerable. True Negative (TN) is the number of non-vulnerable samples correctly identified as not vulnerable. False Positive (FP) is the number of non-vulnerable samples incorrectly classified as vulnerable. False Negative (FN) is the number of vulnerable samples erroneously identified as not vulnerable. Hence, we employ four metrics for our experiments, namely: **Accuracy:** This metric indicates the number of samples that are correctly classified into their respective classes (e.g., positive or negative labels for vulnerable or non-vulnerable function).

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{7}$$

Precision: Precision is the ratio of correctly classified adversarial examples to the total number of adversarial examples.

$$Precision = \frac{TP}{TP+FP} \tag{8}$$

Recall: Recall refers to the ratio of incorrectly classified adversarial examples.

$$Recall = \frac{TP}{TP+FN} \tag{9}$$

F1 Score: F1 Score is a metric that combines precision and recall, providing a simple and convenient way to compare our three classifiers.

$$F1-Score = 2 * \frac{Recall * Precision}{Recall + Precision} \tag{10}$$

4.4 Detection Performance Evaluation

To assess the effectiveness of the proposed technique, we conducted experiments with a total of 16 combinations of centralities on the benchmark SARD and Big-Vul dataset. As we observed in Figure 3 that more than 99% of the functions have thresholds below 200 lines of code, we initiated our evaluations by selecting 10 thresholds (40, 60, 80, 100, 120, 140, 160, 180, and 200 lines). The experimental results of our proposed method with different combination of centralities using SARD dataset are presented in Figure 5. As TokenCNN, VulCNN and ASVD all are evaluated using this dataset that is why to better compare the detection performance of our VulBertCNN approach it is evaluated with the same dataset.

We conducted CodeBERT embedding and centrality analysis on the graph derived from the source code. Since the centralities align with the channels of an image, we conducted our experiment considering three, four, or five channels representing various combinations of the aforementioned five centralities. The experiment consisted of 100 epochs and the final outcomes of the maximum detection performance in each of the combination using three, four, five or without centralities are illustrated in Figure 6. We examined the following four specific cases to observe the influence of centrality on vulnerability detection.

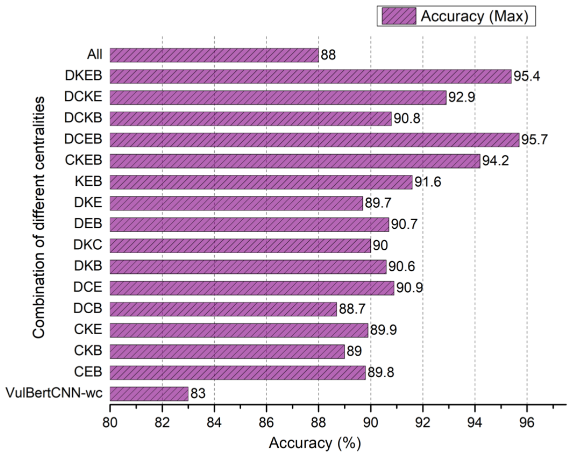


Figure 5: Comparison of the detection accuracy for different centralities using CodeBert embedding and CNN on SARD dataset.

Vulnerability Detection with CodeBert Embedding Using 3 Centralities: We experimented with different combinations of centralities to enhance vulnerability detection. Initially, we explored combinations of three centralities, selecting from a pool of five. The optimal performance, with a maximum accuracy of 90.9%, was achieved using the DCE (Degree-Closeness-Eigenvector) centralities, as illustrated in Figure 6(a). In comparison, the state-of-the-art VulCNN detector, employing the DKC (Degree-Katz-Closeness) combination, achieved a maximum accuracy of 83%.

Vulnerability Detection with CodeBert Embedding Using 4 Centralities: An image constructed with four centralities corresponds to a four-channel image. The highest accuracy, reaching 95.7% was observed with the DCEB combination (Figure 6(b)). Additionally, DCEB and CKEB demonstrated substantial detection performance in comparison to other combinations achieving accuracies of 95.7% and 95.4%, respectively.

Vulnerability Detection with CodeBert Embedding Using 5 Centralities: For the case of five centralities, representing an image with five channels, the maximum detection accuracy reached 88% (Figure 6(c)), which was not as significant as the performance achieved with four centralities.

