DCDetector: An IoT terminal vulnerability mining system based on distributed deep ensemble learning under source code representation

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Abstract:

Context: The IoT system infrastructure platform facility vulnerability attack has become the main battlefield of network security attacks. Most of the traditional vulnerability mining methods rely on vulnerability detection tools to realize vulnerability discovery. However, due to the inflexibility of tools and the limitation of file size, its scalability is relatively low and cannot be applied to large-scale power big data fields.

Objective: The goal of the research is to intelligently detect vulnerabilities in source codes of high-level languages such as C/C++. This enables us to propose a code representation of sensitive sentence-related slices of source code, and to detect vulnerabilities by designing a distributed deep ensemble learning model.

Method: In this paper, a new directional vulnerability mining method of parallel ensemble learning is proposed to solve the problem of large-scale data vulnerability mining. By extracting sensitive functions and statements, a sensitive statement library of vulnerable codes is formed. The AST stream-based vulnerability code slice with higher granularity performs doc2vec sentence vectorization on the source code through the random sampling module, obtains different classification results through distributed training through the Bi-LSTM trainer, and obtains the final classification result by voting.

Results: This method designs and implements a distributed deep ensemble learning system software vulnerability mining system called DCDetector. It can make accurate predictions by using the syntactic information of the code, and is an effective method for analyzing large-scale vulnerability data.

Conclusion: Experiments show that this method can reduce the false positive rate of traditional static analysis and improve the performance and accuracy of machine learning.

Keywords: Vulnerability detection; Distributed deep ensemble learning; Program slice; Directional vulnerability mining; AST stream-based vulnerability code slice

1.Introduction

Vulnerability refers to the defects and weaknesses of a system, and the research based on the vulnerability source code is to study the specific key program statements of the vulnerability. Especially in the field of power system, according to the statistics of the National Cyber Security Administration, there have been more than 10 attacks on the
power system infrastructure in the last year alone, and these attacks are often aimed at the vulnerabilities of the power system infrastructure platform. Vulnerability attacks on platform facilities have become the main battlefield of network security attacks, but nowadays there is a lack of sufficient actual engineering source codes in the field of power systems and even vulnerability mining, so data collection and processing have become particularly important.

In the field of traditional vulnerability mining, most of the domestic power system vulnerability mining is based on conventional fuzzing testing methods, the mining efficiency is low, and still largely depends on the experience of security personnel. There are technical shortcomings. Traditional detection methods, such as those based on manually defined vulnerability patterns, often lead to high false negative rates. In addition, most of the existing vulnerability mining methods are single and general, and their landing effect and possibility are not good, so it may be difficult to implement in massive power scenarios. In general, it is mainly manifested in the following aspects:

1. The distribution of vulnerability test samples is extremely uneven, and the test samples of most vulnerability types are too small, which makes effective vulnerability mining impossible.
2. There is a phenomenon of repeated vulnerability mining, and it is impossible to quickly determine whether the discovered vulnerabilities are known or unknown vulnerabilities, and it is impossible to determine the specific classification of the vulnerabilities.
3. Vulnerability mining is blind, and it is difficult to quickly locate the location of the vulnerability in a limited time, which seriously affects the efficiency of vulnerability mining.
4. Traditional vulnerability mining methods mainly rely on human mining and fuzzing, or rely on vulnerability detection tools to achieve vulnerability discovery. However, due to the inflexibility of tools and the limitation of file size, their scalability is low and cannot be applied to large-scale electricity field of big data. Therefore, how to effectively and efficiently solve the above-mentioned problems has become a technical problem that those skilled in the art urgently need to overcome.

Based on the above problems, the security community has introduced machine learning to automate the detection of vulnerabilities. With the continuous development of artificial intelligence technology, many scholars have begun to apply machine learning technology to the field of vulnerability mining. In 2015, Perl H [1] first proposed to use code metric analysis and SVM classifier to classify vulnerabilities, and applied machine learning to the field of vulnerability mining. The vulnerability detection method has higher accuracy and completeness, and can meet the needs of vulnerability mining in large and complex software systems in actual production. It is a new idea to solve the bottleneck problem in traditional vulnerability mining methods. Dasarathy and Sheela first proposed the idea of ensemble learning [2]. In 1990, Hansen and Salamon showed an ensemble model based on neural network [3], which has lower variance and better generalization ability. Dietterich [4] mathematically explained 3 basic reasons for the success of ensemble methods: statistics, computation and
representation. In addition, the effectiveness of ensemble learning can also be analyzed through bias variance decomposition [5]. Neamtiu [6] introduced that the abstract syntax tree is an abstract representation of the source code structure, the purpose is to build a hierarchical data structure of the syntax analysis tree, and the abstract syntax tree can be used to extract the internal information of the source code, compared with other programs such as text statistics and other programs. Representation and feature extraction methods are more lightweight. This paper also uses the doc2vec sentence vectorization method. The current mainstream vectorization methods are mainly one-hot and word2vec [7]. Although they consider the semantic information between words and compress the dimension, sometimes, When we need to get the vector representation of Sentence/Document, although we can directly take the average of all words in Sentence/Document as the vector representation of Sentence/Document, but this will ignore the arrangement order between words to the sentence or text information. influences. Therefore, we adopt the Doc2Vec method proposed by Tomas Mikolov [8]. Using the Doc2Vec vectorization method can not only retain the context information of the source code structure extracted by the abstract syntax tree, but also vectorize the entire sentence to improve the efficiency of program conversion. Therefore, It is very important that the parallel ensemble learning model based on abstract syntax tree has considerable advantages in the field of vulnerability mining.

In this paper, we propose vulnerability mining system based on distributed deep ensemble learning under source code representation. Specifically, we make three contributions.

- We propose a new data collection algorithm to improve the data quality of vulnerability mining and present a new program intermediate representation sequence flow for source code vulnerability mining, which achieves a higher degree of fine-grained slicing through sensitive word orientation and bidirectional deep search traversal.
- We propose a distributed deep integration learning algorithm model for source code vulnerability mining, making a breakthrough in vulnerability multiclassification research and giving pseudocode.
- We firstly compare the pros and cons of the classifiers longitudinally in the experimental results, and explore the optimal value range of the model hyperparameter N, and on the basis of obtaining the best local optimality, carry out multiple datasets. Horizontal comparison, a series of experimental results are obtained, and a complete experimental analysis is carried out.

