GraphEye: A Novel Solution for Detecting Vulnerable Functions Based on Graph Attention Network

1st Li Zhou
School of Information and Communication Engineering
University of Electronic Science and Technology of China
Chengdu, China
2018010801006@std.uestc.edu.cn

2nd Minhuan Huang
National Key Laboratory of Science and Technology on Information System Security
Beijing, China
darbean@126.com

3rd Yujun Li
School of Computer Science and Engineering
University of Electronic Science and Technology of China
Chengdu, China
liyujun@uestc.edu.cn

4th Yuanping Nie
National Key Laboratory of Science and Technology on Information System Security
Beijing, China
yuapingnie@nudt.edu.cn

5th Jin Li
National Key Laboratory of Science and Technology on Information System Security
Chengdu, China
201922081124@std.uestc.edu.cn

6th Yiwei Liu
School of Computer Science and Engineering
University of Electronic Science and Technology of China
Chengdu, China
2017060901015@std.uestc.edu.cn

Abstract—With the continuous extension of the Industrial Internet, cyber incidents caused by software vulnerabilities have been increasing in recent years. However, software vulnerabilities detection is still heavily relying on code review done by experts, and how to automatedly detect software vulnerabilities is an open problem so far. In this paper, we propose a novel solution named GraphEye to identify whether a function of C/C++ code has vulnerabilities, which can greatly alleviate the burden of code auditors. GraphEye is originated from the observation that the code property graph of a non-vulnerable function naturally differs from the code property graph of a vulnerable function with the same functionality. Hence, detecting vulnerable functions is attributed to the graph classification problem. GraphEye is comprised of VecCPG and GcGAT. VecCPG is a vectorization for the code property graph, which is proposed to characterize the key syntax and semantic features of the corresponding source code. GcGAT is a deep learning model based on the graph attention graph, which is proposed to solve the graph classification problem according to VecCPG. Finally, GraphEye is verified by the SARD Stack-based Buffer Overflow, Divide-Zero, Null Pointer Dereference, Buffer Error, and Resource Error datasets, the corresponding F1 scores are 95.6%, 95.6%, 96.1%, 92.6%, and 96.1% respectively, which validate the effectiveness of the proposed solution.

Index Terms—cyber security, vulnerable detection, code property graph, graph attention network

I. INTRODUCTION

Software vulnerabilities refer to software design or implementation defects, which may be exploited by malicious users to achieve information leakage, resource utilization, and facility destruction. In recent years, with the rapid development of the Industrial Internet and continuously emerging applications, functionalities of different software have become more and more complex and larger in scale. In addition to the complexity of source code quality management, zero-day and n-day software vulnerabilities have shown an upward trend. Thus, cyber incidents caused by this kind of vulnerability have also increased. Hence, software vulnerability detection based on source code, as an old research topic, has once again received significant attention recently [1]–[9].

The mainstream method of software vulnerability detection based on source code is to convert firstly the source code into an abstract representation and then analyze the abstract representation to check whether it matches a certain predefined vulnerability detection rule, to determine finally whether the source code contains the corresponding vulnerabilities [3]. According to specific analysis techniques, the vulnerability detection methods can be divided into three categories: code similarity-based vulnerability detection, pattern-based vulnerability detection, and machine learning-based vulnerability detection.

Code similarity-based vulnerability detection originates that similar codes are likely to contain the same vulnerabilities. Code segments are abstractly represented based on their characteristics, and then judge the similarity between the code to be detected and the code containing a known vulnerability according to their corresponding representations, and determine
Deep learning has been successful in the image and natural language process and is very promising in vulnerability detection. However, most of the recent works focus on how to apply traditional vectorization methods in natural language processing, such as word2vec, glove, and so on, to the program source code [4, 6, 12]. However, the program source code differs from the image and natural language in nature. More efforts for vectorization of program source code are needed to improve deep learning vulnerability detection. Furthermore, research is also needed in terms of detection accuracy, vulnerability location, large-scale labeled datasets, model interpretation, and so on.

