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ARTICLE

A New Framework for Software Vulnerability Detection Based on an Advanced Computing

Bui Van Cong[1] **and Cho Do Xuan**[2,*]

[1]Department of Information Technology, University of Economics and Technical Industries, Hanoi, 100000, Vietnam

[2]Faculty of Information Security, Posts and Telecommunications Institute of Technology, Hanoi, 100000, Vietnam

*Corresponding Author: Cho Do Xuan. Email: chodx@ptit.edu.vn

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ABSTRACT

The detection of software vulnerabilities written in C and C++ languages takes a lot of attention and interest today. This paper proposes a new framework called DrCSE to improve software vulnerability detection. It uses an intelligent computation technique based on the combination of two methods: Rebalancing data and representation learning to analyze and evaluate the code property graph (CPG) of the source code for detecting abnormal behavior of software vulnerabilities. To do that, DrCSE performs a combination of 3 main processing techniques: (i) building the source code feature profiles, (ii) rebalancing data, and (iii) contrastive learning. In which, the method (i) extracts the source code's features based on the vertices and edges of the CPG. The method of rebalancing data has the function of supporting the training process by balancing the experimental dataset. Finally, contrastive learning techniques learn the important features of the source code by finding and pulling similar ones together while pushing the outliers away. The experiment part of this paper demonstrates the superiority of the DrCSE Framework for detecting source code security vulnerabilities using the Verum dataset. As a result, the method proposed in the article has brought a pretty good performance in all metrics, especially the Precision and Recall scores of 39.35% and 69.07%, respectively, proving the efficiency of the DrCSE Framework. It performs better than other approaches, with a 5% boost in Precision and a 5% boost in Recall. Overall, this is considered the best research result for the software vulnerability detection problem using the Verum dataset according to our survey to date.

KEYWORDS

Source code vulnerability; source code vulnerability detection; code property graph; feature profile; contrastive learning; data rebalancing

1 Introduction

1.1 Problems

Source code vulnerabilities are pieces of source code that lead to software [1]. For conventional software errors, encountering such issues poses the risk of rendering the software inoperable. However, unlike typical software flaws, source code vulnerabilities do not directly harm the software itself; rather, they affect potential security breaches within the system. This is because malicious actors can exploit these vulnerabilities in source code to escalate their access to the victim's system. Hence, the timely detection and warning of source code vulnerabilities are of utmost importance.

To detect source code vulnerabilities, traditional approaches often involve extracting and processing source code, then checking that code against known Common Vulnerabilities and Exposures (CVE) and Common Weakness Enumeration (CWE) [2]. However, it lacks the ability to detect new vulnerabilities such as zero-day vulnerabilities. To address this issue, recent approaches have employed techniques involving the feature analysis of source code combined with machine learning or deep learning algorithms to search new vulnerabilities within the code.

In particular, in the study [3], various methods and techniques for extracting source code features and classification methods have been summarized. Concerning the feature analysis of source code, recent approaches often aim to standardize source code using natural language processing methods or to transform the code into graph representations [4,5]. After this preprocessing stage, a combination of data extraction techniques and classification methods is applied to detect source code vulnerabilities. Consequently, it can be observed that modern approaches to source code vulnerability detection typically focus on two main issues [6,7]: source code feature extraction methods and methods for predicting and classifying vulnerabilities based on these source code features.

In this article, we propose a new approach for detecting vulnerabilities in source code written in the C and C++ programming languages. The new approach proposed in this article focuses on addressing two main issues: first, improving the feature extraction method for source code; second, optimizing the process of prediction and detection of source code vulnerabilities based on anomalous features. Thus, for the feature extraction process of the source code, this study transforms the source code into a code property graph (CPG) and then uses Gated Graph Sequence Neural Networks (GGNN) for extraction. To predict and classify source code vulnerabilities, we suggest using a combination of three different processing methods: rebalancing data through the Dropout technique, clustering data through contrastive learning, and classifying source code vulnerabilities using Cross-Entropy Loss.

1.2 Motivation and Objectives

1.2.1 Motivation

As presented above, for the problem of source code vulnerability detection, the two most critical factors determining the accuracy of the classification process are feature extraction and classification processes. However, based on our observations, recent approaches have not effectively addressed both these issues, leading to limited experimental results [8,9]. Specifically, as follows:

– Regarding the approach to source code feature extraction [10,11], it can be easily recognized that the source code data is in text form. Therefore, to extract these features, one can use either of the two methods: semantic and syntax analysis.

• Regarding the syntactic analysis method, natural language processing techniques are commonly used. However, it can be observed that these methods might not be able to extract features from lengthy source code segments. This limitation arises because these models can only handle relatively short data segments, such as 64 and 128. Despite this, in practice, there are source code segments with very large lengths. If these models are used, they inevitably lack crucial data, which leads to difficulties in the detection model. Standardizing the source code segments to uniform lengths introduces significant inaccuracies. The system cannot determine which source code segment contains the vulnerabilities. Furthermore, attempting to make the lengths uniform would result in concatenation of source code segments, leading to skewed classifications.

• Regarding the semantic analysis method [12,13] to extract source code features, approaches based on this method aim to represent the relationships among functions and parameters within the source code as graphs [14,15]. When observing and analyzing these approaches, it becomes evident that representing source code cannot fully depict the intricate relationships between components within functions and variables in the source code. In other words, the traditional method of constructing source-code features does not cover all aspects. Specifically, when these methods were applied to different datasets, the false-positive rate was quite high. This demonstrates that the proposed method is only suitable for specific datasets, making its application to diverse datasets challenging.

- For the method of source code vulnerability detection [16–19]: After obtaining the feature vectors of the source code, these feature vectors are classified through machine learning algorithms and traditional deep learning. Therefore, classifying source code in such an imbalanced dataset is a challenging task. To address this issue, approaches often use balanced or simple datasets created independently. Hence, it is necessary to optimize and improve the effectiveness of the source code vulnerability classification model.

1.2.2 Proposed Solution Approach

To address the two issues presented in Section 1.2.1, in this study, we propose a completely new approach and model. This model was named DrCSE. The novel approach in the DrCSE model enhances the following two issues:

- For the problem of selecting and extracting source code features: In this study, to extract source code features, we aim to transform the source code into a new graph form called CPG [20]. In [21], it was demonstrated that CPG combines three graph representations of AST, CFG, and PDG into a common data structure.
- For the problem of source code vulnerability classification, rather than directly using machine learning or deep learning algorithms to classify source code feature vectors, we combined several advanced data exploration methods to improve the effectiveness of the classification process.

1.3 Principles of Detecting Vulnerabilities in the Source Code of the DrCSE Framework

Based on the analyses in Section 1.2.2, it can be seen that the proposed vulnerability detection process in the DrCSE Framework consists of the following stages:

• **Phase 1.** Building source code feature profiles: As described above, this step normalizes the source code data into feature vectors through several steps.

- Step 1: Analyze the source code in CPG format using the Joern tool [20].
- Step 2: Encoding the vertex information using the glove encoding function.
- Step 3: Extracting edge features with Gated graph neural networks (GGNN).
- Step 4: The edge and vertex features collected in Steps 2 and 3 are synthesized into a single feature vector.

• **Phase 2.** Rebalancing data: Based on the vector obtained in Step 3 of phase 1, we generated additional data containing security vulnerabilities to balance the number of labels in the experiment dataset using the Dropout method.