2. Related Work

2.1 Code Representation

The essence of code representation is to form secondary program fragments based
on certain rules. The representation methods mainly include software code measurement, abstract syntax tree representation and graph representation. These representations are extracted as features to be processed by subsequent intelligent classifiers such as machine learning.

The code measurement of software is a measurement value for evaluating software quality. Code measurement includes CCC measurement, number of lines of code and inheritance depth [9-12]. As an important indicator of software architecture, Chowdhury proposed a vulnerability prediction framework, and Shin proposed a vulnerability prediction framework. Based on the framework, it is concluded that ensemble learning effects such as random forest and C4.5 decision tree are better than traditional machine learning such as logistic regression. Bozorgi [13] proposed a new code metric that pays attention to the working method of vulnerabilities and business logic information. He uses high-dimensional vectors of 93578 dimensions such as text fields to perform SVM classification to predict whether there are vulnerabilities, which is essentially the use of statistics The method of learning has been studied, and experiments have shown that this method is more effective. Younis [14] extracted 8 metrics such as the number of lines of code and information flow of 183 vulnerabilities provided by the NVD database, and made predictions through logistic regression, naive Bayes, random forest and SVM classifier, and finally obtained the F value. The result was 84%. In addition, Perl [15] proposed the VCCFinder model, and Meng [16] proposed to extract the complexity of the array index operation as a feature. The representation method based on the abstract syntax tree is mainly an intermediate representation of the program, which stores the code syntax structure through tree nodes. Commonly used abstract syntax tree generation tools for JS source code include Esprima, UglifyJS2, Traceur, Acorn, Espree, Shfit, etc. Commonly used C/C++ source code abstract syntax tree tools include Joern, Codesensor, SrcML, antlr4, Tree-sitter, etc. Yamaguchi [17] proposed to extract the AST for all functions of the code base and map them to the vector space, and at the same time use semantic analysis technology to infer the potential of the vulnerability. Lin [18] et al. used Antlr to extract abstract syntax trees, and then used word2vec for vectorization to train as the input of the BLSTM model. Compared with the traditional code measurement method, the representation method based on abstract syntax trees is more effective. Medeiros [19] generated AST by extracting the source code of WEB system, and analyzed the taint of AST, and found that logistic regression was more effective by observing the effects of various machine learning classifiers. Anbiya [20] et al. traversed the AST from the PHP web application through the breadth-first traversal algorithm, and then obtained features such as PHP tokens, and finally obtained the highest recall rate by comparing the Gaussian Naive Bayes with the machine learning algorithm.

The representation of the graph can reflect the many-to-many relationship in the program. It is essentially a directed graph composed of function calls and basic blocks, and represents the execution path of the program by calling, returning, and converting. Cheng et al. [21] mine the discriminative graph modeling through software behavior graph and jump search, extract the most discriminative execution flow graph with vulnerability and non-vulnerability to mine the context information provided by the
error, and then generate the different location information including the error. For the first K subgraphs, the goal of vulnerability mining is achieved by discriminating subgraphs. Qian et al. [22] used the attribute control flow graph of different basic blocks as a form of code representation, which has the advantage of not only including statistical attributes such as string constants and numerical constants, but also the number and centrality of child nodes. The location attribute of the basic block finally realizes the ACFG clustering of the dataset to achieve the effect of vulnerability classification. Harer JA [23] adopts two complementary methods for comparison. The first model is to directly send the source code to word2vec for vectorization, and then send the sequence to TextCNN for classification. The second model starts from the intermediate representation of the program, manually defines a 116-dimensional vector through CFG, and then sends the vector into the random forest for vulnerability classification. Experiments show that the first model is better. Compared with abstract syntax tree representation, graph-based representation can reflect richer syntax and semantic features in code, such as CFG, ACFG, etc. But at the same time, when combined with machine learning, because of its high overhead, time and space complexity are often very high, so it is not suitable for the detection of big data.

2.2 Machine Learning-Based Program Analysis

Although the analysis results of classical program analysis are relatively accurate, it cannot solve the problem of path explosion. With the continuous improvement of security technology, the relevant vulnerability data is also increasing. For the research of massive data, security technicians gradually use intelligent and automated algorithms and technologies to carry out research. Research, program analysis based on machine learning came into being.

Heo [24] proposed to combine the outlier detection technology in machine learning with static analysis to reduce the false positives of static analysis. Oh [25] et al. proposed to use the adaptive scheme of Bayesian optimization to improve the accuracy of static analysis and reduce the cost of static analysis. Li.X [26] and others used the machine learning technology MLB model to solve the path accessibility problem of symbolic execution and reduce the deficiencies of the constraint solution scheme in solving nonlinear constraints and function calls. Wang [27] and others combined the greedy algorithm with the dynamic execution technology of Markov process, and then found the strategy corresponding to the optimal performance. Xiong [28] et al. started from probability and proposed a probabilistic synthesis framework L2S, whose goal is to integrate the search space of the program, the path and the solution probability scheme.

Program analysis methods based on machine learning also differ from traditional vulnerability analysis methods in other aspects. First of all, in terms of language, most machine learning models target the C/C++ language, and some analyze the Python language. A few researchers directly study binary programs, such as Grieco G[29], Liu DJ[30] and others have achieved good results. Secondly, in terms of the fine-grained vulnerability, the traditional vulnerability mining method is at the folder and function
level, while the analysis method based on machine learning mainly focuses on code fragments, so the fine-grainedness is higher. Finally, in terms of scenario application, from the test within the project to the transfer learning to achieve cross-project detection.

3. Research Design

3.1 Architecture of IOT terminal source code vulnerability detection system

The overall architecture of the distributed deep integration learning-based source code vulnerability detection system for IoT terminals is shown in Figure 1.