Our contributions. In this paper, we firstly propose that detecting vulnerable functions of c/c++ code is attributed to the graph classification problem. Then, a novel solution named GraphEye for this problem is proposed. GraphEye is comprised of a vectorization for the code property graph and a deep learning model based on the graph attention network. The focus of this paper is centered on answering the following question: How can we detect vulnerable functions based on graph neural network model, given the fact that the code property graphs of these functions have fully captured enough syntax and semantic information to identify the potential vulnerabilities?

The remainder of the paper is organized as follows: Section 2 briefly introduces the code property graph. Section 3 describes the solution framework in detail. Section 4 analyzes experiment results in depth. Section 5 concludes our work and discusses the future directions.

II. CODE PROPERTY GRAPH OVERVIEW

A graph can be formally defined as \( G = (V, E) \) in math theory, where \( V \) is a set of nodes, and \( E \subseteq (V \times V) \) is a set of edges. However, this highly abstract definition ignores the fact that there may be significant differences between entities and the relationships between entities in the real world. Hence, the concept of property graph comes into being, which is an extension of traditional graph definition by characterizing nodes and edges’ properties. A property graph is a directed labeled multigraph with the special characteristic that each node or edge could maintain a set (possibly empty) of property-value pairs [13]. The definition of property graph can be described as following:

Definition 1: A property graph is a five-tuple \( G = (V, E, \lambda, \Gamma, \mu) \), where \( V \) is a set of nodes, \( E \subseteq (V \times V) \) is a set of directed edges from source node to destination, \( \lambda \) is a labeling function for nodes, \( \Gamma \) is a type function for edges and \( \mu \) is a property function for both nodes and edges.

In a property graph, each node has at most one label, and each edge has at most one type, respectively identifying the classes of nodes and edges. Any node or edge in the property graph can have zero or more attributes to identify the characteristics of the node or edge. Figure 1 illustrates a typical property graph about a movie, and the characteristics of \( v_1 \) and \( e_1 \) can be described by functions as follows:
Actor
name = "Hugo Weaving"
birthday = "Apr. 4, 1960"
Director
name = "Lilly Wachowski"
birthday = "Dec. 29, 1967"
Actor
name = "Keanu Reeves"
birthday = "Sep. 2, 1964"
Movie
title = "The Matrix"
released = "1994"

Fig. 1: a simple movie property graph

\[
\lambda(v_1) = \{ \text{Actor} \} \\
\mu(v_1, \text{name}) = \text{"Keanu Reeves"} \\
\mu(v_1, \text{birthday}) = \text{"Sep. 2, 1964"} \\
\Gamma(e_1) = \{ \text{Acted_in} \} \\
\mu(e_1, \text{role}) = \text{"Neo"}
\]

With the help of the property graph, Yamaguchi et al. firstly merge the concept of the abstract syntax tree, control flow, and program flow chart to form a novel representation of program source code that named the code property graph in their publication [10]. The code property graph can be formally defined as follows:

\[
G_{CPG} = (V_{CPG}, E_{CPG}, \lambda_{CPG}, \mu_{CPG}, \Gamma_{CPG}) = G_{AST} \cup G_{CFG} \cup G_{PDG}
\]

where \( G_{AST}, G_{CFG} \) and \( G_{PDG} \) are the representation with property graph for the traditional abstract syntax tree, the control flow graph, and the program dependence graph of a program source code respectively.

This combination is prior to a single representation alone to characterize a vulnerability type in the vast majority of cases. As mentioned in [13], that the code property graph is not limited to the abstract syntax tree, the control flow graph, and the program dependence graph, more additional representations can be overlaid to extend the capability of the code property graph. We also note that more traditional representations, such as data dependence graph and control dependence graph, have been merged into the code property graph in Joern [17] which is an open-source tool to generate the code property graph.