• **Phase 3.** Representation learning: The contrastive learning method is used to find feature vectors of the source code that have similarities-contrasts in the dataset. Thus, with similar data pairs, we can "pull" them closer to learn each other's higher-level features, and conversely, contrasting pairs of data are "pushed" far away. Using this approach, we optimized the source code classification process. The experimental results in this study prove the correctness and reasonableness of our proposal.

• **Phase 4.** Classification: This phase classifies non-vulnerable source code and code containing security vulnerabilities based on the feature vectors collected from phases 2 and 3. In this phase, we propose the use of Fully Connected Layer functions after the Representation Learning block with a Cross-Entropy Loss.

1.4 Contribution of Paper

The main contributions of this paper are summarized as follows:

• A new intelligent calculation method for the DrCSE Framework was proposed to improve the efficiency of the software vulnerability classification process based on a combination of three techniques.

• A method for rebalancing the data using the Dropout technique was proposed. This is a new generation method that has not been studied and applied to generate data for training models to detect software vulnerabilities.

• A method for optimizing software vulnerability detection is proposed based on a contrastive learning technique. The proposed approach enhances the efficiency of the source code vulnerability classification process.

2 Related Studies

Many authors have used AST-based software vulnerability detection approaches. In [11], the authors proposed the VulDee-Locator model for source-code vulnerability detection. The VulDee-Locator has proven its effectiveness compared to another approach based on the four research questions in the experiment. In addition, a study [16] presented a model that combined the LSTM deep learning model for the security vulnerability detection task using a Software Assurance Reference Database dataset. References [16,22] proposed a method of feature extraction of source code based on ten open-source projects. In [23], the LSTM deep learning algorithm was used to classify source code vulnerabilities after analyzing them from an abstract syntax tree. In [24], a Representation Learning method for source-code vulnerability detection was proposed. Specifically, the authors extracted and transformed the source code into AST form and then combined the BiLSTM and Continuous Bag-of-Words algorithms to analyze and classify source code vulnerabilities. Many more approaches for AST-based source code vulnerability detection use machine learning or deep learning, such as [25–28].

In addition, CFG-based software vulnerability detection techniques have been proposed in several studies. Haridas et al. [14] suggested a SiCaGCN model for vulnerability detection based on CFG and GCN. With the support of Graph Edit Distance, the experimental performances were better than those of other deep learning graph networks. Xu et al. [29] had similar ideals when using a Neural Network-based Graph Embedding model for security vulnerability detection based on Cross-Platform Binary Code Similarity. Harer et al. [30] proposed the use of different algorithms to analyze and extract source code features and the Random Forest algorithm is applied to detect source code vulnerabilities. As a result, the model showed high efficiency with a precision-recall curve of 0.49 and an area under the ROC curve of 0.87. Another effective approach was proposed in [31], which proposed a SySeVR model based on syntax-based, semantic-based, and vector representations. Accordingly, the authors used several methods, such as syntax-based vulnerability candidates (SyVCs), semantic-based vulnerability candidates (SeVCs), and vector representation of SeVCs for source code feature extraction and classification.

Research by Nun et al. [32] presented a natural language processing method combined with the inst2vec algorithm for detecting C and C++ source code vulnerabilities. In the experiment, the authors compared their method with other approaches while applying basic machine learning and deep learning models, such as RNN, Tree-Based CNN. The results were higher than those of most approaches for the same experimental dataset. Li et al. [33] built an IVDetect model, which is a combination of two main methods: consider the vulnerable statements and their surrounding contexts via data and control dependencies and artificial intelligence.

A study [34] proposed a method to detect source code vulnerabilities based on CPG using deep learning algorithms. The authors built a REVEAL model consisting of two main phases: Feature Extraction, and Training (Representation Learning). This approach outperformed the others on two datasets: Verum [34] and FFmpeg+Qume [35]. Cho et al. [36] proposed an EFRC model with a combination of four techniques: source embedding, Feature Learning, Resampling Data, Classification. Accordingly, the EFRC model performs feature extraction of the source code in the form of CPG based on the combined model of the GCN and MLP. The Data Resampling process was performed using the SMOTE algorithm. Finally, an MLP model combined with Triploss is proposed to classify source code vulnerabilities. Cho [37] proposed a DGCNN for CPG feature extraction. It can be seen that traditional approaches use only graph networks to extract CPG. Zhang et al. [38] proposed a combined model of the Graph Attention Network and Metric Learning to extract and classify source code vulnerabilities based on CPG. Consequently, he used a Graph Attention Network to extract information of the source code based on CPG and used Metric Learning for classification. The experimental results show that the proposed model improved by 11.5%, 12.3%, 12.57%, and 7.90% according to the Precision, Recall, F1-score, and AUC measures, respectively.

Zhang et al. proposed the VDBFL model for source code vulnerability detection based on federated learning [27]. In this study, the proposed method includes the following steps: first, the source code is converted into CPG format through the Joern tool; next, GNN and CNN networks are used for feature extraction; eventually, the authors use federated learning for source code vulnerability detection and testing. The experimental results show that the model achieves high accuracy. This is 11.8 times higher than that in research [34].

3 Proposing the DrCSE Framework

3.1 Overview of the DrCSE Framework

Fig. 1 depicts the source code vulnerability detection model architecture of the proposed DrCSE Framework. As mentioned in Section 1.2, Algorithm 1 describes in detail the method of detecting source code vulnerabilities based on the intelligent computational model proposed in the DrCSE framework.

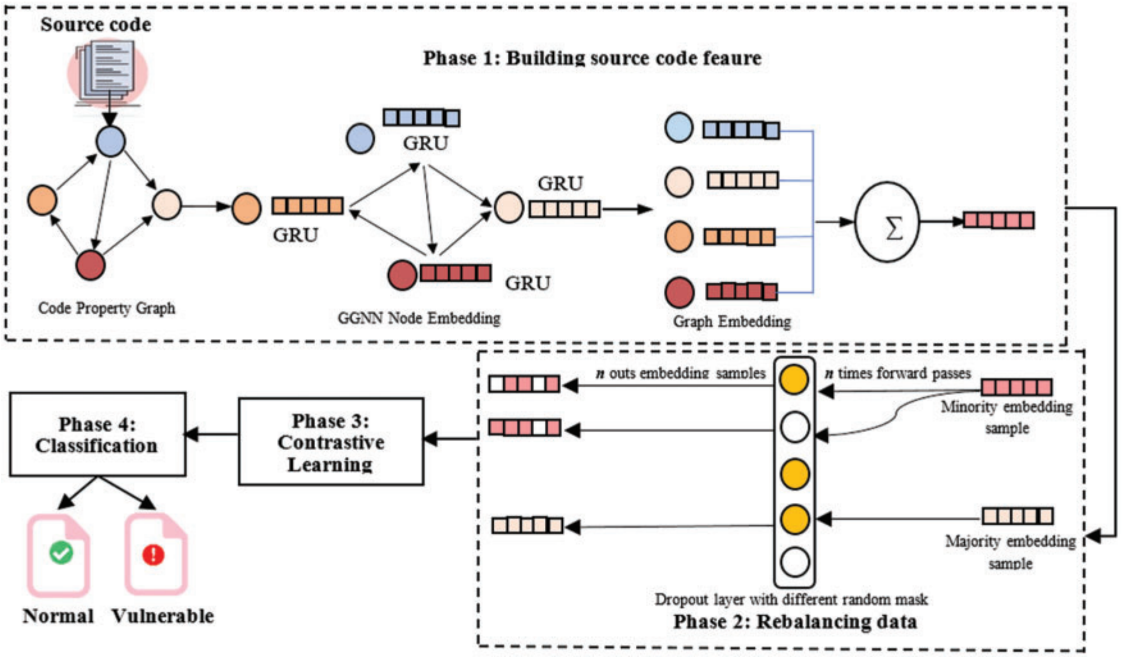

Source code
Phase 1: Building source code feaure
GRU
GRU
GRU
GRU
Code Property Graph
GGNN Node Embedding
Graph Embedding
Σ
n outs embedding samples
n times forward passes
Minority embedding sample
Majority embedding sample
Dropout layer with different random mask
Phase 2: Rebalancing data
Phase 3: Contrastive Learning
Phase 4: Classification
Normal
Vulnerable

