Towards Making Deep Learning-based Vulnerability Detectors Robust

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Abstract—Automatically detecting software vulnerabilities in source code is an important problem that has attracted much attention. In particular, deep learning-based vulnerability detectors, or DL-based detectors, are attractive because they do not need human experts to define features or patterns of vulnerabilities. However, such detectors’ robustness is unclear. In this paper, we initiate the study in this aspect by demonstrating that DL-based detectors are not robust against simple code transformations, dubbed attacks in this paper, as these transformations may be leveraged for malicious purposes. As a first step towards making DL-based detectors robust against such attacks, we propose an innovative framework, dubbed ZigZag, which is centered at (i) decoupling feature learning and classifier learning and (ii) using a ZigZag-style strategy to iteratively refine them until they converge to robust features and robust classifiers. Experimental results show that the ZigZag framework can substantially improve the robustness of DL-based detectors.

Index Terms—Vulnerability detection, deep learning, robustness, source code.

1 INTRODUCTION

The problem of detecting software vulnerabilities is yet to be solved, as evidenced by a large number of vulnerabilities reported in the Common Vulnerabilities and Exposures (CVE) [1]. The wide reuse of open-source software and the increasing complexity of software supply-chains make the problem even more imperative [2]. This can be justified by the Heartbleed vulnerability [3] and the software supply chain attack on the open-source npm package [4], highlighting the importance of detecting vulnerabilities in source code. The importance of the problem has motivated many studies involving two categories: static analysis which analyzes the software’s source code and dynamic analysis which executes software and observes its behavior (e.g., fuzzing). In this paper, we focus on static analysis-based vulnerability detectors. Static analysis-based detectors may analyze the source code in three ways: code similarity-based [5–8] vs. rule-based [9–11] vs. machine learning-based [9–12] approaches. A recent development in machine learning-based detection is to use Deep Learning (DL). DL-based detectors are attractive because they do not need human experts to define features or patterns to represent vulnerabilities while achieving high effectiveness [13–15].

However, the robustness of DL-based vulnerability detectors is unclear, which motivates our study. Although DL models are known to suffer from adversarial examples in many domains, such as image processing [16, 17], speech recognition [18, 19], malware detection [20, 21], and code authorship attribution [22], it is unknown whether or not this robustness problem equally holds for vulnerability detectors. This is so because “adversarial vulnerability examples” must be compiled and executed while preserving semantics and vulnerabilities, a requirement having no counterpart in the aforementioned domains.

Our contributions. We initiate study on the robustness of DL-based vulnerability detectors, by making three contributions. First, to understand the robustness of these detectors, we leverage semantics-preserving code transformation techniques, dubbed “attacks”, to show that four representative DL-based detectors suffer from adversarial vulnerability examples. These detectors are representative because they operate at different granularities, use different vector representations, and employ different neural networks. For instance, some attacks against a state-of-the-art DL-based detector [23] can cause its false-positive rate to increase from 7.0% to 19.9% and false-negative rate to increase from 9.9% to 68.1%.

Second, to make DL-based detectors robust against adversarial vulnerability examples, we propose an innovative framework, dubbed “ZigZag”. The key insight is to...
decouple feature learning and classifier learning and make the resulting features and classifiers robust against code transformations. Specifically, ZigZag iteratively employs two classifiers, which have different decision boundaries but offer similar prediction results. In each iteration, the feature learning phase aims to extract robust features, which characterize input examples well and thus lead to similar, if not the same, predictions by the two different classifiers. Then, the classifier learning phase aims to train two robust classifiers, which have largely discrepant decision boundaries and few classification errors. In other words, the classifier learning phase optimizes two classifiers by increasing the discrepancy between their decision boundaries, whereas the feature learning phase optimizes features by reducing the two classifiers’ prediction discrepancy. This procedure is iterated as many times as needed, explaining the term “ZigZag”. When the iterative process converges, we obtain features and classifiers robust against code transformations.

To show the effectiveness of ZigZag, we apply it to the aforementioned detector. Experimental results show that when compared with the original detector, the hardened detector’s false-positive rate (8.4%) and false-negative rate (19.2%) are much lower than the original 19.9% and 68.1% incurred by adversarial examples, respectively.

Third, our experiments are based on a new dataset we collected, which might be of independent value. This dataset is derived from the National Vulnerability Database (NVD) and the Software Assurance Reference Dataset (SARD). It contains 6,803 programs and their variants, leading to 50,562 vulnerable examples and 80,043 non-vulnerable examples at the function level. We have made the dataset and source code of ZigZag publicly available at [link](https://github.com/ZigZagframework/zigzag).

**Paper organization.** We analyze the robustness of existing DL-based detectors in Section 2. Then, we present the design of our framework ZigZag and evaluate its robustness in Section 3 and Section 4, respectively. Further, Section 5 discusses the limitations and future work, and Section 6 reviews the related prior work. In the end, Section 7 concludes the paper. Table 1 summarizes the main notations.