**Listing 1** A bad function with divide-zero error

1: static void bad(float Data)
2: {
3: float data = Data;
4: {
5: /* POTENTIAL FLAW: Possibly divide by zero */

For instance, Fig. 2 illustrates the code property graph of a simple function depicted in Listing 1 from Juliet [16]. In Fig. 2, the edges of the abstract syntax tree, control flow graph, program dependence graph, and data dependence graph are indicated by the black solid lines, the red dashed lines, the purple dotted lines, and the green dashed-dotted lines respectively. All the syntax structs such as variable, data type, operate, statement, the function call, and so on are included in the subgraph consisting of black solid edges and the corresponding nodes. All the control flow information, i.e., the execution order of statements, described by the subgraph consisting of the red dashed edges and the corresponding nodes. All the control dependencies are depicted in the subgraph consisting of the purple dotted edges and the corresponding nodes. All the data dependencies are illustrated by the subgraph comprising of the green dashed-dotted edges and the corresponding nodes.

III. Solution Framework

A. Motivation and Overview

Our motivation comes from both the capture of vulnerability characteristics by the code property graph and the development of graph neural network technology. We first observe that the code property graph of the non-vulnerable source code differs naturally from the code property graph of the vulnerable source code with the same functionality. Then, we also notice that graph neural networks have been used for graph classification [19].

The differences in the code property graph of the non-vulnerable source code and the vulnerable can be illustrated by the following example. The fixed code of bad() function in Listing 1 is depicted in Listing 2 and its code property graph is shown in Fig. 3. There is a lack of a subgraph to judge whether data is equal to zero in Fig. 2 and the judgment is essential to lead to the error of divided by zero. It must be pointed out that the difference is not limited to the above vulnerability type, and it does exist in all vulnerability types as long as that the code property graph is enough overlaid.

**Listing 2** A good function without divide-zero error
The code property graph of good() function

```java
1: static void good(float Data)  
2: {  
3:    float data = Data;  
4:    if (fabs(data) > 0.000001)  
5:    {  
6:      int result = (int)(100.0/data);  
7:      printIntLine(result);  
8:    }  
9:    else  
10:    {  
11:      println("This would result in a divide by zero");  
12:    }  
13: }
```

Hence, detecting vulnerable functions of C/C++ code is modeled as the graph classification problem, and the solution framework is illustrated in Fig 3. The solution framework can be divided into three components. The first component is the generation of the code property graph for the program source code, which is the basis of our works and can be done by Joern. The second component is the vectorization of the property graph, and which is the foundation for the application of graph neural network model and can be done by our novel schema called VecCPG (Vectorization for the Code Property Graph of a program source code). The third component is the deep learning model, and we propose a novel model, named GcGAT (Graph Classification based on Graph Attention Networks), to detect vulnerable functions. The combination of VecCPG and GcGAT is called GraphEye, which is the core of the solution framework.

### B. Vectorization

Although the extension of the code property graph for a program source code has captured most vulnerability types so far, there is still a gap that must be filled before the model of graph neural network can be used to detect vulnerable functions. That is to say, how to vectorize the code property graph? VecCPG is proposed to fill the gap. VecCPG is comprised of the feature matrix and the adjacent matrix. The feature matrix represents nodes’ information, which captures the syntax characteristics of a program source code. For a given code property graph $G_{CPG} = (V_{CPG}, E_{CPG}, \lambda_{CPG}, \Gamma_{CPG}, \mu_{CPG})$, the feature matrix of $G_{CPG}$ is defined as follows:

$$X = R^{V_{CPG} \times |F|}$$

where $|V_{CPG}|$ is the cardinalities of the node-set $V_{CPG}$, and $|F|$ is the dimension of the selected properties of nodes. $F$ represents the features related to vulnerabilities, which is consisted of five different components illustrated in Table I.

#### TABLE I: The structure of VecCPG.

| label | operator | function | literal | type |
|-------|----------|----------|---------|------|
| 13 + 2| 25 + 2   | 39 + 2   | 32      | 16 + 2|

The structure of VecCPG characterizes the syntax details of the node label, operator, API function call, constant, and variable type.