Figure 1: The architecture of the DrCSE Framework

Algorithm 1: The method of detecting source code vulnerabilities using the DrCSE Framework

```
Input: Training Model
Train data-$D_{train}$
    Dropout rate-$\alpha$
    Temperature hyper-parameter-$\tau$
    Learning rate-$lr$
    Number of new samples per original sample-$n$
Output: Trained model

Procedure:
Function Training Model:
    # Extract features from code
    for $(C, l)$ in $D_{train}$ do
        $features \leftarrow graphEmbed(C)$;
        $labels \leftarrow l$; end
    # Rebalance with Dropout
        $D_{balanced} \leftarrow Dropout(features,;$
            $labels, \alpha, n)$; $M_{\Theta} \leftarrow \Theta_{init}$;
    # Training with Contrastive learning
        $L_{cl} \leftarrow contrastiveLossFunction$
            $(M_{\Theta}, D_{balanced}, \tau)$
        # Update model
        $M_{\Theta} \leftarrow M_{\Theta} - lr\Delta_{\Theta}(L_{cl})$ end
    # Training with Classification
        $L_{ce} \leftarrow crossEntropyLossFunction$
        $(M_{\Theta}, D_{balanced})$
            # Update model
            $M_{\Theta} \leftarrow M_{\Theta} - lr\Delta_{\Theta}(L_{ce})$
            end
return $M_{\Theta}$
```

where:

- Initial parameters-Θ_{init}
- Model with parameter Θ-M_{Θ}
- Contrastive Loss-L_{cl}
- Derivative of parameter Θ-Δ_{Θ}

3.2 Building Source Code Feature Profiles (Phase-I)

In this phase, we convert the raw code into a numeric vector that contains both semantic and syntactic information. The following four steps explain in detail how to build a feature profile of the source code using CPG:

- **Step 1:** Convert the source code to the CPG form. CPG is a useful tool for extracting graph information from control and data flows [21]. Accordingly, with the input of the source code segments, the output of these segments was CPG. CPG is a graph $G = (V, E)$, where V is the vertices (nodes) and E is the edge of the graph G. In CPG, each vertex $v \in V$ is a small piece of code and is classified into one of the different types of vertices (e.g., Arithmetic Expression, CallStatement, etc.). Edges $e \in E$ show the relationship between vertices v. To convert the source code to CPG form, the study uses the Joern tool [20].
- **Step 2:** Vertex information is encoded. To encode the semantic information of vertex v, we used a glove encoder to convert the code representing vertex v to vector E_v. Furthermore, to combine the information about the vertex v type, we concatenate the vector E_v with the one-hot-encoding vector of the corresponding vertex type T_v into a representative vector X_v.
- **Step 3:** Extracting edge information: The results obtained in Steps 1 and 2 have helped us successfully build a vector X_v representing each vertex, but the edge connection information is still missing. The above is information on the surrounding vertices. This study uses Gated Graph Sequence Neural Networks (GGNN) [39] which is an improved model of Graph Neural Networks [40] to extract information about these vertices. Formula (1) describes the application of the GGNN model to extract the edge information.

$$X_g = \sum_{v \in V} \left(GRU \left(X_v, \sum_{u \in E} g\left(X_u\right) \right) \right) \tag{1}$$

where,

- $GRU(.)$ is the Gated recurrent function
- X_v is the vector representation of the vertex v
- $g(.)$ is a transformation function that helps synthesize information about vertices u that are neighboring vertices of vertex v and the corresponding vector representation X_u

- **Step 4:** Synthesizing and building feature vectors: To synthesize all the graph's information according to each vertex v as the output vectors of GRU, we take the sum of each corresponding component of all these vectors to take a vector X_g representing the original code. Finally, to train the above GGNN model, we placed a classification layer after this GGNN block and used cross-entropy loss.

Algorithm 2 demonstrates in detail how to build source code feature profiles from CPG analysis in the DrCSE Framework.

Algorithm 2: Building source code feature profiles

```
Input: Code-$C$
Output: Feature vector $x_g$ represent for $C$
Procedure:
Function $graphEmbed(C)$:
    $(V, E) \leftarrow$ Code_property_graph($C$)
    for $v \in V$ by:
        $T_v \leftarrow onehot(v.type())$; $C_v \leftarrow glove(v.code())$; $x_v \leftarrow concat(T_v, C_v)$; $X \leftarrow x_v \cup X$; end
    $\boldsymbol{X'} \leftarrow \boldsymbol{GGNN(X, E)}$; $\boldsymbol{x_g} \leftarrow \boldsymbol{Aggregate(X')}$
    return $\boldsymbol{x_g}$
```

3.3 Rebalancing Data (Phase-II)

The feature profile obtained from the building and synthesizing process in Section 3.2 is classified to detect non-vulnerable source code and source code containing vulnerabilities. To deal with data imbalances during training, some common workarounds are to use the synthetic minority oversampling technique (SMOTE) [41] to adjust the number of samples in each class until the number of records is balanced. To overcome the disadvantages of Smote, in this paper, we propose a new method for generating data for the minority class using the Dropout function. Dropout was first introduced in 2014 [42] to avoid overfitting during training by randomly disabling connections from the previous layer (output is zero). The study [43] presented some concepts and definitions of Dropout. A study [44] used Dropout on a vector representation $x = (x_1, x_2, \ldots, x_d)$, with each component $x_k (k = 1, 2, \ldots, d)$ as follows:

$$\widehat{x_k} = a_k.x_k \tag{2}$$

where, $a_k \sim P$ is a random variable with a Bernoulli distribution:

$$P(a_k) = \begin{cases} 1 - p, a_k = 0 \\ p, a_k = 1 \end{cases} \tag{3}$$

Based on this idea, we passed the feature vector through the Dropout function n times to generate n samples with the same class and close to the original feature vector. With this approach, the generated sample vectors are still spatially neighboring the original feature vectors, even though they are not spatially generated. Algorithm 3 describes the data-generation process using the Dropout function in detail.

3.4 Contrastive Learning (Phase-III)

When applying traditional supervised learning methods to detect source code vulnerably, the model depends heavily on the amount of pre-labeled data, whereas the amount of unlabeled data is extremely large.

Algorithm 3: Rebalancing data using Dropout

```
Input: Features -$features$
           Labels -$labels$
       Dropout rate -$\alpha$
       Number of new samples per original sample -$n$
Output: Balanced Dataset -$D_{balanced}$
Procedure:
Function: $Dropout(features, labels, \alpha, n)$:
    for $f_i, l_i \in features, labels$ do:
        if $l_i$ of Minority class do:
            for $t := 1$ to $n$ do:
                $f_i' \leftarrow random\_zero\_output\_with\_rate(\alpha)$;        Add $f_i'$ to $D_{balanced}$;
        end; end; end
    return $D_{balanced}$
```

Contrastive learning aims to help the model learn features by "pulling" similar data points together while "pushing" different data points away in the embedding space.

In this paper, we propose the use of contrastive learning to learn the important features of source-code feature vectors. The working principle of the contrastive learning method is as follows.