## 2 Robustness of DL-based Detectors

A DL-based detector D is trained from a set of programs in source code. The defender uses D to determine whether a given target program in source code is vulnerable or not. Fig. 1 highlights the basic idea: the attacker attempts to manipulate a program, while preserving its semantics, to cause D to classify (i) a manipulated program containing no vulnerability as “vulnerable” or (ii) a manipulated program containing a vulnerability as “non-vulnerable”. In this paper, we call manipulated programs adversarial examples regardless of whether the degree of code manipulation is small or not.

### 2.1 Attack Requirements

The first attack requirement is to preserve the semantics of a program. This is important because the manipulated program should be as useful as the original program. The second attack requirement is not to use obfuscation technique because users may not use any obfuscated code from a third party that is not known to be trustworthy (in fear of malicious code). The third attack requirement is the preservation of the vulnerability itself. This means that given a piece of vulnerable code, where the vulnerability can be detected by some existing DL-based detectors, the manipulated code remains vulnerable but the vulnerability it contains can evade those detectors. This is important because the attacker’s goal is to make vulnerabilities evade vulnerability detectors.

### 2.2 Attack Experiments

#### 2.2.1 Selecting DL-based Detectors

Since DL-based detectors can be characterized by the granularity (e.g., function [27], [28], [32] vs. program slice [23], [25]), the vector representation (e.g., sequence-based [23], [25]...
vs. Abstract Syntax Tree or AST-based \[26, 29, 31\], and the neural network (e.g., Bidirectional Gated Recurrent Unit or BGRU \[24\] vs. Bidirectional Long Short-Term Memory or BLSTM \[23, 29\] vs. Convolutional Neural Network or CNN \[34\]), we consider the following four DL-based detectors.

**Program Slice + Sequence + BGRU.** It can be instantiated as the detector SySeVR \[24\], which is an extended version of VulDeePecker \[23\], is publicly available, and operates at the fine granularity in that each program is represented by multiple program slices. A program slice is composed of a small number of program statements that are semantically related to each other. A slice is parsed as a sequence of tokens (e.g., identifiers, operators, constants, and keywords) and transformed into a vector. This vector representation is used to train a BGRU model for classifying program slices as vulnerable or not.

**Function + Sequence + CNN.** It can be instantiated as the detector presented in \[34\], which operates at the coarse granularity in that each function is treated as a unit. Specifically, each program is divided into multiple functions; each function is interpreted as a sequence of tokens and transformed into a vector; and these vectors are used for training a CNN model, which classifies the functions as vulnerable or not.

**Function + Sequence + BLSTM.** It can be instantiated as the detector presented in \[32\]. It operates at a coarse granularity by dividing a program into multiple functions, representing each function as a sequence of tokens, and training a BLSTM model to classify functions as vulnerable or not.

**Function + AST + BLSTM.** It can be instantiated as the detector that extends and enhances the DL-based detector \[32\] to capture more syntactic and structural information of program source code, by replacing its sequence-based representation with AST-based representation \[35\] and using the code2vec tool \[47, 48\] to aggregate multiple AST paths into a vector.

### 2.2.2 Preparing Dataset

The present study needs a dataset that satisfies the following requirements: (i) the dataset can support the generation of examples at different granularities; (ii) the programs in the dataset can be compiled for code transformation purposes; and (iii) the dataset should contain vulnerabilities in real-world software for training because our goal is to detect real-world software vulnerabilities which may be different from synthetic vulnerabilities. Because existing datasets \[23, 24, 28, 32, 34, 49\] do not satisfy the preceding three requirements, we create a new dataset by considering two vulnerability sources: NVD \[45\] and SARD \[46\]. For NVD, we collect: (i) vulnerable program files that are reported before 2017 and belong to open-source software written in C; and (ii) their patches, which can be obtained from the software vendors’ websites. The rationale for (i) is that we conduct experiments on real-world open-source software to detect vulnerabilities reported from 2017 to 2019 (Section 2.2.4 and Section 4.1). For SARD, each program is labeled as good (not vulnerable), bad (vulnerable), or mixed (vulnerable functions and their patched versions). In total, we collect 6,803 programs, each of which is vulnerable or patched. We take vulnerable (i.e., positive) examples and non-vulnerable (i.e., negative) examples at the function level as the ground truth, because each vulnerability can map to a function and each function has at most one vulnerability in our dataset. The 6,803 original programs includes 6,865 vulnerable examples and 10,843 non-vulnerable examples. The 6,803 programs and their variants generated by applying code transformations include 50,562 vulnerable examples and 80,043 non-vulnerable examples in total.