**Label**: This label indicates which class a node belongs to, which is similar to the meaning of a label in a traditional property graph. There are 13 different classes are considered in this paper, and all the labels and their corresponding implications are listed in Table II. All these labels are encoded in a one-hot way, one additional bit for the unknown node, another additional bit for reservation.

#### TABLE II: Labels and implications.

| Label           | implications                                      |
|-----------------|--------------------------------------------------|
| IDENTIFIER      | variables                                        |
| LITERAL         | constants, such as strings, integers             |
| LOCAL           | variables in the function body that has been declared |
| BLOCK           | separator                                        |
| METHOD_RETURN   | the return of a method                           |
| METHOD          | a method definition                              |
| CONTROL_STRUCTURE | the control statement structure, such as if, while |
| FIELD_IDENTIFIER | a reference to a namespace, usually is ::        |
| UNKNOWN         | unknown types                                    |
| RETURN          | the return of a function                         |
| PARAM           | the parameters of a function                     |
| JUMP_TARGET     | the label used by goto                           |
| CALL            | a call to a function or operator                 |

**Operator**: 25 types of operators including arithmetic operators, rational operators, logical operators, bitwise operators, pointer operators, and so on are considered in these components. The detailed operators and the corresponding meaning are described in Table III. Operators are also encoded in a one-hot way, one additional bit for the unknown node, another additional bit for reservation.

**Function**: Considering some API function calls, for example, memcpy(), may lead to vulnerabilities, hence API function names are encoded into VecCPG in a one-hot way. The number of different API functions varies in different datasets. Thus, the simplest way to encode all API functions for a certain language. However, Limited to the dataset used in this paper, 39-bit encodes are enough to represent all API functions, one additional bit for unknown, another additional bit for...
float bad(int data){
... float b = 2/data;
...}

0 1 ⋮ ⋱ ⋮ 1 0 ⋮ ⋱ ⋮ 0 1

Adjacency matrix
1 1 ⋯ 0 0
⋮ ⋱ ⋮
0 1 ⋯ 0 1

Feature matrix

Source code
→ Joern
→ VecCPG
→ Deep Learning Model
→ output

Program source code
Code property graph generated by Joern
Adjacency and feature matrix generated by VecCPG.
Deep learning framework
Probability indicated whether a function has vulnerabilities

Fig. 4: The solution framework

Table III: Operators and Implications.

| operator | meaning |
|----------|---------|
| =        | assignment |
| /        | indirect IndexAccess |
| size()   | sizeof |
| +        | multiplication |
| ()       | cast |
| -        | subtraction |
| .        | field Access |
| <        | less Than |
| ++       | post Increment |
| &        | address Of |
| +        | addition |
| ==       | equals |
| -        | minus |
| !=       | not Equals |
| >=       | greater Equals Than |
| ->       | indirect Field Access |
| [        | logical Or |
| /        | division |
| &        | logical And |
| delete() | delete |
| &&       | and |
| >        | greater Than |
| %        | modulo |
| new      | new |

Literal: Some constants are also factors for the vulnerabilities, such as the divide-by-zero vulnerability. Due to the fact that the dataset in this paper is limited to 32 bits, all integers are encoded into 32 bits same to the underlying storage method of the system, and the floating-point constants are encoded according to IEEE 754 standard [17]. Of course, this encoding is easily extended to 64-bit systems.

Type: For C/C++ languages, 10 basic variable types and 6 complex variable types are considered. These basic variable types are char, int, short, float, double, long, string, void, struct, and union. Those complex variable types are signed, unsigned, *, array, map, and vector. A basic variable type and a complex variable type can be combined together, such as “char *”. Basic variable types and complex variable types are independently encoded in a one-hot way with an additional one-bit reservation.