Figure 1. Architecture of IOT terminal source code vulnerability detection system

1) The IoT terminal layer
   The source code from the IoT terminal firmware is collected and uploaded to the cloud database of the cloud platform via wireless network and administrator's control, etc.

2) The vulnerability detection layer
   The source code is pre-processed with data and then subjected to distributed deep integration learning to finally form the training model DCDetector.

3) The application layer
   For users who need to use the IoT terminal source code vulnerability detection, the access to vulnerability detection is carried out through the client provided. The user submits the source code of the firmware to be tested in the client side of the interaction layer, and the detection system processes it and returns the results. It is important to note that this is vulnerable to data eavesdropping and active attacks by hackers, which is why VPN channels are used here for transmission.

4) The virtualization layer
   In order to integrate the resources of the server, so that the utilization of resources is greatly improved, the design of server virtualization, storage virtualization, etc.
3.2 Design of DCDetector

The overall structure of the system is shown in Figure 2. The system mainly includes two stages, namely the learning stage and the testing stage. In the training phase, the collected C/C++ training source code is first classified into source code CWE, such as CWE119 Improper Restriction of Operations within the Bounds of a Memory Buffer, CWE120 Buffer Copy without Checking Size of Input, CWE476 NULL_Pointer_De_reference, CWE469 Use_of_Pointer_Subtraction_to_Determine_Size, Vulnerability classifications such as CWE510 Trapdoor and CWE570 Expression_Always_False. Then, locate the sensitive words in these classified vulnerability source codes. The location of sensitive words mainly depends on the tool joern. After locating the sensitive words, mark the number of lines where the sensitive words are located, and then use the AST abstract syntax tree information to detect sensitive words. The word is used as the starting point, and the tree is traced forward and backward respectively, and finally the AST forward and backward program flow slices related to the sensitive words are formed, and finally the AST flow slices are formed according to the fine-grained extraction of nodes. Further, distributed random sampling is performed on the program flow slices of each classification to form a data set formed by multiple random sampling, and then the source code in the data set is added with tags, and doc2vec is used for vectorization processing, and the vectorized information is sent to the distributed deep integrated learning model for training, and finally the training classification results of the training set and the parameters of the optimal model are obtained; In the testing phase, after preprocessing the C/C++ test source code, the program slices of the AST stream are extracted at the same time, and after vectorized processing, they are sent to the trained model for training. Get multiple classification results, and then get the final classification result by voting.

Before introducing the design module, the definition of AST-based program slice is given first. **Definition 1.** AST-based program slices are forward and backward slices related to sensitive words formed by the intermediate representation of the source code, that is, the AST abstract syntax tree according to the node information. We suppose $C_i = \{"1": c_{i,1}, "1": c_{i,2}, "1": c_{i,3}, \ldots, "1": c_{i,j}\}$, where the $C_i$ represents the ith code fragment, the $c_{i,j}$ of the value value represent the source code of the jth line of the ith code, and the key indicates the index position of the source code in the training set. The module is divided into a learning phase and a testing phase.
As shown in Fig.1, the training phase is divided into seven steps.

Step1. Source code CWE classification
   It mainly collects relevant vulnerability source codes from mainstream data sets such as SARD. This paper mainly studies six vulnerabilities: CWE119, CWE120, CWE476, CWE469, CWE510 and CWE570 with the purpose of multi-classification detection.

Step2. Sensitive word localization
   It mainly uses the API of joern-scan in the joern tool for detection. Through the matching of the rule base, the location information of sensitive words, sensitive issues, etc. can be located, and returned as Results.

Step3. AST stream slices related to sensitive words
   Record the number of lines where the sensitive words are located in stage 2, and generate the abstract syntax tree of the program, and perform upward and downward traversal searches based on the location of the sensitive words. The search method adopts breadth-first traversal.

Step4. Extract AST stream slices
   Based on the traversal results, extract the node information related to the abstract syntax tree, and then convert it into a high-level language program to form a program slice. For specific steps, refer to 3.4.

Step5. Distributed random sampling
   In this paper, the random multi-segment stratified sampling method is used to randomly sample the vulnerability code, in order to keep the ratio of vulnerability samples in the training set to non-sensitive function codes at 1:1, which is convenient for subsequent deep ensemble learning.

Step6. Add labels and quantify
   Most vulnerability mining mainly focuses on the presence or absence of
vulnerabilities, that is, the problem of binary classification. This paper mainly implements multi-classification vulnerability mining, that is, to determine whether the code not only has vulnerabilities, but also whether it is such a vulnerability. Therefore, the CWE119 code is labeled as "1", the CWE120 code is labeled as "2", the CWE476 code is labeled as "3", the CWE469 code is labeled as "4", the CWE510 code is labeled as "5", the CWE570 code is labeled as "6", and the insensitive function code is labeled as "0". The vectorization method mainly adopts sentence vectorization doc2vec, converts it into paragraph vector, and sets the dimension to 300 dimensions.

Step7. Distributed training model
In this paper, multiple Bi-LSTMs are used for parallel learning, and the vectorized source code is sent to the parallel Bi-LSTMs to realize model learning. The results of model parameters are shown later.

(b) Testing phase
As shown in Fig 1, the testing phase is divided into four steps.

Step8. Source code preprocessing
In order to speed up the judgment of the model and improve the test performance of the model, it is necessary to process the source code. By excluding the unclosed symbols of the source code, the original code is cleared of comments and other irrelevant program statements to achieve concise and efficient source code.

Step9. Extract AST stream slices
The purpose of further extracting AST program slices is to improve the judgment accuracy of the deep integrated neural network, maintain semantic synchronization, and reduce the influence of irrelevant information.

Step10. Vectorization
Convert the source code to be tested into data that can be processed by deep ensemble learning.

Step11. Distributed training model detection
The model in the training phase is used for multi-classification of test samples.

3.2 Methodology
The flowchart of parallel ensemble learning for vulnerability mining is shown in Figure 3. Before introducing the design module, the definition of AST-based program slice is given first.