Suppose we have a set of data points $D = \{(x_i, x_i^+, x_i^-)\}$, where x_i and x_i^+ are two data points that are similar or have the same label and x_i and x_i^- are two distinct data points or labels. Call h_i, h_i^+, h_i^- are the representative vectors of x_i, x_i^+, x_i^-, respectively, and the training objective of a mini-batch N is defined by formula (4):

$$L_{cl} = \sum_{i=1}^{n} L_i \tag{4}$$

With L_i is defined by formula (5) as follows:

$$L_i = -\frac{1}{N_{y_i}} . \sum_{k=1}^{N} 1_{i \neq k} . 1_{y_i = y_k} .log \frac{e^{sim(h_i, h_k)/\tau}}{\sum_{j=1}^{N} 1_{i \neq j} . 1_{y_i \neq y_j} e^{sim(h_i, h_j)/\tau}} \tag{5}$$

where,

y_i, y_j, y_k is the label of source code which is 0 with vulnerable source and 1 with clean source.

τ is a positive constant temperature hyper-parameter,

$sim\,(h_1, h_2)$ is cosine similarity $\dfrac{h_1^T h_2}{||h_1|| \,.\, ||h_2||}$,

$1_B = 1$ when B is true, otherwise $1_B = 0$,

where, N_y is the total number of samples in the mini-batch with the same label y,

i is the index of the example in the mini-batch,

k is the index of other examples in the mini-batch with the same label as example index i or $x_k = x_i^+$,

j is the index of other examples with index i in mini-batch.

In the above equation, h_k is the representative vector of x_i^+. Simultaneously, graph embedding is used to extract the representative vector $h = f_\Theta(x) = graphEmbed(x)$ and then train the model using the contrastive learning objective (formula (5)).

Algorithm 4 explains the implementation process of contrastive learning proposed in this paper.

Algorithm 4: Contrastive learning

```
Input: Model-$M$
       Balanced Dataset-$D_{balanced}$
       Temperature hyper-parameter-$\tau$

Output: Contrastive Loss

Procedure:
Function $contrastiveLossFunction(M, D_{batch}, \tau)$:
    $L_{cl} \leftarrow 0 L_{cl} \leftarrow 0$
    for $x_i, l_i \in D_{batch}$ do:
        $N_{l_i} \leftarrow 1; L_i \leftarrow 0; h_i \leftarrow M.encode(x_i); L_i \leftarrow 0;$
        for $x_k, l_k \in D_{batch}$ do:
            if $(k \neq i)$ and $(l_i = l_k)$ do:
                $N_{l_i} \leftarrow N_{l_i} + 1;\ P_i \leftarrow e^{sim(h_i,h_k)/\tau};$
                for $x_j, l_j \in D_{batch}$ do:   $N_i \leftarrow 0;$
                    if $j \neq i$ do:
                        $h_j \leftarrow M.encode(x_j);$
                $N_{l_i} \leftarrow N_{l_i} + 1; P_k \leftarrow e^{sim(h_i,h_k)/\tau}; N_k \leftarrow 0;$
                for $x_j, l_j \in D_{batch}$ do:
                    if $(j \neq i)$ and $(l_j \neq l_i)$ do:
                $h_j \leftarrow M.encode\left(x_j\right); N_k \leftarrow N_k + e^{sim(h_i,h_j)/\tau}$
                end; end
                $N_i \leftarrow N_i + \leftarrow L_i + e^{sim(h_i,h_j)/\tau}$
                end   $L_i \leftarrow L_i + log\frac{P_i}{N_i}$
                end; end; end
                $L_i \leftarrow -L_i/N_{l_i}$; end; end
        $L_i \leftarrow -L_i/N_{l_i};$   $L_{cl} \leftarrow L_{cl} + L_i$   end; end
    return $L_{cl}$
```

3.5 Classification (Phase-IV)

After the data were balanced in Phase 3 by the Dropout method and grouped into clusters according to the same features by contrastive learning, we classified the source code feature profiles to detect non-vulnerable and vulnerable source code. We suggest using a Fully Connected Layer after the contrastive learning block with a Cross-Entropy Loss described in formula (6) as follows:

$$L_{ce} = -\frac{1}{N}\sum_{k=1}^{N} y_i \cdot \log\left(\sigma\left(h_i\right)\right) + \left(1 - y_i\right).\log\left(1 - \sigma\left(h_i\right)\right) \tag{6}$$

In which, h_i is the vector representation of x_i,

$\sigma(x)$ is the sigmoid function.

During this process, only the parameters in the last classification layer are tuned, and all parameters in the previous representation block are frozen.

Algorithm 5 below describes the vulnerability detection process of the source code.

Algorithm 5: Cross-Entropy loss function

```
Input: Representation Model-$RM$
       Balanced Dataset-$D_{balanced}$
Output: Cross-Entropy Loss
Procedure:
Function $crossEntropyLossFunction(RM, D_{balanced})$:
$L_{ce} \leftarrow 0$
    for $x_i, l_i \in D_{balanced}$ by:
    $h_i \leftarrow RM.encode(x_i); y_i \leftarrow RM.predict(h_i); L_i \leftarrow y_i.log(\sigma(h_i)) + (1-y_i).log(1-\sigma(h_i)); L_{ce} \leftarrow L_{ce} + L_i$
    end;  $L_{ce} \leftarrow -L_{ce}/N$
return $L_{ce}$
```

4 Experiment and Evaluation

4.1 Experiment Dataset

Table 1 lists the statistics of the experimental datasets used to evaluate the effectiveness of the proposed method.

Table 1: Experiment dataset summary

	Sample counts	Vulnerability (vul)	Normal (non-vul)
Verum dataset	18.169	1.658	16.511
FFmpeg+Qume dataset	25.905	11.804	14.101

We used Verum [34] and FFmpeg+Qume [35] as the experimental datasets in this study because these two datasets are considered the most consistent with real-world datasets. Current main approaches are often used in these two datasets to detect vulnerabilities. Specifically, researchers used the Verum dataset [34] to apply the data-processing model according to the CPG. The FFmpeg+Qume dataset is often used in structural and semantic approaches. In this study, we used the Verum dataset to evaluate the effectiveness of the proposed model and the FFmpeg+Qume dataset to test its suitability on different datasets.

4.2 Evaluation Metrics

Below are the four metrics and their formulas used in this study to evaluate the effectiveness of the proposed model.

$$\text{accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \times 100\% \tag{7}$$

$$\text{precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \times 100\% \tag{8}$$

$$\text{recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \times 100\% \tag{9}$$

$$\text{F1} = \frac{2 \times \text{precision} \times \text{recall}}{\text{precision} + \text{recall}} \tag{10}$$

where,

- **Accuracy:** is the ratio of the number of samples classified correctly to the total number of samples.
- **Precision:** is the ratio of true positive points to the total number of points classified as positive ($TP + FP$).
- **Recall:** The ratio of true positive points to the total number of real positive points ($TP + FN$).
- **F1-score:** is the harmonic mean of precision and recall.
- TP–True positive: The number of *vul* samples classified correctly.
- FN–False negative: The number of *vul* samples classified as *non-vul*.
- TN–True negative: The number of *non-vul* samples classified correctly.
- FP: False positive: The number of *non-vul* samples classified as *vul*.