### 2.2.3 Attack Methods

To demonstrate the feasibility of the attacks, we leverage real-world code transformation tools to launch attacks because they are designed to preserve program semantics. There are multiple real-world code transformation tools \[50–53\]; we choose Tigress \[50\] because it provides various code transformations without obfuscating code. Table 2 describes 8 code transformations, denoted by CT-1, …, CT-8, which are selected from what are offered by Tigress. We apply each of the 8 code transformations to each of the original programs to generate manipulated programs. Fig. 2(a) illustrates a vulnerable program containing an integer overflow vulnerability CVE-2012-0849 (vulnerable Line 6). Fig. 2(b) shows its manipulated version obtained by applying the code transformation CT-6 (i.e., SplitTop). CT-6 splits the original vulnerable function _ff_j2k_dwt_init into two new functions _1_ff_j2k_dwt_init and _2_ff_j2k_dwt_init. The code in the dashed box highlighted with \(\circ\) in Fig. 2(a) corresponds to the code in the dashed box highlighted with \(\bullet\) in Fig. 2(b). CT-6 also replaces the for loop with the while loop (i.e., the code in the dashed box highlighted with \(\circ\) in Fig. 2(a) and the code in the dashed box highlighted with \(\bullet\) in Fig. 2(b)), replaces arrays with pointers (e.g., Line 15 in Fig. 2(a) and Line 35 in Fig. 2(b)), and replaces macro definition identifiers with static values (e.g., Line 6 in Fig. 2(a) and Line 11 in Fig. 2(b)).

### 2.2.4 Experimental Results

Our attacks satisfy the aforementioned attack requirements as follows. The requirement of *semantics preservation* is assured by Tigress, which is used to conduct code transformations and is designed to preserve program semantics. The requirement of *no-obfuscation* is satisfied by choosing 8 code transformations that do not involve any obfuscation operations. The requirement of *vulnerability preservation* is assured by manual examination. To check whether semantics-preserving transformations can preserve vulnerabilities, we

| No. | Name | Description |
|-----|------|-------------|
| CT-1 | EncodeStrings | Replace the literal strings with calls to the function that generates these literal strings. |
| CT-2 | RndArgs | Reorder function arguments and/or add bogus arguments. |
| CT-3 | Flatten | Remove some control flows from a function. |
| CT-4 | MergeSimple | Merge multiple functions into one without control-flow flattening. |
| CT-5 | MergeFlatten | Merge multiple functions into one with control-flow flattening. |
| CT-6 | SplitTop | Split top-level statements into multiple functions. |
| CT-7 | SplitBlock | Split a basic block into multiple functions. |
| CT-8 | SplitRecursive | Split a basic block into multiple functions, and split the calls to split functions. |
add a flag to each vulnerable line of code in the original program to trace its corresponding line(s) of code in the manipulated program. We randomly select 200 vulnerable programs and manually check if the manipulated programs are still vulnerable. It takes about 105 hours of domain experts to confirm that the manipulated programs contain the same vulnerabilities as in the original programs.

**Evaluation of vulnerability detection evasion.** To show the lack of robustness of DL-based detectors, we conduct attacks against four DL-based detectors. We randomly choose 80% of the 6,803 programs for training and use the rest for test. Target programs $Q^+$ involve the original test programs $Q$ and their manipulated programs with 8 code transformations, which are available to the attacker. At the function level, the training programs contain 4,079 vulnerable examples and 6,530 non-vulnerable examples; the target programs contain 17,516 vulnerable examples and 28,206 non-vulnerable examples.

Let TP denote true positives, FP denote false positives, TN denote true negatives, and FN denote false negatives. We use three standard metrics for evaluation [54]: (i) False-Positive Rate $FPR = \frac{FP}{FP + TN}$; (ii) False-Negative Rate $FNR = \frac{FN}{FP + FN}$; (iii) overall effectiveness or F1-measure $F1 = \frac{2TP}{2TP + FP + FN}$, where precision $P = \frac{TP}{TP + FP}$. We train four DL-based detectors and choose the hyperparameters that lead to the highest F1. Table 6 summarizes the results. Compared with the function-level detectors, the program slice-level detector achieves better results for original test programs $Q$ with a 1.4% lower FPR, a 4.5% lower FNR, and a 2.0% higher F1 on average, but achieves a 19.4% lower FPR, a 20.7% higher FNR and a 13.9% lower F1 for target programs $Q^+$ on average. This indicates that the program slice-level detector misses many more vulnerabilities in manipulated programs. We speculate that this is caused by the following: a program slice has a finer granularity than a function, thus the detector at the program slice-granularity is more sensitive to the changes of vulnerable code. In contrast, the coarser-grained function-level detector can accommodate more changes in both vulnerable and non-vulnerable code. Therefore, the function-level detector causes more false-positives and fewer false-negatives for manipulated programs. In addition, each detector exhibits similar phenomena with respect to different code transformations. Take the “Program Slice + Sequence + BGRU” detector for instance. We observe that the manipulated programs achieve a high FPR of 21.8%, a high FNR of 74.8%, and a low F1 of 28.8% on average, which indicates that the DL-based detectors can easily make mistakes by manipulating programs.