**Definition 2.** *AST-based program slices* are forward and backward slices related to sensitive words formed by the intermediate representation of the source code, that is, the AST abstract syntax tree according to the node information. We suppose $C_i = \{1": c_{i,1}, "1": c_{i,2}, "1": c_{i,3}, \ldots, "1": c_{i,j}\}$, where the $C_i$ represents the $i$th code fragment, the $c_{i,j}$ of the value value represent the source code of the $j$th line of the $i$th code, and the key indicates the index position of the source code in the training set.
Use the dataset as the public vulnerability dataset SARD, and use the CWE vulnerability classification as the label. Use 70% of the data as the training set and the remaining 30% as the test set. Fig. 1 depicts the exact procedure required for distributed deep ensemble learning for vulnerability mining.

1. The obtained data source code is made into a vulnerability training set, and the vulnerability training set is preprocessed, including the removal of annotations, the replacement of common variables, etc.

2. Then the CWE vulnerability codes were integrated and the mainstream CWE119, CWE120, CWE476, CWE469, CWE510 and CWE570 vulnerability codes were combined and uniformly tagged as positive samples.

3. The combination of vulnerability code to do sensitive statements to locate, sensitive statements mainly include such as memory leaks, null pointer references, variables not released and other sensitive functions, will be numbered, and made into json format data table such as: 

   ```json
   Vulnerability{FunctionId:X42,Childnum:4,Dangerfunction:gets,IsAstnode:yes,Dangersentence:gets(str)}
   ```

   It mainly includes information such as the vulnerability function, the location of sensitive statements, and the number of sensitive statements.

4. The whole function code of the vulnerability code obtained in step (3) is extracted, and the abstract syntax tree stream is generated using joern, and other program statements related to sensitive statements are extracted based on
the abstract syntax tree information and combined into AST abstract syntax
tree slices for code characterization.
(5) The tree depth of the abstract syntax tree slicing is judged, and the upward and
downward slicing depth thresholds are set from the sensitive statement
position as the starting point; experiments show that a threshold value of 5
works best. Above the threshold, the tree is re-sliced, and below the threshold,
the tree moves to the next stage.
(6) According to the results obtained in step (5), the training set of bug-free codes
is mixed with the AST abstract syntax tree to prepare for the uniformity of
random sampling later.
(7) Perform $N$ random sampling according to the uniformly mixed training set
code in step (6). Random sampling uses put-back sampling, etc. Each data is
sampled with equal probability and may be repeatedly sampled, and the
sampling termination condition for each module is that the number of samples
is equal to the number of training sets.
(8) Next, the individual sampled source codes are subsampled and sentence
vectorization is performed using the doc2vec algorithm, which outputs a
characteristic fixed-length vector for utterance texts of different lengths.
(9) The vectors are fed into the distributed Bi-LSTM for training, and for each Bi-
LSTM classifier a classification result is formed, which is determined by
voting, i.e., the binary classification result tends to be valid if the proportion
of positive samples or negative samples is greater than 50% of the total.
When performing model evaluation, we feed the test data into the model and run it.
Then we obtain the value of $N$ through experiments.

3.2 Data Processing for Analysis

This paper mainly trains and tests on three datasets of SARD, SySeVR and Draper,
in which SARD is used for experimental vulnerability dataset distribution as shown in
Figure4.
Figure 4. Visualization of some experimental data of SARD

In the data set, the number of CWE476 vulnerability functions is randomly selected as 628, the number of CWE469 vulnerability functions is 600, the number of CWE510 vulnerability functions is 630, the number of CWE570 vulnerability functions is 620, and 2478 non-sensitive function codes are used for experiments[31], the above data were used for classifier comparison experiments.

In addition, from the datasets SARD, SySeVR and Draper, the vulnerability data of CWE119, CWE120, CWE476, CWE469, CWE510, and CWE570 were re-extracted to test the generalization ability of the model. In order to further improve the data quality and the learning effect of the model, we give A data acquisition algorithm is defined as follows:

**Definition 2.** *Vulnerability data collection algorithm* is a technology proposed in this paper for deep learning vulnerability collection. Let $S$ be the number set of each classification of the collected data set, $S = \{s_1, s_2, ..., s_n\}$, where $s_1, s_2, ..., s_n$ is arranged in order from small to large, where $n$ is the number of classification types, $1 \leq i \leq n$, such as $s_i = \left\{ \begin{array}{ll}
1 \leq \frac{s_{(n+1)/2}}{s_1} \leq 1.2 & \text{and} \quad 1 \leq \frac{s_n}{s_{(n+1)/2}} \leq 1.2 & \text{n is odd} \\
1 \leq \frac{s_{n/2}}{s_1} \leq 1.2 & \text{and} \quad 1 \leq \frac{s_n}{s_{n/2}} \leq 1.2 & \text{n is even} \end{array} \right.$, Vulnerability data collected according to the above definition is shown in the above table, let $s_{n+1}$ be the number of non-vulnerable codes, then $s_{n+1} = \frac{\sum_{i=1}^{n} s_i}{n}$.

According to the above algorithm, the data is collected, and the experimental data set...
is obtained as shown in Table 1.

| Data set  | CWE119 | CWE120 | CWE476 | CWE469 | CWE510 | CWE570 | Security | Total |
|----------|--------|--------|--------|--------|--------|--------|----------|-------|
| SARD     | 4562   | 3979   | 3876   | 3923   | 3976   | 3283   | 3933     | 27532 |
| SysyVR   | 5062   | 4976   | 5124   | 4988   | 5013   | 4935   | 5016     | 35114 |
| Draper   | 6728   | 6348   | 6451   | 6434   | 0      | 0      | 6512     | 32473 |

It is worth noting that since the Draper [32] dataset mainly studies CWE119, CWE120, CWE476 and CWE469, only the above four vulnerability codes are collected recently.