Vulnerability Detection with CodeBert Embedding Without Using Centrality: To assess the impact of centrality analysis on vulnerability detection, we conducted another experiment which is Vulnerability Detection with CodeBert Embedding using CNN without centrality (VulBertCNN-wc). This experiment achieved only 83% accuracy. However, upon incorporating centrality analysis, the accuracy significantly improved to approximately 96%. This underscores the importance of considering centrality measures in code lines to enhance the accuracy of vulnerability identification in software.

In summary, the analysis highlights that the best accuracy (95.7%) was achieved with combinations of four centralities, specifically CKEB, DCEB, and DKEB in SARD dataset. Furthermore, VulBertCNN emphasizes the significant role of CodeBERT, eigenvector and betweenness centrality measures in effective vulnerability detection.

4.5 Baseline Methods Comparison

We evaluate VulBertCNN's performance in vulnerability detection with three state-of-the-art detection approaches based on image processing which are TokenCNN, VulCNN and ASVD.

4.5.1 TokenCNN

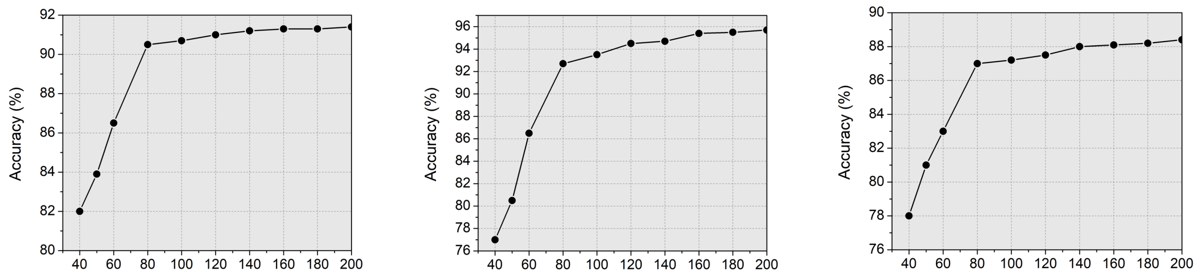
Russell et al. annotate the source code and transform it into the corresponding matrix. They utilize convolutional neural networks, integrated learning, and a random forest classifier for detecting vulnerabilities in the code (Russell et al., 2018). In TokenCNN no semantic relation is considered here only simple lexical analysis is done on source code which is then given input in CNN. Thats why it cannot accurately detect vulnerability from source code.

4.5.2 VulCNN

Wu et al. (Wu et al., 2022) developed VulCNN, a vulnerability detection method using CNN. They used a dataset with both vulnerable and non-vulnerable C/C++ functions, created program dependency graphs (PDGs), and applied a sentence embedding technique i.e., Sent2Vec (Pagliardini et al., 2018) to each statement. Utilizing centrality techniques, they transformed functions into images and trained a CNN model. In a case study involving projects such as Libav, Xen and Seamonkey, VulCNN detected 73 previously unknown vulnerabilities. VulCNN achieves 83% accuracy but it only considers three centralities there are other centralities yet to be explored.

4.5.3 ASVD

Mim et al. (Mim et al., 2023b) developed ASVD with comparison to VulCNN method with sentence embedding and five centralities. The detection accuracy obtained in ASVD is 88% which outperforms the accuracy of VulCNN (83%) by 5% which we targeted to



(a) Number of lines of code analyzed with 3 centralities

(b) Number of lines of code analyzed with 4 centralities

(c) Number of lines of code analyzed with 5 centralities

Figure 6: Maximum vulnerability detection performance in VulBertCNN with CodeBert embedding and different centralities.

improve further by leveraging CodeBert embedding instead of Sent2Vec embedding approach.

4.5.4 Analysis of Comparison

To evaluate the efficiency of our embedding approach utilizing the CodeBERT model (as detailed in Section 3) we performed experiments to assess the performance of both the Sent2vec and CodeBERT embedding models. The results were then compared with those of three related studies, TokenCNN, VulCNN and ASVD. Tables 3 provides a summary of the evaluation results in terms of Accuracy (A), Precision (P), Recall (R) and F1 score.

Table 3: Evaluation of VulBertCNN using CodeBert Embedding.