To show the feasibility of the attack against real-world open-source software, we test it against three open-source software products to detect the vulnerabilities reported in the NVD from 2017 to 2019, while recalling that these detectors are trained using the vulnerabilities reported prior to 2017. We use the four DL-based detectors to detect vulnerabilities in three software products and their manipulated versions. We observe that the program slice-level detectors can detect more vulnerabilities than the function-level detectors and some vulnerabilities detected by different detectors are the same. Table 4 summarizes the vulnerabilities in three software products that can evade the DL-based detectors. We observe that there are 19 vulnerabilities, 8 vulnerabilities, 10 vulnerabilities, and 12 vulnerabilities that can respectively evade the “Program Slice + Sequence + BGRU”, the “Function + Sequence + CNN”, the “Function + Sequence + BLSTM”, and the “Function + AST + BLSTM” detectors. Considering the “Program Slice + Sequence + BGRU” detector, we observe that 5 vulnerabilities in FFmpeg 2.8.2, 9 vulnerabilities in Wireshark 2.0.5, and 5 vulnerabilities in OpenSSL 1.1.0 are missed; these vulnerabilities are listed in Table 4. In summary, **Insight 1.** DL-based vulnerability detectors are not robust against evasion.

### 3 ZigZag Framework

#### 3.1 Characterizing DL-based Detectors

Fig. 3(a) and (c) depict the training phase and detection phase of a DL-based detector. The training phase consists of Steps 1, 2, and 3; the detection phase consists of Steps 1, 2, and 4. These steps are elaborated below.

**Step 1: generating code fragments.** In the training phase, training programs are used to train a DL-based detector. In
Table 3: Experimental results showing that the 4 DL-based detectors are lack of robustness against code transformations (metrics unit: %)

| Program Slice + Sequence + BGRU | Function + Sequence + CNN | Function + Sequence + BLSTM | Function + ASI + BLSTM |
|----------------------------------|---------------------------|-----------------------------|-------------------------|
| **CT-1**                         | **CT-2**                  | **CT-3**                    | **CT-4**                |
| n/a                             | n/a                       | n/a                         | n/a                     |
| PPR 7.0                         | PPR 16.7                  | PPR 22.7                    | PPR 24.0                |
| FNR 9.9                         | FNR 67.9                  | FNR 75.4                    | FNR 77.7                |
| F1 88.1                        | F1 39.3                    | F1 47.8                     | F1 60.7                 |
| **Total**                       | **Total**                 | **Total**                   | **Total**               |
| 19.9                            | 68.1                      | 35.7                        | 47.0                    |

Step 4: detecting vulnerabilities. This step only applies to the detection phase. It uses the trained DL-based detector to determine whether a vector, which corresponds to a code fragment extracted from a target program, is vulnerable or not.

3.2 System and Threat Model

In the system model, we consider a defender, denoted \( D \). The defender trains a DL-based detector, denoted by \( D \), from a set of training programs \( P = \{p_1, \ldots, p_n\} \). Let \( M \) be the set of all possible code transformation methods whereby one can modify or manipulate one program into another program such that these two programs have the same semantics, dubbed semantics-preserving code transformations. Let \( P(D, q) \) denote the probability that program \( q \) is vulnerable, according to detector \( D \). For the given threshold probability \( \delta \), \( D \) predicts \( q \) as vulnerable if \( P(D, q) > \delta \) and non-vulnerable otherwise.

In the threat model, the attacker, denoted by \( A \), has access to a set \( M_A \), where \( M_A \subseteq M \), of code transformation methods by which the attacker can manipulate a program \( q \) into a new program \( q^\ast \) via semantics-preserving code transformations. The attacker’s objective is to induce mistakes from the defender’s detector \( D \), namely achieving:

\[
\Pr(D, q^+) \begin{cases} 
> \delta & \text{if } P(D, q) \leq \delta; \\
\leq \delta & \text{if } P(D, q) > \delta, 
\end{cases}
\]

where \( P(D, q^+) > \delta \) means a false positive and \( P(D, q^+) \leq \delta \) means a false negative. \( A \) may be interested in causing false negatives, which is known as the evasion attack [55].