4.3 Evaluation Scenarios

To demonstrate the effectiveness of the intelligent computational method proposed in the DrCSE Framework, we performed the following experiments:

- Scenario 1: Evaluating the effectiveness of the proposed method when classifying source code vulnerabilities.
- Scenario 2: What is the role and influence of the components in the proposed approach for effectively detecting security vulnerabilities? To answer this question, we conducted several experiments to assess Dropout and Reverse Learning.
- Scenario 3: Is the proposed method more effective than the other methods on the same dataset? To answer this question, we compared our proposed method to other approaches using the same experimental dataset.
- Scenario 4: Can the proposed method perform well on the other datasets? Specifically, we tested our method on the FFMpeg+Qemu Dataset and compared it with other approaches using this dataset.

4.4 Experiment Results

4.4.1 Parameter Configuration of Experiment Models

Some requirements for hardware and software for the experimental process include:

Software installs: Python 3.9.12; Torch 2.1

Hardware requirements: 32 GB RAM; CPU Intel Core i7-11800 @ 2.30 GHz $\times$ 16; GPU 3060.

In addition, during the experiment, we configured several key parameters of the model.

Table 2 lists the parameters used for the experimental DrCSE Frameworks in this study.

4.4.2 Experiment Results of Scenario 1

As described in Section 4.3, this experiment used the Verum dataset to detect the security vulnerabilities. A study [34] pointed out that the Verum dataset has a large difference in terms of data labels. In addition, this dataset had a small duplicate code rate of approximately 0.6%. Therefore, this dataset is appropriate for applications in security vulnerability classification. Table 3 summarizes the results of the proposed method based on the metrics defined in Section 4.2.

In Table 3, we changed two parameters, α and τ, where α is the Dropout probability, and the larger α is, the more deactivated the values in the vector representation. τ is the temperature parameter that controls punishment for negative samples. Research [45] showed that as τ decreases, contrastive loss tends to focus more on regions with a significant degree of similarity. However, when τ is too small, the contrastive loss can be concentrated on only a few samples closest to the trained ones; in this case, τ has a significant influence on the quality of the model.

Table 2: Selecting and configuring the Hyper-parameters of the DrCSE Framework

Model	Hyper-parameter	Value
Glove	Dimensions	100
GGNN	Input embedding size	169
	Hidden size	256
	Number of graph layers	8
	Graph activation function	fishy
	Learning rate	1e-4
Dropout	Dropout probability	0.1
Contrastive Learning	Batch size	32
	Temperature	0.1
	Learning rate	1e-4
	Loss function	Supervised contrastive loss
Classifier	Activation	Softmax
	Loss function	Cross-entropy

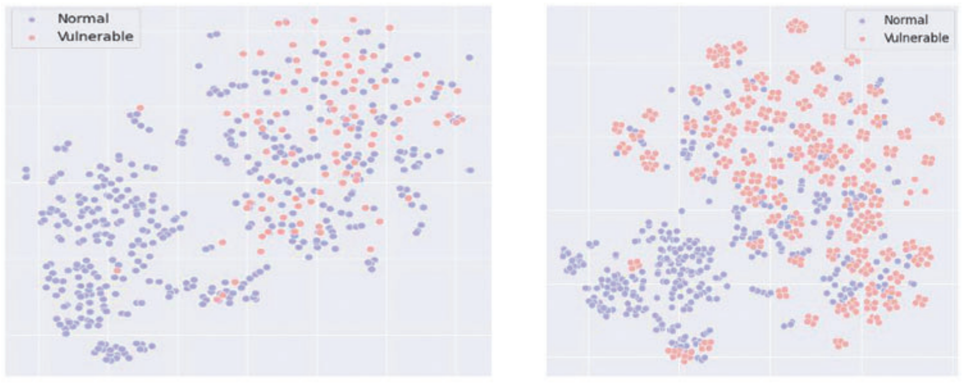
Table 3: Experiment results for the DrCSE model

τ	α															
	0.05				**0.1**				0.2				0.3			
	Acc	Pre	Rec	F1	Acc	Pre	Rec	F1	Acc	Pre	Rec	F1	Acc	Pre	Rec	F1
0.05	85.47	35.61	61.16	45.01	85.96	36.41	63.35	46.24	85.89	36.75	62.21	46.20	85.39	37.62	60.30	46.33
0.1	87.46	39.12	67.19	49.45	**87.72**	39.35	**69.07**	**50.14**	87.34	37.81	66.33	48.16	86.72	38.57	63.24	47.91
0.2	85.58	36.51	63.57	46.38	86.16	**40.08**	66.72	50.01	85.92	36.75	64.11	46.72	85.03	36.41	62.01	45.88

In Table 3, the model gave the best results when $\tau = 0.1$ and $\alpha = 0.1$ with the labels containing security vulnerabilities rate up to 69.07%. When the Dropout ratio α was small, the data points generated from the Dropout layer are more similar to the original data points than the data points generated with a larger Dropout ratio α. This helped the model to be better compatible with the small Dropout rate, when increasing α from 0.1 up to 0.2, 0.3, the recall scores decrease by about 2.74% and 5.83%. With the temperature parameter τ, obviously, with τ neither too small nor too large, the model achieved markedly better results for the security vulnerability classification task. When $\tau = 0.05$ (too small), the model only focused on a small area of similar data points, reducing the precision and recall by 2.94% and 5.72%, respectively, compared to $\tau = 0.1$. Conversely, when $\tau = 0.2$ (large), the model was significantly affected by distant data points that may not be similar to the current data point, which directly affected the training results when the recall was also reduced by 4% compared to $\tau = 0.1$. However, with $\tau = 0.2$ and $\alpha = 0.1$, we obtained the best precision of 40.08%. During training with $\tau = 0.2$, the model performed worse in the classification of both non-vulnerable and vulnerable labels. Nevertheless, the number of non-vulnerable labels was much larger than that of vulnerable labels; therefore, the correctly classified non-vulnerable label counts were much less than the correctly classified vulnerable labels, increasing the precision by approximately 1%. In addition, there was a clear difference between the ability to classify non-vulnerable labels and labels containing security vulnerabilities. For instance, for non-vulnerable labels, the model yielded relatively high classification results (nearly 88% accuracy) for all measures. In contrast, with the vulnerability classification, the results were relatively low. Specifically, the precision score was only 39.35%, the recall was 69.07%, and the F1-score was 50.14%. Overall, the results of this classification were relatively low. Nonetheless, this result was good regardless of the experimental dataset having a difference of approximately ten times between the number of non-vulnerable source codes and the source code containing security vulnerabilities, and with the data duplication rate of 0.6%, the 69.07% recall rate was quite effective. Three main factors contributed to improving the efficiency of source-code vulnerability detection in the proposed DrCSE model:

i) The effectiveness of the Dropout method for rebalancing data

Fig. 2 shows the difference in the data distributions when using and not using the dropout method to rebalance the data.