Dataset	Methods	A	P	R	F1
SARD	TokenCNN	78.6	55.7	71.6	61.9
	VulCNN	83.4	86.9	81.9	84.3
	ASVD	88.2	89.5	85.3	87.3
	VulBertCNN	**95.7**	**90.4**	**87.3**	**89.0**
Big-Vul	TokenCNN	61.4	50.6	79.7	62.6
	VulCNN	80.3	83.3	78.2	82.3
	ASVD	89.6	94.2	86.5	90.2
	VulBertCNN	**91.8**	89.1	**87.4**	88.2

Table 3 indicates that our embedding approach which is utilizing the CodeBERT model has demonstrated significantly superior evaluation outcomes when compared to existing state-of-the-art approaches. Our method achieved an accuracy of 95.7% and F1 score of 89% on SARD dataset and 91.8% accuracy on Big-Vul dataset showcasing a substantial enhancement over other existing methods. Moreover, both Precision (90.4%) and Recall (87.3%) metrics exhibited improvements in SARD dataset. While the F1 measure with CodeBERT (88.2%) on Big-Vul did not outperform ASVD, it displayed improvement in accuracy when contrasted with our experimental evaluation using Sent2Vec (90.2%). In these scenarios, the accuracy metric proves more suitable for evaluating vulnerability detection performance.

In summary, the result analysis reveals that our embedding method using CodeBERT outperforms the Sent2Vec embedding method used by VulCNN and ASVD. By combining CNN with CodeBERT embeddings and centrality analysis, we achieved a significant improvement in the F1-score increasing it from 62.6% to 89% and detection accuracy from 78.6% to 95.7% which is about 21.7% and 26.3% improvement compared to the state-of-the-art approaches.

5 THREATS TO VALIDITY

In this section, we discussed below the potential threats which may affect the validity of this study.

External Validity: External validity presents challenges in generalizing study findings. Differences in programming languages (e.g., C/C++ vs. Java or Python) and caution in extending results to various code vulnerabilities are key considerations. Generalizing findings to a broader range of open-source and industrial systems requires careful handling due to the complexity of obtaining and analyzing diverse industrial systems. To overcome these challenges, future plans include collecting data from industrial systems across industries and countries to enhance dataset diversity.

Internal Validity: Internal validity concerns the accuracy of causal inferences in our vulnerability detection research. Variations in dataset characteristics and algorithmic parameters pose potential confounding issues. To enhance internal validity, we employ a rigorous experimental design, exercise precise variable control, and conduct sensitivity analyses. For instance, strategic dataset partitioning over time ensures a robust assessment of temporal dynamics, contributing to the internal validity of our vulnerability classification methodology.

Construct Validity: Construct validity focuses on the tool used for extracting Program Dependency Graphs (PDGs), namely Joern. While commonly used, Joern may have inherent flaws. Despite this, we chose Joern for PDG extraction and performed manual reviews to identify and address any issues. There's a potential threat from modifying baseline approaches, but we mitigate this risk by retrieving the original source code directly from GitHub repositories associated with analyzed techniques.

Criterion Validity: In vulnerability detection, metrics like precision, recall, and F-measure quantify the alignment of identified vulnerabilities with actual vulnerable functions. High value of criterion validity indicates our algorithm effectively predicts vulnerabilities in line with widely accepted standards.

6 CONCLUSION AND FUTURE WORK

This paper introduces an automated Software **Vul**nerability Detection with Code**B**ert and **C**onvolutional **N**eural **N**etwork named VulBertCNN, aiming to overcome the limitations of state-of-the-art individual text and graph-based approaches in vulnerability detection.

In this paper, a vulnerability detection approach is proposed which focuses on integrating Codebert embedding model with multiple centralities in image generation from PDGs to assess the overall impact of each line of code within a function, thereby determining its vulnerability status. The evaluation involves the generation of 16 centrality combinations derived from 5 centralities, revealing that the highest accuracy is attained with a combination of 4 centrality measures. This achieves an accuracy surpassing the previous state-of-the-art techniques from 78.6% to 95.7% and F1-score increasing it from 62.6% to 89%. It is observed that leveraging codebert embedding with CNN emerges effective role in vulnerability detection.

Future plans involve optimizing program dependency graph generation time with tools like Frama-C, incorporating dynamic analysis for improved detection. Additionally, efforts will be made to narrow down the search space within a function by comparing source code with vulnerability reports from National Vulnerability Database aiming to identify statement-level vulnerabilities.

ACKNOWLEDGEMENTS

This research is supported by the fellowship from Information and Communication Technology (ICT) Division, Ministry of Posts, Telecommunications and Information Technology, Bangladesh. No-56.00.0000.052.33.001.23-09; Date: 04.02.2024.

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