3.3 Code representation

In the code characterization stage, take the following code as an example, as shown in Figure 5.

```c
void client_delete (struct client *c) {
    //Close Log File...
    vte_logclose(c->v);
    //Release Spec Variable...
    free(c->spec);
    //Release Name Variable...
    free(c->name);
    //Release object C
    FREE_OBJ(c);
}
```

Figure 5. An example of code slicing based on AST stream

On the far left is the original data source code, which contains complete information about the function, including the original function name, comments, and complete program statements. Then, after code preprocessing, after removing comments and detecting unclosed symbols, use joern to extract AST stream information, as shown in Figure 6.

```c
void client_delete ( ) {
    free(c->spec);
    free(c->name);
}
```

```c
void W ( ) {
    free(c->spec);
    free(c->name);
}
```

Figure 6. The source code of ‘client_delete’ and its bidirectional AST in the serialized format

In Figure 5, the preprocessed source code is intermediately represented according to the fine-grained and dependencies of nodes. In Joern, the position of sensitive words can be easily located and the information can be stored after querying according to
Scala rules. Based on the above sensitive word node positions, the depth-first traversal method is used to track up and down, as shown in Figure 5 (a), and the slice result after bidirectional deep tracking is shown in Figure 5(b), which includes the four attributes of slice words, namely type, depth, search value, etc. Finally, the code slice result of the figure in Figure 4 is formed, and then the user-defined function name is added. Replace it with the name of the public function, here W is used as an example, as shown in the rightmost figure in Figure 4.

3.4 Distributed deep ensemble learning algorithm model architecture

The model architecture of the DCDetector algorithm is shown in Figure 7.

![Figure 7. Model structure of DCDetector](image)

The algorithm model architecture mainly includes the following steps:

1. **Generation of AST-based program slices**: After randomly sampling the vulnerable C language source code, the AST node information is used to form program slices of the AST stream.

2. **Sentence vectorization**: Sentence vectorization is performed on program slices, and the vectorization fixed length is 300 dimensions. Assume that each word of a syntax
tree-based source code slice maps to a unique vector, represented by a column of matrix Z, indexed by word position. The concatenated vectors are then used as predictions for the next slice word feature. Assuming that the source code program statement has m lines, each line has n words, and the training word space feature is defined as follows:

\[ W_j = \{ D_j, w_{j1}, w_{j2}, w_{j3}, \ldots, w_{jn} \} \quad 1 <= j <= m \]  

(1)

Where \( W \) is the source code program statement, \( w_{li}, w_{l2}, w_{l3}, \ldots, w_{lm} \), which is the word of the program statement, \( D_j \) represents the id number of the statement in this line. Here we take a line of source code as an example, and generalize the statement number \( D_j \) of the changed line to the word number \( w_{lj} \). The goal of the model is to maximize the average log probability.

\[
\frac{1}{n} \sum_{i=1}^{n-l} \log p(w_j | w_{j-l}, \ldots, w_{j+l}) \quad 0 <= l <= i
\]

(2)

Vulnerability prediction is mainly done through a classifier, such as the softmax layer, which is defined as follows:

\[
p(w_j | w_{j-k}, \ldots, w_{j+k}) = \frac{e^{y_j}}{\sum_i e^{y_i}}
\]

(3)

where each \( y_i \) is the unnormalized log probability of each output word, calculated as:

\[
y_i = b + K h(w_j | w_{j-l}, \ldots, w_{j+l}; W)
\]

(4)

Where \( b \) and \( K \) are softmax layer parameters, \( h \) is the concatenated combination of word vector and paragraph vector.

(3) Feature representation: Then the vector \( W \) is sent to the forward propagation hidden layer as follows:

\[
\vec{h}_j = \text{LSTM}(w_j) \quad 1 <= j <= n
\]

(5)

The back-propagation hidden layer looks like this:

\[
\overrightarrow{h}_j = \text{LSTM}(w_j) \quad 1 <= j <= n
\]

(6)

The output of the forward propagation hidden layer is combined with the output of the backward hidden layer to obtain the output of the first layer Bi-LSTM network as shown in the formula:

\[
h_j = [\overrightarrow{h}_j, \overrightarrow{h}_j]
\]

(7)

At the same time, the attention mechanism is used to obtain the importance \( \alpha'_j \) of each word in the sentence to the sentence feature representation, that is, the importance of the j-th word in the i-th sentence, that is, the main information \( u \) and the vulnerability code statement related to the j-th word. The correlation degree of the object information \( p \), the calculation formula of \( \alpha'_j \) is as follows:
\[ \alpha_j^i = \frac{\exp(e(h_j^i, u, p))}{\sum_{k=1}^{w} \exp(e(h_k^i, u, p))} \] (8)

Among them, \( e(h_j^i, u, p) \) represents the hidden layer output \( h_j^i \), the data information subject \( u \), and the calculation of the importance of the data information object information to the word \( W \). The calculation formula is as follows:

\[ e(h_j^i, u, p) = v^T \tanh(W_H h_j^i + W_U u + W_p p + b) \] (9)

Finally, the weight information \( \alpha_j^i \) obtained by the attention mechanism and the input of the hidden layer \( h_j^i \) are accumulated and summed, and the formula is as follows:

\[ z_i = \sum_{j=1}^{w} \alpha_j^i h_j^i \] (10)

And because there are \( m \) lines of program statements, then the feature \( z_i \) needs to be sent to the second layer Bi-LSTM to get the hidden layer output, where the forward hidden layer is as follows:

\[ \overrightarrow{h_j^i} = LSTM(z_i) \quad 1 \leq j \leq m \] (11)

The back-propagation hidden layer looks like this:

\[ \overleftarrow{h_j^i} = LSTM(z_i) \quad 1 \leq j \leq m \] (12)

The output of the forward propagation hidden layer is combined with the output of the backward hidden layer to obtain the output of the second layer Bi-LSTM network as shown in the following formula:

\[ h_i = [\overrightarrow{h_j^i}, \overleftarrow{h_j^i}] \] (13)

The importance \( \beta_j^i \) of each word in the sentence for the sentence feature representation is obtained, and the formula is as follows:

\[ \beta_j^i = \frac{\exp(e(h_j^i, u, p))}{\sum_{k=1}^{m} \exp(e(h_k^i, u, p))} \] (14)

\[ e(h_j^i, u, p) = v^T \tanh(W_H h_j^i + W_U u + W_p p + b) \] (15)