The adjacency matrix is composed of AST, CFG, and DDG edges in the code property graph of a program source code, reflecting semantic information such as dependence and control between nodes. The adjacency matrix is defined as $A = R^{(|V_{CPG}| \times |V_{CPG}|)}$ where $|V_{CPG}|$ is the cardinalities of the node-set $V_{CPG}$. Compared to the feature matrix, the adjacent matrix is easier to construct. As long as there is at least one edge between two nodes, regardless of the type and number of edges, the element in the corresponding adjacency matrix is set to 1; otherwise, it is set to 0.

C. Deep Learning Model

A novel deep learning model, named GcGAT is proposed to detect vulnerable functions of the program source code. This model illustrated in Fig. 5 includes GAT, SAGpool, MLP, and softmax.

In traditional graph attention network application scenarios, the input is a feature matrix and an adjacency matrix. After the feature extraction of the multi-head attention model, the feature vectors of all nodes are output to label different nodes. However, what we need is to classify graphs rather than labeling nodes in a graph. If GAT’s output feature matrix is directly expanded into a vector and then input into MLP for classification, it may lead to the problem of excessive MLP parameters and the consequent high-dimensional curse. Inspired by the convolutional layer and pooling layer of CNN which is introduced to solve the classification problem by converting the output feature matrix of the graph into a vector. An improved SAGPool after GAT is introduced as our graph pooling.
Traditional SAGPool is an implementation of hierarchical pooling. It adaptively learns the importance of nodes from the graph through graph convolution and discards non-important nodes based on the TopK mechanism. Instead, we use GCN to directly reduce the dimensionality of the feature matrix output by GAT and then convert it into a vector to represent the whole graph. After obtaining the feature vector of the graph, we input it into MLP with fewer layers and parameters for classification. The number of nodes in the input layer of MLP is the dimension of the feature vector of the graph, and the number of nodes in the output layer of MLP is 2, which indicates that the results are divided into two categories. Finally, a common function named softmax is introduced for normalization to meet requirements of probability for MLP’s output. The definition of softmax is as follows:

$$S_i = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}}$$

where $z_i$ is the $i_{th}$ element and $S_i$ is the corresponding output of softmax.

IV. EXPERIMENTS

A. Data Preprocessing

SARD [18] is a dataset of different types of vulnerabilities, which has been widely used for researchers to evaluate their methods. In terms of model training and testing, we have selected three classic sub-datasets, namely, CWE 121 Stack-based Buffer Overflow, CWE 369 Divide-Zero, CWE 476 NULL Pointer Deference. In comparison with other models, we have selected two more widely used vulnerability types: CWE 199 Buffer Error and CWE-399 Resource Management Error.

Remember that this paper discusses whether there are vulnerabilities in functions. Hence, for training and testing the proposed deep learning model, the first thing that needs to do is to label the functions in the dataset classified by whether a function has vulnerabilities. At first, the concept of root bad function and root good function is introduced as follows:

**Root good function:** The function that has no vulnerabilities or its vulnerabilities are caused by user-defined function calls is a root good function. That is to say, there are no vulnerabilities under the exception of user-defined function calls.

**Root bad function:** The function that its vulnerabilities are caused by either the statements themselves or API function calls is a root bad function. That is to say, the vulnerabilities in this function are not caused by user-defined function calls.

| CWE   | Name                        | good | bad  | Total |
|-------|-----------------------------|------|------|-------|
| 121   | Stack-based Buffer Overflow | 529  | 3643 | 4172  |
| 369   | Divide-Zero                 | 845  | 593  | 1368  |
| 476   | NULL Pointer Dereference    | 410  | 274  | 684   |
| 119   | Buffer Error                | 844  | 4682 | 5526  |
| 399   | Resource Error              | 1179 | 802  | 1915  |

Then, based on the above definitions, all the functions without user-defined function calls are picked up and labeled “good” or “bad” respectively in the dataset, as illustrated in Table IV.