The design objective is to harden \( D \) into \( D^+ \) such that \( D^+ \) can detect the vulnerability in \( q^\ast \), namely achieving:

\[
\Pr(D^+, q^+) \begin{cases} 
\leq \delta & \text{if } P(D, q) \leq \delta; \\
> \delta & \text{if } P(D, q) > \delta. 
\end{cases}
\]

3.3 The ZigZag Framework

To achieve the design objective, it is intuitive to allow the defender to extend the set \( P \) of training programs into a new set \( P^+ \) by mimicking what the attacker would do to evade \( D \). This enhanced set \( P^+ \) is leveraged to harden \( D \) into \( D^+ \). To produce \( P^+ \), the defender needs to use some semantics-preserving code transformation methods. Let \( M_D \) denote the set of code transformation methods that are available to the defender, where \( M_D \subseteq M \). The goal of the defender is to harden \( D \) into \( D^+ \) to detect the vulnerability in \( q^\ast \), produced by applying some code transformation methods in \( M \) to \( q \).
Why is conventional adversarial training incompetent? It may sound intuitive to use the examples corresponding to the programs in $P^+$ as input to the detector $D$ to train a detector $D'$, which is the conventional adversarial training. However, our experiments show that the effectiveness of $D'$ is far from satisfactory (see Fig. 3 in Section 4.1). This is because the training process tries to make the distribution of the examples corresponding to the programs in $P$ and that corresponding to the programs in $P^+ - P$ similar, causing many examples close to the decision boundary, which would cause misclassifications with small perturbations, as shown in Fig. 4(a).

Basic idea. The ZigZag framework can be seen as a “compiler” that compiles an input DL-based detector, which uses a single classifier, into a robust detector, which uses two classifiers. The key insight is that adversarial vulnerability examples often reside near the boundary of a classifier. Since it is possible that there are always some examples residing near the boundary of any given classifier, the ZigZag framework leverages two classifiers with distant decision boundaries and assures that a successful adversarial example must “fool” these two classifiers, which is harder to achieve when the two classifiers are required to predict consistently. This intuition can be enforced by decoupling feature learning and classifier learning when training a DL-based detector as follows: (i) feature learning aims at optimizing the feature representation such that the two classifiers use different decision boundaries but predict consistently, which implies robust features; and (ii) classifier learning aims at optimizing two classifiers by “pushing” their boundaries away from each other as illustrated in Fig. 4(b) where the ZigZag-enabled detector $D^+$ consists of classifiers $C_1^*$ and $C_2^*$ with distant decision boundaries. Putting the preceding (i) and (ii) together, when the training process converges, a ZigZag-enabled detector is hard to evade because an adversarial example must “fool” both classifiers.

Fig. 3 highlights the ZigZag framework. A ZigZag-enabled detector differs from a DL-based detector in the training phase, as shown in Fig. 3(b) vs. Fig. 3(a). Note that as depicted in Figure 3(c), they share the same detection phase. The training of a DL-based detector has three steps, namely Steps 1, 2, and 3. For training a ZigZag-enabled detector, a new step (Step 0) is introduced and Step 3 is extended to what is called Step 3’.

Step 0: augmenting source code. The input includes (i) the source code of a set of training programs $P$ and (ii) the set of code transformations $M_D$ that is available to the
defender. This step generates a set of programs, denoted by $P^+$, which includes all programs in $P$ and the programs that are transformed from the programs in $P$ via the code transformations in $M_D$, meaning $P \subset P^+$. This step mimics the way a defender generates additional examples for adversarial training [55].

Step 1: generating code fragments. This is the same as in training a DL-based detector.

Step 2: mapping code fragments into vectors. This is the same as in training a DL-based detector.

Step 3': training a ZigZag-enabled detector. The goal of this step is to train vulnerability features robust against code transformations. Denote the set of all code fragments generated from the training programs in $P$, where $x_s$ ($1 \leq s \leq \mu$) is the vector of a code fragment with label $y_s \in \{0, 1\}$ where “0” is non-vulnerable and “1” is vulnerable. We denote the set of all code fragments generated from the manipulated programs in $P^+ - P$ by $X' = \{x'_1, \ldots, x'_s\}$, where $x'_w$ ($1 \leq w \leq \nu$) is the vector of a code fragment with label $y_w \in \{0, 1\}$. This step has three substeps.

Step 3.1: training a feature generator and two classifiers. This substep aims to train a feature generator $F$ and two classifiers $C_1$ and $C_2$ to correctly classify almost all examples in programs in $P$. Let $c_1(x_s, F)$ and $c_2(x_s, F)$ respectively be the probability that $C_1$ and $C_2$ predict $x_s$ as vulnerable when using $F$, where $0 \leq c_1(x_s, F), c_2(x_s, F) \leq 1$. Classifiers $C_1$ and $C_2$ are the same as classifier $C$ except that they use different initial parameter values. We initialize $C_1$ and $C_2$ differently at the beginning of training. We use all examples in $X$ to train $F$, $C_1$, and $C_2$ to minimize the classification loss, which is the sum of cross entropies of $C_1$ and $C_2$:

$$
\min_{F, C_1, C_2} \sum_{i=1}^{2} \left\{ E_{x_s \sim X} \left[ y_s \cdot \log(c_1(x_s, F)) + (1 - y_s) \cdot \log(1 - c_1(x_s, F)) \right] \right\},
$$

where $E_{x_s \sim X}[\cdot]$ denotes the statistical expectation in $X$. Fig. 5(a) illustrates an instance of classification results of $C_1$ and $C_2$ after Step 3.1. Almost all examples from programs in $P$ are correctly classified, while many examples from manipulated programs in $P^+ - P$ are incorrectly classified.