For the parameters \( W_H, W_U, W_p, b, v \), they are continuously optimized to the optimal value. Finally, the product of the weight \( \beta_j^i \) and the hidden layer \( h_i \) of the second layer of the network is summed to obtain the feature \( f \). The formula is as follows:

\[ f = \sum_{j=1}^{m} \beta_j^i h_j^i \] (16)
(4) **Sensitive vulnerability classification:** The feature $f$ is sent to the softmax function for classification, and the calculation formula is as follows:

$$f_c = \tanh(w_c d + b_c)$$  \hspace{1cm} (17)

Where $c$ is the sensitive information category space, $w_c$ is the text feature parameter matrix, $b_c$ is the deviation vector, and the vulnerability classification result is obtained by using \textit{soft max}. The formula is as follows:

$$P_c = \frac{\exp(f_c)}{\sum_{k=1}^{c}\exp(f_k)}$$  \hspace{1cm} (18)

where $P_c$ is the discriminant probability, and the discriminant is defined as follows:

$$P_c = \begin{cases} 1 & y_i = c \\ 0 & y_i \neq c \end{cases}$$  \hspace{1cm} (19)

(5) **Distributed Integrated Voting:** Parallel learning is performed at the same time to generate multiple classification results, $P = \{P_{c,1}, P_{c,2}, ..., P_{c,j}\}$, and the final discrimination result is according to the following formula:

$$P = \begin{cases} 1 & \text{count}(P_i = 1) > \frac{j}{2} \\ 0 & \text{or} \quad 1 \text{ count}(P_i = 1) = \frac{j}{2} \\ 0 & \text{count}(P_i = 1) < \frac{j}{2} \end{cases}$$  \hspace{1cm} (20)

Algorithm 1 presents a distributed deep ensemble learning algorithm for vulnerability mining:

**Algorithm 1** Distributed Deep Ensemble Learning model

**Input:** Labelling SARD Dataset

**Preprocessing:**
- Removal of redundant comments
- Replace public variables
- Stemming the dataset

**Extract sensitive words from source code:**

**Extract abstract syntax tree information for function fragments:**

**Extract AST-based program slices related to sensitive words:**
- Combine step 1 and 2:
  - Preprocessed file = file path name
  - Extracted SARD = file path of extracted SARD CWE list

**Control the tree depth of AST-based program slices**
- if the value of tree depth <= 5
  - Accept AST-based program slices
else
Next AST-based program slices

**Control the output of the sigmoid function**

**Vulnerability classification**

While (n != optimal random sampling hyperparameter N) do {

doc2vec sentence vectorization
Provide the feature as input to Bi-LSTM
Obtain the textual feature representation
Determine the output of Bi-LSTM Vulnerability(\(P_c\)) for the input sequence \(f\)
Classify the Vulnerability (\(P_c\)) = \{CWE119, CWE120, CWE476, CWE469, CWE510, CWE570\} }
Distributed Integrated Voting \(P\)
end

4. Results

This section mainly describes the experimental environment and evaluation indicators, describes the experimental content, and analyzes the results.

**Environment.** The experiments in this paper are based on the graphics card RTX 3070, the memory 32GB, and the 12th Gen Intel(R) Core(TM) i7-12700H device.

4.1 Selection of evaluation indicators

The index evaluation of the classifier mainly includes false positive rate (FPR), false negative rate (FNR), accuracy (ACC), precision (P), recall rate (R) and F1 measure (F1)\[^{[32]}\]. In this paper, we introduce these metrics to evaluate the state of the experiments. Let FP be the number of source codes that have no sensitive functions but are detected as having corresponding sensitive vulnerabilities, TP is the number of sensitive programs detected as having sensitive functions, FN is the number of sensitive programs detected as not having vulnerabilities, TN is the number of patches that are free of vulnerabilities and detected as non-vulnerable.

The false positive rate (FPR) is the ratio of the number of program slices without corresponding sensitive vulnerabilities but detected as having vulnerabilities to the actual number of program slices without corresponding vulnerabilities (including false detections as vulnerabilities and correct detections as vulnerabilities) as formula:

\[
FPR = \frac{FP}{FP + TN}
\]  

(21)

The false negative rate (FNR) is the ratio of the number of sensitive program fragments detected as non-vulnerable by the system to the number of all real sensitive program fragments (including false detection as non-vulnerable and correct detection as vulnerability), as shown in formula (22).

\[
FNR = \frac{FN}{TP + FN}
\]  

(22)

Accuracy (ACC) is the ratio of the number of correctly detected patches to the total...
number of patches, as in Equation (23).

\[ ACC = \frac{TP + TN}{TP + TN + FP + FN} \]  

(23)

In order to evaluate the experimental results more comprehensively, this paper balances the data, but still increases the precision (P) and F1 measures. Precision (P) is the ratio of the number of vulnerable patches detected as vulnerable to the number of all patches detected as vulnerable by the system. The accuracy reflects the false positive situation of vulnerability detection from the side, such as formula (24).

\[ P = \frac{TP}{FP + TP} \]  

(24)

The recall rate (R) is the ratio of the number of sensitive patches detected as having vulnerabilities to the number of all sensitive patches. The recall reflects the completeness of the system, that is, the system's false negatives, as shown in formula (25).

\[ R = \frac{TP}{FN + TP} \]  

(25)

The F1 measure (F1) is the weighted harmonic average of the accuracy and recall (R) describing the system capability, which is used to balance the precision and recall and reflect the overall detection effect of the system. The higher the F1, the better the performance of the system, as shown in Equation (26).

\[ F1 = \frac{2*P*R}{P + R} \]  

(26)

4.2 Experiment results

4.2.1 Comparison Experiment of Deep Learning Algorithms

The experiment mainly uses part of the data of the SARD dataset for classifier comparison experiments. In addition to the distributed deep Bi-LSTM ensemble learning model proposed in this paper, we also designed and constructed other common deep learning methods, namely CNN, TextCNN, RNN, LSTM and GRU, We use 70% of the SARD dataset for training and 30% for test and the iterative effect obtained is shown in Figure 8.
From the above figure, we compared six deep learning training situations, in which CNN overfitted when iterated to 19 rounds; and Bi-LSTM loss can be minimized, which shows the robustness of Bi-LSTM. The stickiness is the best among the five types of deep learning mentioned above. In addition, after 20 rounds, the loss value drops below 0.05, indicating that the model is well trained on the training set. After the test set is processed according to the processing method of the model, it is sent to the trained model. The confusion matrix obtained by Bi-LSTM is shown in Figure 9. In particular, the confusion matrix of Bi-LSTM for vulnerability mining is constructed as five different types, such as CWE476, CWE469, CWE510, CWE570 and No vulnerability, and the ground-truth label values are plotted according to the predicted labels for vulnerability mining and the Bi-LSTM classification data are shown in Table 2.