B. Training Process

Since the feature matrix of a code property graph is relatively sparse, the gradient update needs more epochs to obtain better parameters. A module named ray.tune is applied to perform a grid search on hyperparameters and pick up the best hyperparameters. Then based on the best hyperparameters, training by some epochs for the fixed dataset. Generally, the model is seriously underfitting from the 1st to 5th epochs. By the 7th epoch, the model performance has been greatly improved. After 10 epochs, the model performance has stabilized, and the training can be considered to be over. The hyperparameters finally used in GcGAT are as follows: learning rate equals 8.6e-4, the number of epochs is 15; the dropout is 0.3; the dimension of the hidden layer is 64 and the dimension of the pooling layer is 32.

Due to the imbalance problem of the dataset under the two classifications [19], a penalty factor strategy is adopted in GcGAT. For frequently occurring classes, the penalty is reduced by multiplying a number less than 1. For losses in small samples, the penalty is increased by multiplying a number greater than 1. In our experiments, the penalty factor is optimized to 0.6 for frequently occurring classes, and the penalty factor is optimized to 1.7 for small samples by hyperparameters searching.
TABLE V: The comparison with others for CWE 119

|          | FPR  | FNR  | TPR  | P   | F1   |
|----------|------|------|------|-----|------|
| Flawfinder | 56.6% | 44.8% | 55.2% | 39.9% | 46.3% |
| RATS     | 68.7% | 31.3% | 68.7% | 40.5% | 51.0% |
| Paper [3] | 14.3% | 14.6% | 85.4% | 80.4% | 82.8% |
| GraphEye | 9.4%  | 12.2% | 87.8% | 98.0% | 92.6% |

For CWE 121 Stack-based Buffer Overflow, the large-sample down-sampling technique is adopted to balance the positive samples and negative samples. The large-sample down-sampling technique is not adopted for CWE 369 Divide-Zero and CWE 476 NULL Pointer due to their balanced samples. CWE 119 Buffer Error and CWE 399 Recourse Error are used for comparisons with other methods, the large-sample down-sampling technique is not adopted to ensure fairness. For all types of vulnerabilities, the dataset is randomly divided into the training set and test set according to the ratio of 8:2.

We implement our framework in Python using Pytorch. The computer running experiments has two NVIDIA RTX TITAN GPUs and an Intel Xeon E5-2678 v3 CPU running at 3.30GHz. When training the neural networks to find vulnerabilities, the framework only consumes 2.46G memory with 1.16% average load on CPU, and 1.4G GPU memory with 29% average load on GPU. And when we leverage our model for inference, the speed reaches 185.69 functions per second on average, which indicates that our model can detect vulnerabilities rapidly under the condition of low resource usage.

C. Experiment Results

FPR (False Positive Rate), FNR (False Negative Rate), TPR (True Positive Rate), P (Precision) and F1 are common metrics for evaluating the effectiveness of a deep learning model. In terms of software vulnerabilities detection, their definitions can be described as follows:

\[
\begin{align*}
FPR &= \frac{FP}{FP + TN} \\
FNR &= \frac{FN}{TP + FN} \\
TPR &= \frac{TP}{TP + FN} \\
P &= \frac{TP}{TP + FP} \\
F1 &= \frac{2 \times P \times TPR}{P + TPR}
\end{align*}
\]

where FP denotes the number of samples that are non-vulnerable but detected as vulnerable, TN denotes the number of samples that are non-vulnerable and detected as non-vulnerable, FN denotes the number of samples that are vulnerable but detected as non-vulnerable, and TP denotes the number of samples that are vulnerable and detected as vulnerable. It is clear that the lower FRR and FNR, the higher TPR, P and F1 implicates the better effectiveness of the model.