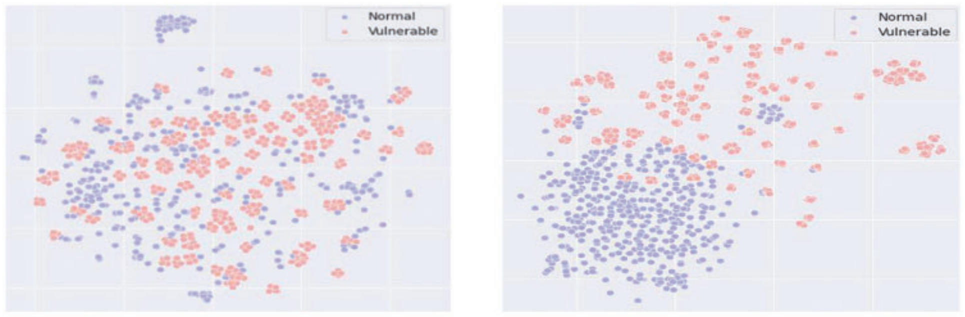
(a) Before rebalancing (b) Rebalancing data with Dropout

Figure 2: Differences in data distributions during Rebalancing data. Where (a) before rebalancing data; (b) perform rebalancing data using the Dropout method

As shown in Fig. 2, this method helped balance the labels in the dataset, thereby improving the training results for the classification model. When data rebalancing methods are not used, the model is prone to bias by non-vulnerable labels because it has many more data points than those containing security vulnerabilities. Therefore, rebalancing data is an important step in optimizing the classification results of the training model.

ii) The effectiveness of the representation learning method demonstrated through contrastive learning

Fig. 3 shows the data distributions when using and not using representation learning with contrastive learning. As expected, the influence of representation learning methods in clustering similar data points is the basis for the model to better classify non-vulnerable labels and labels containing security vulnerabilities. In Fig. 3a, the data points of the two labels are confusingly distributed with no clear separation between them. In contrast, when using representation learning to cluster similar data points by pulling the similarities closer and pushing the dissimilar data points further away in the embedding space, as illustrated in Fig. 3b, the data points of the two labels exhibited a clear separation, and the classification results of the model improved significantly.



(a) Without representation learning (b) With representation learning

Figure 3: Differences in data distributions. In which, (a) data when not using representation learning method; (b) data when using representation learning method

iii) The correctness of combining the Dropout method with contrastive learning

We believe that each Dropout component with contrastive learning had a noticeable effect compared to not using them. However, the successful combination of these two methods in a unified model also contributed significantly to the effectiveness of the model. Fig. 4 shows the data distribution in the representation space of the model that combined Dropout with contrastive learning.

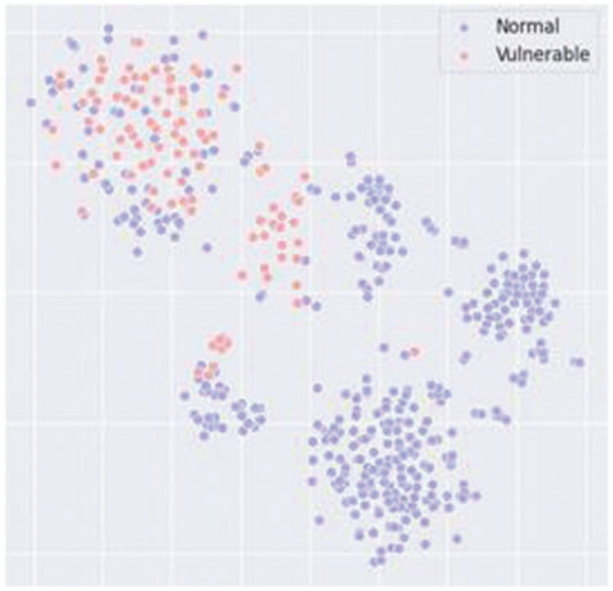


Figure 4: The data distribution in the representation space when using the combined method of Dropout with contrastive learning

As shown in Fig. 4, most of the data on non-vulnerable and vulnerable labels were classified into separate clusters, making it possible for the model to detect them easily. Using the Dropout method, we can generate many positive data points from one original data point. At the same time, contrastive learning helped the model synthesize all the information from these positive data points. Making the most of each other's advantages, the combination of Dropout and contrastive learning methods has shown better classification results than the current vulnerability classification methods.

4.4.3 Experiment Results of Scenario 2

In Scenario 1, we present some experimental results proving the effectiveness of the proposed model for classifying source code vulnerabilities. For scenario 2, our goal was to answer two research questions (RQ) as follows:

- RQ1: What is the role and importance of each component of Dropout and contrastive loss in optimizing the vulnerability detection of the source code?
- RQ2: Why do you combine Dropout with contrastive loss and no other methods? Are other combinations more effective than Dropout and contrastive loss combinations?

To answer these two RQs (ARQs), we conducted the following experiments:

- For RQ1:
  - ARQ1: Evaluate the role and effectiveness of the Dropout method in the process of rebalancing data. To do this, we used the Smote method to replace the Dropout method. The empirical model was a combination of smoke and contrastive loss. In addition, to be more objective, this paper also evaluates the approach without using any data generation algorithm.
  - ARQ2: Evaluating the role and effectiveness of contrastive loss in the representation-learning process. In this case, the proposed experimental method included the following:
  + The contrastive loss method was replaced by the trip-loss method. The experimental model was a combination of Dropout and trip loss.
  + After the Dropout method processed the data, it was classified using traditional machine learning and deep learning methods, such as MLP and RF. Therefore, the experimental model would be a model combining Dropout with MLP or RF.

- For RQ2:
  - ARQ3: The experiments in ARQ1 and ARQ2 have demonstrated the role and importance of Dropout and contrastive loss methods for classifying source code vulnerabilities. It has also been shown that the Dropout method is more effective than the Smote algorithm, and that the contrastive loss method is more effective than the trip loss method. However, the idea is how effective the model would be if we combined the smoke and loss of trip compared with the Dropout and contrastive loss combination. This concept was proposed in [34]. Thus, the experiment of ARQ3 will clarify which approach is better: the Smoke and Tripet loss method in [34], or Dropout and Contrastive loss.

Table 4 presents the results of the proposed models for ARQ1, ARQ2, and ARQ3 under scenario 2.

Table 4: Experiment results of scenario 2

RQ	ARQ	Approach	Acc	Pre	Rec	F1
RQ1	ARQ1 (a)	Smote and Contrastive Loss	**87.25**	**36.32**	**67.19**	**47.15**
	ARQ1 (b)	Do not use Dropout or smote data generation techniques (only use Contrastive Loss)	88.57	35.52	31.00	33.12
	ARQ2	Dropout and Triplet Loss	87.23	34.51	66.47	45.43
		Dropout and MLP	86.89	31.12	46.55	37.30
		Dropout and RF	85.25	29.34	47.09	36.15
RQ2	ARQ3	Smote+ Tripet loss [34]	86.94	34.03	64.24	44.49

Based on the experimental results in Table 4 and the experimental results in Table 4, we have the following discussion.

- **Discussion 1 on ARQ1 (a) of RQ1:** Comparing the results of Tables 3 and 4, the model combining Dropout and contrastive loss yielded much better performance than the smooth and contrastive loss combination models. This result was worse than that of our proposed model by 3%, 2%, and 3%. Similarly, for the non-vulnerable code prediction process, our proposed model was approximately 1% higher than that of the combined model on the F1-score. The Dropout method was more effective than Smote in terms of rebalancing the data in the embedding space. Fig. 5 depicts the distribution of the dataset when the Smoke method was used to rebalance the data.