| Vulnerability | FPR(%) | FNR(%) | ACC(%) | P(%) | F1(%) |
|---------------|--------|--------|--------|------|-------|
| CWE476        | 0.50%  | 14.77% | 98.64% | 91.46% | 88.23% |
| CWE469        | 0.41%  | 10.35% | 99.03% | 92.86% | 96.87% |
| CWE510        | 0.62%  | 20.43% | 98.18% | 89.16% | 84.11% |
| CWE570        | 0.76%  | 11.88% | 98.52% | 89.00% | 88.56% |
The overall test results of the test set are shown in Table 3.

| Neural network algorithm | FPR(%) | FNR(%) | ACC(%) | P(%) | F1(%) |
|--------------------------|--------|--------|--------|------|-------|
| CNN                      | 15.2%  | 9.1%   | 83.1%  | 79.5%| 81.3% |
| TextCNN                  | 14.1%  | 8.7%   | 86.1%  | 80.1%| 82.1% |
| RNN                      | 12.2%  | 7.1%   | 90.2%  | 80.3%| 83.2% |
| LSTM                     | 10.2%  | 4.9%   | 93.1%  | 81.6%| 84.3% |
| GRU                      | 10.3%  | 5.2%   | 92.5%  | 85.1%| 85.4% |
| Bi-LSTM                  | 9.8%   | 4.7%   | 94.1%  | 85.5%| 87.83%|

As shown in the table above, on the classifier, we compared six deep learning algorithms: CNN, TextCNN, RNN, LSTM, GRU, Bi-LSTM. Through deep ensemble learning, we can integrate ensemble learning based on the original deep learning. Among them, the Bi-LSTM accuracy ACC reaches 97.1%, the precision rate P reaches 87.2%, and the F1 measure reaches 88.9%. In this experiment, the effect of CNN convolutional neural network is worse than the above deep learning algorithm, and it is prone to overfitting; the effect of LSTM classifier and GRU is similar, slightly better than that of RNN recurrent neural network, which is Because LSTM combines contextual semantics, it has the function of memory; compared with LSTM neural network, Bi-LSTM can use contextual information for learning. In summary, Bi-LSTM has good classification performance.

4.2.2 Experiments on distributed random sampling hyperparameter N

We use three vulnerability data sets SARD, SySeVR and Draper, they are used for 30% of the test set and 70% of the training set for the distributed random sampling N experiment, and according to the distributed deep ensemble learning in 3.2 for vulnerability mining methodology, N represents the number of sampling times, because in the selection of the training set, we have introduced hidden randomness, that is, 70% of the training set is randomly selected for training, so the randomly obtained training set is divided into relatively small N parts for distributed training. It enables DCDetector to fully learn the training data, and obtain the final classification type according to the results given by the N distributed deep learning models according to the voting mechanism, and then test the integrated learning effect of DCDetector under relatively small samples, and explore three data The best value of N in the set. The experimental results are shown in Figure 10.
Figure 10. Experiment of distributed random sampling N

It can be seen from the above experiments that in the SARD data set, when the training set is 5, the maximum accuracy is 97.3%, and in the test set, when N is 4, it reaches 94.0%; In the SyseVR data set, the training set is at N is 6 taken, the maximum accuracy is 94.2%. In the test set, when N is 6, the maximum accuracy is 88.7%; in the Draper dataset, when N is 4 in the training set, the maximum accuracy is 95.8%, and in the test set, when N is 3, the maximum accuracy is 93.2%. In addition, it can be seen from the trend that for the amount of data collected, the value range of N is more suitable in the range of 4-6, and if N is too large, the result will be poor. This is because although the number of classifiers increases, but at the same time The small number of training samples is relatively small, and the learning effect will also decrease, so N is in a constant range, and the distributed deep ensemble learning training and testing effect is the best.

4.2.3 DCDetector generalization ability experiment

DCDetector generalization ability experiment, the generalization ability of the model needs to be tested. Therefore, we use the training set and test set of the SARD, SyseVR and Draper vulnerability datasets in 4.2.2. At the same time, we all conduct system tests when N is the optimal value, and the following experimental results are obtained, as shown in Figure11.
As can be seen from the above figure, only consider when \( n \) is a local optimum, that is, the training set is randomly sampled \( n \) times. From the above figure, DCDetector on the SARD data set can be seen that after about 14 iterations on the training set, the Loss value is reduced to about 0.005, and the accuracy reached nearly 96.7%. After about 11 rounds of iterations on the test set, the Loss value was reduced to 0.03, and the accuracy reached 93.1%; DCDetector in the SyseVR data set, after about 17 rounds of iterations on the training set. About 0.023, and the accuracy reaches 93.5%. After about 13 iterations on the test set, the Loss value is reduced to 0.055, and the accuracy reaches 88.05%; DCDetector in the Draper data set, after about 13 iterations on the training set. It is about 0.022, and the accuracy reaches 94.1%. After about 11 iterations on the test set, the Loss value is reduced to about 0.039, and the accuracy reaches 91.6%. As shown in Table 3.

### Table 3 DCDetector generalization experimental results

| Data Set | Number of training iterations | Number of test iterations | Training Set accuracy (%) | Test Set accuracy (%) |
|----------|-------------------------------|---------------------------|---------------------------|-----------------------|
| SARD     | 14                            | 11                        | 96.7%                     | 93.1%                 |
| SyseVR   | 17                            | 13                        | 93.5%                     | 88.05%                |
| Draper   | 13                            | 11                        | 94.1%                     | 91.6%                 |

Further, we give the result data of each vulnerability classification. The selected mixture matrix for the SARD test dataset, the selected SyseVR test dataset mixing matrix and the selected Draper test dataset mixing matrix is shown in Figure 12.