For CWE 119 Buffer Error and CWE 399 Recourse Error, the experiment results compared with Flawfinder, RATS, and Paper [4] are shown in Table V and Table VI. Results of Flawfinder, RATS and Paper [4] come from [3]. Both FlawFinder and RATS are vulnerability detection tools based on pattern recognition, while Paper [4] adopts deep learning models to detect vulnerabilities. It is obvious from Table V and Table VI that the effectiveness of Flawfinder and RATS is poor. This is because the predefined rules for vulnerabilities are usually simple and are difficult to handle complex and flexible implementation. The effectiveness of Paper [4] has been greatly improved, and far better than Flawfinder and RATS in all FPR, FNR, TPR, P, and F1 metrics. Unlike natural language processing adopted in Paper [4], GraphEye is rooted in graph attention network and can capture more syntax structure and semantic information characteristics from the program source code. Hence, the overall effectiveness of GraphEye is much better than Paper [4].

The experiment results for CWE 121 Stack-based Buffer Overflow, CWE 369 Divide-Zero, and CWE 476 NULL Pointer Deference are shown in Table VII. F1 of these three types of vulnerabilities are all higher than 95%. For CWE 121 Stack-based Buffer Overflow, the difference between a root good function and a corresponding root bad function mainly lies in the value of the variable or constant, rather than the logical structure of the program source code. While GAT is sensitive to structure but is a little obtuse to constants. Hence, GraphEye adopts the penalty for bad function samples in the training process, which leads to the high false alarm rate. For CWE 369 Divide-Zero and CWE 476 NULL Pointer Deference, the results are similar. This is because that these two types of vulnerabilities mainly depend on whether there are branch statements for different values of variables. Some useless structures such as if(0) can Interference GraphEye, so the false-negative rate is higher.

V. Conclusion and Future Work

This paper firstly proposes that detecting vulnerable functions can be attributed to the graph classification problem. Then, a novel solution named GraphEye for this problem is proposed. GraphEye is comprised of VecCPG and GcGAT. VecCPG is a vectorization for the code property graph, which
reflects the grammatical structure and semantic information. GCgGAT is a deep learning model, which introduces SAGPool, MLP, and Softmax based on GAT to classify vulnerable functions and non-vulnerable functions. Finally, the experiment results validate the correctness and effectiveness of our solution. However, our current work is limited to detecting vulnerable functions caused by function internal statements and system calls. In the future, we will study how to detect vulnerable functions under the existence of custom function calls that are more general in actual situations.

ACKNOWLEDGMENTS

This work was supported in part by the Key Research and Development Project of Sichuan Province (no. 2021YFG0160), the National Key Research and Development Program of China (no. 2019QY1406). The authors would like to thank the anonymous reviewers for their valuable comments and suggestions.

REFERENCES

[1] R. Russell et al., "Automated Vulnerability Detection in Source Code Using Deep Representation Learning," 2018 17th IEEE International Conference on Machine Learning and Applications (ICMLA), Orlando, FL, USA, pp. 757-762, 2018. DOI: 10.1109/ICMLA.2018.200120.

[2] Young-Su JANG, Jin-Young CHOL, "Automatic Prevention of Buffer Overflow Vulnerability Using Candidate Code Generation," IEICE Trans. Information and Systems, Vol.E101-D, No.12, pp.3005-3018, 2018.

[3] Zhen Li, Deqing Zou, Zeli Wang, Hai Jin. "Survey on static software vulnerability detection for source code," Chinese Journal of Network and Information Security, Vol. 5, No. 1, pp.1-14, 2019.

[4] X. Duan, J. Z. Wu, T. Y. Luo, M. T. Yang, and Y. J. Wu, "Vulnerability Mining Method Based on Code Property Graph and Attention BiLSTM," Journal Software, Vol. 31, No. 11, pp. 3404–3420, 2020.

[5] H. Wang et al., "Combining Graph-Based Learning With Automated Data Collection for Code Vulnerability Detection," IEEE Transactions on Information Forensics and Security, Vol. 16, pp. 1943-1958, 2021. DOI: 10.1109/TIFS.2020.304773.