Step 3.2: training two classifiers while attempting to maximize their prediction discrepancy. Because the classifiers $C_1$ and $C_2$ obtained from Step 3.1 may be similar, this substep aims to train $C_1^*$ and $C_2^*$ to maximize their prediction discrepancy. The initial values of $C_1^*$ and $C_2^*$ are $C_1$ and $C_2$ obtained from Step 3.1. For the examples in $X$, we follow the training process of Step 3.1 to minimize the classification loss, because Step 3.1 is able to ensure that there are hardly any incorrectly classified examples in $X$; for the examples in $X'$, we transform the misclassification of examples into the large prediction discrepancy of two classifiers.

Let $c'_1(x_s, F)$ and $c'_2(x_s, F)$ respectively be the probability that $C_1^*$ and $C_2^*$ predict $x_s$ as vulnerable when using feature generator $F$. For the examples in $X$, the classification loss $L_c(X)$ is the sum of cross entropies of $C_1^*$ and $C_2^*$:

$$
L_c(X) = -\sum_{i=1}^{2} \left\{ E_{x_s \sim X} \left[ y_s \cdot \log(c'_1(x_s, F)) + (1 - y_s) \cdot \log(1 - c'_1(x_s, F)) \right] \right\}.
$$

From $X'$, we identify the examples for which $C_1^*$ or $C_2^*$ make an incorrect prediction; we call them hard examples and denote them by a set $X'' \subseteq X'$. Hard examples satisfy (i) $C_1^*$ and $C_2^*$ make different predictions, meaning one makes a wrong prediction, or (ii) both classifiers make wrong predictions. We denote the set of hard examples by $X'' = \{x''_1, \ldots, x''_s\}$, where $x''_d (1 \leq d \leq \gamma)$ is the vector of a code fragment with label $y''_d \in \{0, 1\}$, which is obtained as follows:

$$
X'' = \text{hard_example}(X', \text{binary}(c'_1(x'_w, F)) \neq y'_w \lor \text{binary}(c'_2(x'_w, F)) \neq y'_w),
$$

where binary is a function that maps a probability to a label “1” or “0” and hard_example is a function that outputs the hard examples satisfying $\text{binary}(c'_1(x'_w, F)) \neq y'_w$ or $\text{binary}(c'_2(x'_w, F)) \neq y'_w$. If the probability that an example $x'_w$ is predicted as vulnerable is greater than threshold $\delta$ with $0 < \delta < 1$, the prediction is “1”; otherwise, the prediction is “0”. The discrepancy loss of two classifiers for hard examples $L_h(X'')$ is the absolute values of the difference between the probabilities that two classifiers predict them as vulnerable:

$$
L_h(X'') = E_{x''_d \sim X''} \left[ |c'_1(x''_d, F) - c'_2(x''_d, F)| \right].
$$

In summary, we train $C_1^*$ and $C_2^*$ while using a fixed feature learner $F$ to minimize the classification loss for the examples in $X$ (i.e., minimize $L_c(X)$) and maximize the discrepancy loss of two classifiers for the examples in $X''$ (i.e., minimize $-L_h(X'')$), which can be represented as

$$
\min_{C_1^*, C_2^*} \left[ L_c(X) - L_h(X'') \right].
$$

Fig. 5(b) illustrates the classification of $C_1^*$ and $C_2^*$ after the first iteration in Step 3.2. “Fig. 5(a)→(b)” shows the training of new classifiers, denoted by $C_1^*(1)$ and $C_2^*(1)$ where “1” indicates the first iteration that continues the training but correspondingly starting at $C_1$ and $C_2$ (rather than from scratch). This explains the changes in the two classification boundaries in Fig. 5(b). Note that the training of classification functions penalizes the discrepancy between the classification of $C_1^*(1)$ and that of $C_2^*(1)$. For “Fig. 5(a)→(b)”, the positions of the examples remain unchanged and the decision boundaries are changed because the two classifiers are changed.