Figure 12. Confusion matrix of DCDetector in three datasets
The classification data table of DCDetector used for vulnerability mining in the SARD test set is shown in Table 4. As shown in the chart, the SARD test set contains about 8258 function codes, including 3213 sensitive functions and 5045 normal functions. The research includes six types of vulnerabilities, including CWE119, CWE120, CWE476, CWE469, CWE510, and CWE570. Type discrimination of insensitive slices on the SARD dataset is the best, with P, R and F1 measures reaching 98.70%, 94.59% and 96.60%, respectively. At the same time, the CWE469 type discrimination effect of the model on the SARD dataset is relatively the worst, with P, R and F1 measures of 79.05%, 92.71% and 85.34% respectively.

Table 4 SARD test dataset results

| Vulnerability type | P(%)  | R(%)  | ACC(%) | F1(%)  |
|--------------------|-------|-------|--------|--------|
| CWE119             | 81.80%| 94.60%| 98.28% | 87.74% |
| CWE120             | 87.63%| 94.30%| 99.15% | 90.08% |
| CWE476             | 81.62%| 97.12%| 97.63% | 88.70% |
| CWE469             | 79.05%| 92.71%| 97.99% | 85.34% |
| CWE510             | 86.56%| 94.89%| 98.40% | 90.53% |
| CWE570             | 83.88%| 87.03%| 98.09% | 85.43% |
| Normal slices      | 98.70%| 94.59%| 93.09% | 96.60% |

The classification data table of DCDetector used for vulnerability mining in the SyseVR test set is shown in Table 5. As shown in the figure above, the SyseVR test set contains 10,634 function codes, including 4,832 sensitive functions and 5,802 normal functions. The research includes six types of vulnerabilities, including CWE119, CWE120, CWE476, CWE469, CWE510, and CWE570. The type discrimination of insensitive slices on the SyseVR dataset is the best, with the P, R and F1 measures reaching 88.940%, 87.45% and 88.19%, respectively. At the same time, the CWE469 type discriminant effect of the model on the SyseVR dataset is relatively worst, with P, R and F1 measures of 68.33%, 70.75% and 70.10% respectively.

Table 5 SyseVR test dataset results

| Vulnerability type | P(%)  | R(%)  | ACC(%) | F1(%)  |
|--------------------|-------|-------|--------|--------|
| CWE119             | 83.76%| 79.38%| 95.66% | 81.51% |
| CWE120             | 73.78%| 77.37%| 96.31% | 75.53% |
| CWE476             | 72.89%| 71.73%| 94.15% | 72.31% |
| CWE469             | 68.33%| 70.75%| 94.57% | 70.10% |
| CWE510             | 80.95%| 83.44%| 98.34% | 82.18% |
| CWE570             | 63.81%| 83.44%| 98.34% | 82.18% |
| Normal slices      | 88.94%| 87.45%| 87.22% | 88.19% |

And the classification data of DCDetector used for vulnerability mining in the Draper test set is shown in Table 6. As shown in the figure above, the Draper test set contains 9,734 function codes, including 4,929 sensitive functions and 4,805 normal functions. The research includes four types of vulnerabilities: CWE119, CWE120, CWE476, and CWE469. The model is in the Draper dataset. The type discriminative effect of the insensitive slices is the best, with the P, R and F1 measures reaching 88.99%, 94.63% and 91.72%, respectively. At the same time, the CWE119 type discriminant effect of the model on the Draper dataset is relatively worst, with P, R and F1 measures of 69.98%, 61.00% and 65.18% respectively.

Table 6 Draper test dataset results

| Vulnerability type | P(%)  | R(%)  | ACC(%) | F1(%)  |
|--------------------|-------|-------|--------|--------|
| CWE119             | 69.98%| 61.00%| 85.63% | 65.18% |
In summary, after the horizontal comparison of the models, it is found that the model performs the best in the SARD dataset, because the National Institute of Standards and Technology of the SARD dataset improves the quality of the data through a combination of technology and labor. The effect of the model in the Draper data set is relatively poor, because the Draper data set is mainly labeled by the static analyzer, so there is a certain error in the data label.

5. Conclusion

This paper analyzes six vulnerabilities of CWE119, CWE120, CWE476, CWE469, CWE510 and CWE570 in SARD, SyseVR and Draper datasets, investigates some mainstream methods in this field, and proposes a vulnerability mining model based on distributed deep ensemble learning. Then, the definition of data collection is given, and the analysis is carried out according to the technical modules. The method of forward and backward slicing based on sensitive words is described in detail, which improves the fine-grained slice of vulnerability mining. The advantages of the model algorithm over the other five deep learning algorithms of CNN, TextCNN, RNN, LSTM and GRU and the best classification effect. The reason why this model can achieve good results is that on the one hand, it combines the advantages of distributed training and ensemble learning, and on the other hand, it improves the quality of data and the fine-grained improvement of sensitive function program slicing. In order to verify the learning and training effect of the deep learning classifier, on the SARD data set, the overall experimental evaluation of the test set is carried out for six indicators such as FPR, FNR, ACC, P and F1, and the specific vulnerability classification data results are given. In the end, Bi-LSTM works best. At the same time, on the deep ensemble learning algorithm model, three datasets are used to conduct experiments on the horizontal generalization ability. In distributed random sampling, we explored the value range of the hyperparameter N, which further improved the accuracy of the model in terms of data quality, which was improved compared to other deep learning algorithms. Under the condition that N achieves the local optimum, the horizontal generalization of SARD, SyseVR and Draper is compared, and the overall results of the four indicators of training iterations, test iterations, training accuracy and test accuracy are given. The specific vulnerability classification data results in each dataset. This paper fully proves the excellent effect of this model method in source code vulnerability mining from the perspectives of the time-space complexity and efficiency of the algorithm.

Data Availability

The data used to support the findings of this study are included in the article.

Conflicts of Interest
The author states that the publishing of this paper does not include any conflicts of interest.

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