[6] Z. Li, D. Zou, S. Xu, H. Jin, Y. Zhu, and Z. Chen, "SySeVR: A Framework for Using Deep Learning to Detect Software Vulnerabilities," IEEE Transactions on Dependable and Secure Computing, 2021 DOI: 10.1109/TDSC.2021.3051525.

[7] J. Jang, A. Agrawal and D. Brumley,"ReDeBug: Finding Unpatched Code Clones in Entire OS Distributions". 2012 IEEE Symposium on Security and Privacy, San Francisco, CA, USA, pp. 48-62. 2012. DOI: 10.1109/SP.2012.13.

[8] Z. Li, D. Zou, S. Xu, H. Jin, H. Qi, and J. Hu, "VulPecker: an automated vulnerability detection system based on code similarity analysis," In Proceedings of the 32nd Annual Conference on Computer Security Applications. Association for Computing Machinery, New York, NY, USA, 201-213, 2016. DOI: 10.1145/2991079.2991102.

[9] S. Kim, S. Woo, H. Lee and H. Oh, "VUDDY: A Scalable Approach for Vulnerable Code Clone Discovery," 2017 IEEE Symposium on Security and Privacy (SP), San Jose, CA, USA,pp. 595-614, 2017. DOI: 10.1109/SP.2017.62.

[10] F. Yamaguchi, N. Golde, D. Arp, and K. Rieck, "Modeling and discovering vulnerabilities with code property graphs," 2014 IEEE Symposium on Security and Privacy, San Jose, CA, USA, pp. 590–604, 2014. DOI: 10.1109/SP.2014.44.

[11] F. Yamaguchi, A. Maier, H. Gascon and K. Rieck, "Automatic Inference of Search Patterns for Taint-Style Vulnerabilities," 2015 IEEE Symposium on Security and Privacy, San Jose, CA, USA, pp. 797-812, 2015. DOI: 10.1109/SP.2015.54.

[12] Y. Zhuang, Z. Liu, P. Qian, Q. Liu, X. Wang, and Q. He, "Smart contract vulnerability detection using graph neural networks," IJCAI Int. Jt. Conf. Artif. Intell., vol. 2021-Janua, pp. 3283–3290, 2020. DOI: 10.24963/ijcai.2020/454.

[13] R. Angles, "The property graph database model," Proceedings of the 12th Alberto Mendelzon International Workshop on Foundations of Data Management, Cali, Colombia, May 21-25, 2018.

[14] Yamaguchi, Fabian. "Pattern-based methods for vulnerability discovery," in the PhD Program in Computer Science (PCS) of the Georg-August University School of Science (GAUSS), 2015.

[15] Joern, "Joern, Open-Source Code Querying Engine for C/C++," ShiftLeft, https://joern.io, accessed in Mar. 14, 2021

[16] Information Technology Laboratory, "Juliet Documents," Software and Systems Division PRIVACY/SECURITY ISSUES, https://samate.nist.gov/SARD/around.php, accessed Mar. 3. 2021.

[17] W. Kahan, "IEEE Standard 754 for Binary Floating-Point Arithmetic," in IEEE Std 754-2008, vol., no., pp.1-70, 29 Aug. 2008. DOI: 10.1109/IEEESTD.2008.4610935.

[18] Information Technology Laboratory, "NIST Software Assurance Reference Dataset Project," Software Assurance Reference Dataset, https://samate.nist.gov/SRD/index.php, accessed Mar. 14. 2021.

[19] He, Haibo Garcia, E.A. "Learning from Imbalanced Data." IEEE Transactions on Knowledge and Data Engineering, vol. 21, no. 9, pp. 1263-1284, Sept. 2009. DOI: 10.1109/TKDE.2008.239.

[20] Z. Li et al., "VulDeePecker: A deep learning-based system for vulnerability detection," Network and Distributed Systems Security (NDSS) Symposium 2018, 18-21 February 2018, San Diego, CA, USA DOI: 10.14722/ndss.2018.23158.

[21] Z. Zhang et al., "Hierarchical graph pooling with structure learning," arXiv:1911.05994, 2019.