Step 3.3: training a feature generator while attempting to minimize the two classifiers’ prediction discrepancy. To generate robust vulnerability features, this substep aims to train the feature generator $F^*$ to learn the features that minimize the prediction discrepancy of $C_1^*$ and $C_2^*$. The initial value of $F^*$ is $F$ obtained from Step 3.1. We use all examples in $X'$ and fixed $C_1^*$ and $C_2^*$ from Step 3.2 to train $F^*$. The objective is to minimize the discrepancy loss of $C_1^*$ and $C_2^*$:

$$
\min_{F^*} \quad E_{x''_d \sim X'} \left[ |c'_1(x''_d, F^*) - c'_2(x''_d, F^*)| \right].
$$
4 Evaluation of ZigZag-enabled Robustness

We conduct experiments on a computer with two NVIDIA GeForce TITAN RTX GPUs and an Intel i9-9900X CPU running at 3.50GHz, and focus on answering the following three Research Questions (RQs):

- **RQ1:** Are ZigZag-enabled detectors robust against code transformations? (Section 4.1)
- **RQ2:** Does the robustness of ZigZag-enabled detectors depend on the defender’s choices of code transformations? (Section 4.2)
- **RQ3:** Are ZigZag-enabled detectors more effective than other widely-used vulnerability detectors? (Section 4.3)

### 4.1 Robustness against Code Transformation Attacks (RQ1)

To evaluate the robustness of ZigZag-enabled detectors against the code transformation attacks, we set $M_{D,1} = \{CT-2, CT-7, CT-8\}$, namely $M_{D,1} \subseteq M_{D}$, as a concrete set of code transformation methods for the defender; we will discuss the impact of different choices of $M_{D,1}$ later. The input training programs are the programs in $P$; the input target programs $Q^+$ are composed of the original test programs $Q$ and their manipulated programs with 8 code transformations. The programs in $P^+$ are generated in Step 0 and contain 26,181 vulnerable examples and 40,994 non-vulnerable examples. We train the four ZigZag-enabled detectors and choose the hyperparameters that lead to the highest F1. Take the “Program Slice + Sequence + BGRU” detector for instance. The main hyperparameters are as follows: the batch size is 64; the number of hidden layers is 2; the dimension of hidden vectors is 900; the dropout is 0.2; the output dimension is 512; the learning rate is 0.002; the number of iterations $\beta$ for Steps 3’2 and 3’3 is 8; and the probability threshold $\delta$ is 0.4.

Table 5 summarizes the experimental results. Compared with four DL-based detectors, four ZigZag-enabled detectors can respectively improve the FPR, FNR, and F1 by 18.4%, 29.4%, and 29.9% on average for target programs $Q^+$. This means that the ZigZag framework can significantly improve the robustness of DL-based detectors, especially program slice-level ones. When compared with three ZigZag-enabled function-level detectors, the ZigZag-enabled program slice-level detector achieves a 10.3% lower FPR, a 5.2% lower FNR, and a 7.5% higher F1 on average, which can be attributed to its finer granularity. In addition, ZigZag-enabled detectors exhibit a similar degree of effectiveness. Taking the “Program Slice + Sequence + BGRU” detector for instance, we observe that the ZigZag-enabled program slice-level detector, when applied to the manipulated programs, can significantly improve the effectiveness in terms of all three metrics. We also observe that the effectiveness with respect to the known code transformations is a little higher than the effectiveness with respect to the unknown code transformations, with a 1.7% lower FPR, a 2.8% lower FNR, and a 3.0% higher F1 on average. This can be explained because the examples, which correspond to target programs and are generated via known code transformations, are more similar to the examples which correspond to the training programs in $P^+$ and are generated via the same code transformations in $M_{D,1}$.

**Comparing effectiveness of $D$, $D'$, and $D^+$**. For each of these detectors, we consider four options: “Program Slice + Sequence + BGRU” vs. “Function + Sequence + CNN” vs. “Function + Sequence + BLSTM” vs. “Function + AST + BLSTM”. Fig. 6 compares FPR, FNR, and F1 of the original detector D trained from $P$, detector $D'$ trained from $P$ (i.e., conventional adversarial training), and ZigZag-enabled detector $D^+$ trained from $P^+$. Consider the “Program Slice + Sequence + BGRU” instances of these detectors. When compared with $D'$, $D^+$ achieves a 6.9% lower FPR, a 12.9% lower FNR, and an 11.9% higher F1 for target programs $Q^+$. Figure 5: The ZigZag framework iteratively tunes the classifiers and the feature generator, where a positive (negative) example indicates a vulnerable (non-vulnerable) code fragment.

| Step | Description |
|------|-------------|
| 3.1  | After Step 3'.1 |
| 3.2  | Changing feature generator |
| 3.3  | Repeating Step 3'.2 and Step 3'.3 multiple times |
| 3.4  | Final classification results |