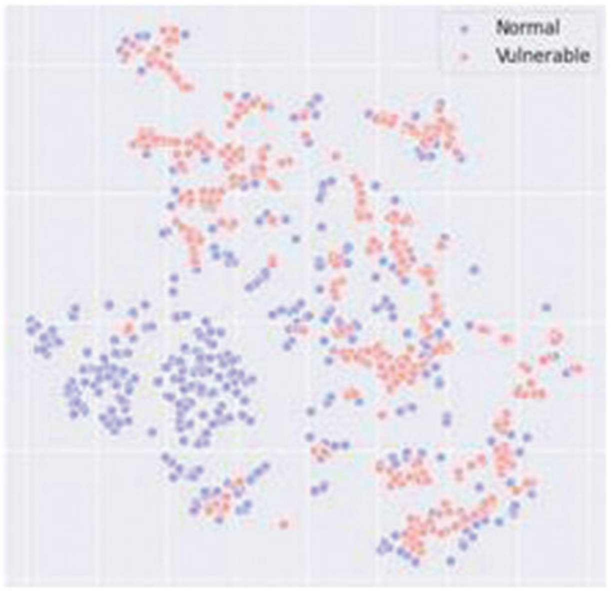


Figure 5: Data distribution when rebalancing data by Smote method

Fig. 5 shows that the Smote method succeeded in adding new data points to balance the distribution between the two labels in the dataset. Comparing the data distribution between Fig. 5

(using the Smote method) and Fig. 2b (using the Dropout method), it is clear that the Dropout method has demonstrated advantages over the Smote method in adding new data points from the original dataset. Specifically, the Smote creates a new data point using interpolation between two or more neighboring data points in the representation space. Therefore, Smote was quite sensitive to noisy data points with an unfocused distribution, and the variance was quite large, which changed the distribution of the original dataset. To overcome this shortcoming, the Dropout method uses only one data point to generate similar data points. Although the generated data points did not have a relationship between the distances between neighbors in the representation space, such as Smote, Fig. 2b clearly shows that these data points still had similarities and neighbors in the representation space. In addition, the Dropout was less sensitive to noise because the generated data points could only be located in the vicinity of the original data point, which helped the balanced dataset maintain the distribution, as in the original dataset. This further proves the suitability and advantages of using the Dropout for rebalancing data. In addition, based on the experimental results, we can see that the results of the model using data generation technique are much better than those without using this technique. However, there is only one measurement, accuracy, which is about 1% lower. The reason is that the value of accuracy is calculated in terms of both TP and TN, and TP increases but does not increase as much as the number of TN decreases (because the number of labels of normal source code is much larger than the number of labels of vulnerability), the value of accuracy can still decrease even though the values of precision and recall both increase.

- **Discussion 2 on ARQ1 (b) of RQ1:** When data generation techniques are not used, the source code vulnerability prediction results are completely low. Comparing Table 4 with Table 3, we see that this is the worst result. This result once again proves the correct and reasonable use of data generation techniques.
- **Discussion 3 on ARQ2 of RQ1:** Our proposed model combining Dropout and contrastive loss resulted in much better performance than the combination of Dropout and Triplet loss. This efficiency clearly demonstrates the ability to accurately detect source code vulnerabilities when the proposed method was 3% higher than that of the combined model. This is considered to be an excellent result for the vulnerability classification task using real datasets. Therefore, the contrastive loss performed better than the triplet loss in training the model to provide a vector representation. Fig. 6 shows the distribution results of the data after processing by the combined model of Dropout and Triplet loss.

Comparing Fig. 6 with Fig. 4, we can see that because of triplet loss traits, the model can only be trained through a pair of positive and negative data (x^+, x^-). In contrast, our proposed method can generate more than one pair (x^+, x^-). Therefore, with data containing several generated positive samples, Triplet Loss did not take full advantage of the rebalancing data methods. However, using Contrastive Loss successfully overcame this limitation from Triplet Loss when it helped the model train with many generated positive samples, making the most of the benefits of the method of rebalancing data.

- **Discussion 4 on ARQ2 of RQ1:** For models that did not use contrastive loss, it is no surprise that their effectiveness is deficient. Accordingly, if only the Dropout method is used to generate data for the training model without using contrastive loss methods to optimize the classification process, then the Dropout method is not useful. Specifically, the models combining Dropout with MLP and Dropout with RF were approximately 22% worse than the proposed model. From Fig. 3 in scenario 1 of the paper, we present the data distribution after using the data rebalancing technique. The cause of this problem is that the vector representations of the source code containing vulnerabilities and the clean source code in the embedding space are still fragmented and not centrally distributed. Meanwhile, classification methods such as MLP or RF are not capable of identifying and classifying non-vulnerable and vulnerable source codes.

- **Discussion 5 on ARQ3 of RQ2:** For the model replacing the Dropout and contrastive loss method with the smoke and trip loss method, our proposed method yields better results for both the non-vulnerable source code prediction and source code security vulnerability prediction. The experimental results of this model show that the method [34] resulted in 4%, 7%, and 5% lower efficiency on precision, recall, and F1 scores, respectively, than our method. These results were also reasonable because, through the experimental process of replacing Dropout with smoke and contrastive loss with trip loss, the results were less effective. In general, each proposed method is more effective than the individual methods indicated in [34]. Fig. 7 shows the difference in the data distribution in the embedding space of the model combining Smote with triplet loss with our proposed method.

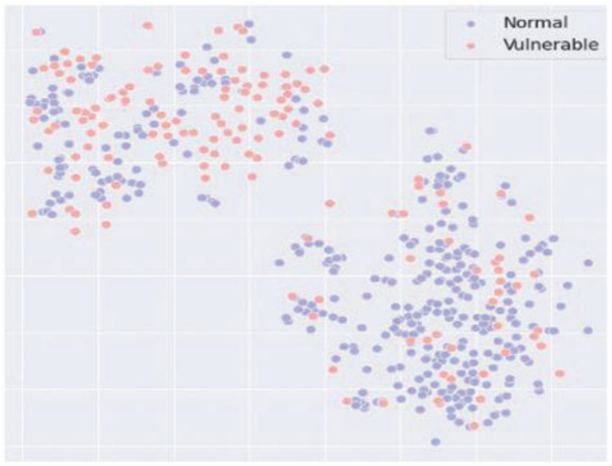
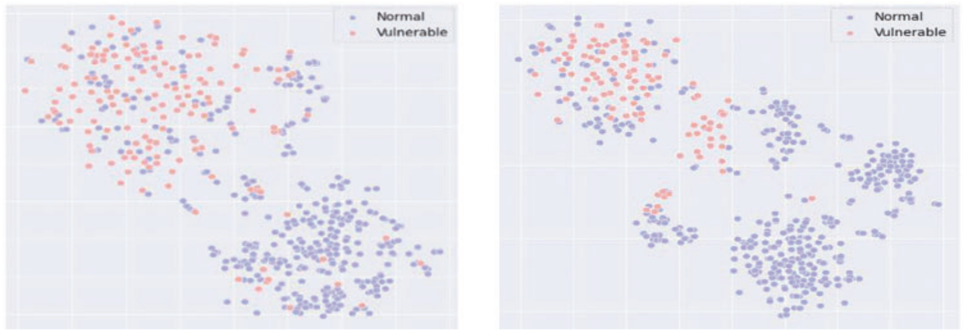


Figure 6: Data distribution when using a combination of Dropout and Triplet loss



(a) Smote + Triplet Loss (b) Dropout + Contrastive

Figure 7: Differences in data allocation when using the loss function. Where (a) data when using Smote + Triplet Loss model; (b) data when using the Dropout + Contrastive Loss model

Fig. 7 clearly shows that the combination of Dropout and Contrastive loss was able to distinguish clusters containing vulnerable and non-vulnerable labels better than the Smote and Triplet loss.

Comparing Figs. 7a and 7b, we can see that using Dropout and Contrastive loss is much more successful in grouping data points with the same label than the Smote and Triplet loss methods. From this, we can see the success of combining the two methods of Dropout and Contrastive loss.

Finally, with the experimental results in Table 4, the model that did not use the representation learning method exhibited the worst performance on all measurements.

4.4.4 Experiment Results of Scenario 3

As mentioned above, we experimented with this scenario to test and evaluate the effectiveness of our proposed method with other methods on the same Verum experiment dataset. For research on detecting source code vulnerabilities based on this dataset, we have found that there are studies [34] that we evaluated in Table 4 of scenario 2. In addition, reference [34] conducted experiments and evaluated several algorithms, methods, and techniques of other approaches on the Verum dataset. In this study, we reuse the experimental results presented in [34]. The approaches compared and evaluated with our method include REVEAL [34], Russell [8], VulDeePecker [11], SySeVR [31], and Devign [46]. Table 5 lists the experimental results of other approaches on the Verum dataset.

Table 5: Experiment results of scenario 3

Approach	Accuracy	Precision	Recall	F1
Our DrCSE	**87.72**	**39.35**	**69.07**	**50.14**
REVEAL [34]	86.94	34.03	64.24	44.49
Russell [8]	90.98	24.63	10.91	15.24
VulDeePecker [11]	89.05	17.68	13.87	15.7
SySeVR [31]	84.22	24.46	40.11	30.25
Devign [46]	88.41	34.61	26.67	29.87

A comparison of the experimental results in Tables 5 and 3 shows that our proposed method was more effective than the other approaches. Specifically, Russell's approach [8] was inferior to ours for all the measurements. In particular, with the recall score, this method was lower than our proposed method by more than 60%. Similarly, the VulDeePecker, SySeVR, and Devign methods were much worse.

4.4.5 Experiment Results of Scenario 4

For this scenario, we demonstrated the effectiveness of the proposed method using other datasets. Therefore, we used the FFMpeg+Qemu Dataset for the experiment. The Qemu dataset is a collection of software programs that allow the creation, management, and administration of virtual machines and the operation of virtualized environments on physical servers. FFmpeg includes software programs and libraries for processing videos, audio, and other multimedia streams.

The experimental results in Table 6 show that the DrCSE model was also more effective than the other approaches on the FFMpeg+Qemu Dataset. Specifically, the DrCSE Framework gave experimental scores for Accuracy, Precision, Recall, and F1 of 64.37%, 58.19%, 76.29%, and 66.02%, respectively. This result was approximately 2% higher than that of REVEAL [34] for all the measurements. Meanwhile, the DrCSE Framework performed better than the REVEAL model on both the Verum and FFmpeg+Qume datasets [35]. Moreover, the DrCSE was also much more optimized when experimented on the FFMpeg+Qemu Dataset. For example, when comparing DrCSE with Russell [8], SySeVR [31], and Devign [46], the DrCSE model was 6%–25% more efficient. Likewise, VulDeePecker [11] was less effective than DrCSE by 10% to 35% for all measurements.

Table 6: Experiment results of scenario 4

Approach	Accuracy	Precision	Recall	F1
Our DrCSE	**64.37**	**58.19**	**76.29**	**66.02**
Russell [8]	58.13	54.04	39.50	45.62
VulDeePecker [11]	53.58	47.36	28.70	35.20
SySeVR [31]	52.52	48.34	65.96	56.03
Devign [46]	58.57	53.60	62.73	57.18
REVEAL [34]	62.51	56.85	74.61	64.42

From Tables 5 and 6, although the SySeVR [31] and Devign [46] approaches were designed to detect source code vulnerabilities based on the FFMpeg+Qemu dataset, when comparing them with the DrCSE Framework, these two approaches were both less effective. Therefore, the DrCSE framework has brought about flexibility and optimization for detecting software vulnerabilities in many different datasets. This result shows that the combination of Dropout and contrastive learning helped the DrCSE Framework improve the difficulty of detecting source code vulnerabilities on real datasets with different structures.

4.5 Discussion

4.5.1 The DrCSE Framework: An Adaptive Software Vulnerability Detection Based on CPG Analysis

With different scenarios proposed, we proved the superior effectiveness of the DrCSE Framework for source code vulnerability detection. Therefore, the three problems posed previously in the paper have been overcome and improved by the DrCSE Framework, including the following:

a) Source code representation problem.

Although we are not the proponent of a method to process and represent source code in CPG form, but based on CPG documents provided by Joern [20] and the results reported in this paper, we have demonstrated that CPG is more efficient than other code representations, such as AST, CFG, and PDG. In addition, in scenario four's results when applying the DrCSE Framework on several different datasets, such as FFMpeg+Qemu or Verum, the DrCSE Framework has mostly resulted in higher efficiency than other approaches using AST, CFG, or PDG source code representations. In general, processing source code into CPG form and then applying data mining techniques are considered the current trending solutions for source code vulnerability detection.

b) Source code vulnerabilities classification in unbalanced datasets

The experimental results in scenarios 1 and 2 show the absolute effectiveness of the DrCSE Framework when handling unbalanced data. For instance, the data distribution in Fig. 2 and the RAQ2 experimental results prove the stability and effectiveness of the Dropout method in rebalancing data to support the training models. In addition, with the proposed scenarios, applying Dropout is correct and reasonable when it yields better results than the approach using Smote [34] or when not using the data rebalancing method.

c) Source code vulnerability detection method

In this study, the DrCSE Framework uses the representation learning method with a contrastive learning model to improve the efficiency of the vulnerability detection task. Several scenarios have proven that the DrCSE Framework is much more effective than the approach that does not use representation learning or the approach using representation learning with the triplet loss model. This result reaffirms the effectiveness of the DrCSE Framework in detecting security vulnerabilities using imbalanced datasets. At the same time, based on the experimental results of scenario 4, the DrCSE Framework works effectively not only on one particular dataset but also on many other datasets with different features and structures.

4.5.2 Improving Research Direction

Recently, the development of deep learning models has gradually led to the significant problem of training data shortage. Since then, training methods based on unsupervised learning have become an urgent and essential issue to help improve deep-learning models. In addition to the advantages and benefits of the method combining Dropout and Contrastive Learning in the supervised learning problem presented in this article, DrCSE can also be an unsupervised learning model applied to new tasks. In particular, Dropout can generate similar data points x^+ from the original data point x. We then pass these pairs of similar data through Contrastive Learning to "pull" x^+ and x come closer together in the representation space and "push" other data points away. This training process can help the model find hidden structures in new data and generate vector representations of new data points.

In addition, when doing this research, we found that the source code representation problem is crucial in detecting security vulnerabilities tasks and many other related works. We empirically used CPG to represent the source code in a graph form. In addition to the advantages of this method, there are still some problems when the extracted information is not accurate, and it still needs a function to convert text to vectors, etc. In the past few years, the fields of natural language processing and language modeling have proven their superiority and effectiveness with text-to-vector representation. For instance, some models have been developed and widely used, such as BERT and GPT. In general, through this study, we found that with source code processing problems, developing a full vector representation model of the source code is essential to improve the results of the prediction task, because some of the current vector representation methods still have certain disadvantages.

5 Conclusion

In this article, we proposed the DrCSE Framework with a combination of new intelligent computing techniques based on data rebalancing and representation learning methods to improve the efficiency of detecting source code vulnerabilities and minimize false warnings in non-vulnerable source code. Our investigation with four experimental scenarios answered a wide range of questions and proved the correctness and science of the DrCSE Framework for classifying source code vulnerabilities. The scientific correctness of DrCSE is reflected in its flexible combination of Dropout and contrastive learning methods. In addition, the outstanding performance of the classification results on many different datasets demonstrates the practical significance of the DrCSE model. Finally, based on this proposal, we successfully built a new framework that yields good vulnerability prediction results and can be tailored to actual needs.

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Availability of Data and Materials: In this study, we used a public dataset, which can be downloaded from the website if needed (https://github.com/VulDetProject/ReVeal).

Conflicts of Interest: The authors declare that they have no conflicts of interest to report regarding the present study.

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