- A positive example from programs in $P$ |
- A positive example from programs in $P'$ |
- A negative example from programs in $P$ |
- A negative example from programs in $P'$ |
- Decision boundary of classifier |
- ZigZag
Table 5: Effectiveness of the ZigZag-enabled detectors when using $M_{D,1}$ (metrics unit: %)

| Program Slice + Sequence + BGRU | Function + Sequence + CNN | Function + Sequence + BLSTM | Function + AST + BLSTM |
|---------------------------------|----------------------------|----------------------------|-------------------------|
| CI                              | FPR           | FNR           | F1            | FPR           | FNR           | F1            | FPR           | FNR           | F1            |
| n/a                             | 2.2           | 10.9          | 92.0          | 7.5           | 16.3          | 85.5          | 7.5           | 14.3          | 86.6          |
| Known code transformations ($M_{D,1}$) |
| CT-2                            | 6.4           | 15.7          | 85.2          | 15.2          | 30.4          | 72.3          | 19.3          | 19.5          | 76.8          | 17.1          | 18.1          | 78.9          |
| CT-7                            | 8.7           | 19.6          | 81.2          | 22.1          | 33.9          | 66.2          | 22.6          | 20.1          | 74.5          | 19.2          | 21.6          | 75.5          |
| CT-8                            | 8.9           | 19.5          | 81.2          | 23.0          | 35.7          | 64.5          | 20.2          | 23.2          | 73.9          | 19.7          | 22.4          | 74.7          |
| Unknown code transformations ($M_{D,1}$) |
| CT-1                            | 9.8           | 19.1          | 80.3          | 23.5          | 25.1          | 70.9          | 21.3          | 20.9          | 74.6          | 17.9          | 18.7          | 77.8          |
| CT-3                            | 9.7           | 21.2          | 79.5          | 23.3          | 26.7          | 70.2          | 14.9          | 28.1          | 73.9          | 15.8          | 24.3          | 75.8          |
| CT-4                            | 9.4           | 21.7          | 79.5          | 32.4          | 34.5          | 63.1          | 19.5          | 29.2          | 72.3          | 19.7          | 27.1          | 73.4          |
| CT-5                            | 10.3          | 21.6          | 78.8          | 33.4          | 35.5          | 62.1          | 20.8          | 29.5          | 71.4          | 19.2          | 25.4          | 74.8          |
| CT-6                            | 9.5           | 21.7          | 79.4          | 22.6          | 31.7          | 66.8          | 19.6          | 22.3          | 74.2          | 19.7          | 21.8          | 74.0          |
| Total                           | 8.4           | 19.2          | 81.7          | 21.4          | 29.5          | 69.3          | 17.8          | 22.7          | 75.8          | 16.8          | 21.1          | 77.3          |

Figure 6: Comparing the effectiveness of the original detector D trained from P, the detector D’ trained from P+, and the ZigZag-enabled detector D+ trained from P+ with respect to four DL-based detectors, where P+ is derived from P via CT-2, CT-7, and CT-8 in $M_{D,1}$.

When compared with D, D’ achieves a 3.9% lower FPR, a 35.6% lower FNR, and a 34.1% higher F1. The effectiveness gained by the ZigZag framework can be understood as follows. D’ makes the features of the programs in P and their manipulated programs in $P+\ldots P$ similar, which causes their examples close to the decision boundary to be misclassified. In contrast, D+ makes the decision boundaries of two classifiers, $C_1$ and $C_2$, largely discrepant, while reducing their classification errors.

For the computational time cost of the “Program Slice + Sequence + BGRU” detectors, the training and the test time of D are about 2.5 hours and 5.3 hours, respectively; the training and the test time of D’ are about 4.7 hours and 5.3 hours, respectively; the training and the test time of D+ are about 11.5 hours and 5.8 hours, respectively. The test time is relatively long because of the large numbers of test examples, but the averaged test time cost is only 0.029 seconds per test example for D and D’ and 0.032 seconds for D+. The costs of D+ would be justifiable by the enhanced robustness.

Effectiveness of the ZigZag framework when applied to real-world open-source software. As discussed in Section 2.2.4, we can respectively manipulate 19, 8, 10, and 12 vulnerabilities in the aforementioned three real-world open-source software products to evade the four DL-based detectors. Table 6 lists the vulnerabilities detected in these three software products by the four ZigZag-enabled detectors. We observe, for instance, that the “Program Slice + Sequence + BGRU” detector detects all of the 19 vulnerabilities, but there is still much room for improvement because there are 12 vulnerabilities that can be transformed to evade the detector. Another open problem is to explain why some code transformations can evade the detection but others cannot. This leads to:

**Insight 2.** ZigZag-enabled detectors are substantially more robust than the original DL-based detectors and the detectors obtained via conventional adversarial training.

4.2 Dependence on Defender’s Code Transformations (RQ2)

To show whether the robustness of ZigZag-enabled detectors depend on the code transformations used by the defender, namely $M_D$, we consider the following 6 instances of $M_D$: $M_{D,0} = \emptyset$, $M_{D,1} = \{CT-2, CT-7, CT-8\}$, $M_{D,2} = \{CT-3, CT-4, CT-6\}$, $M_{D,3} = \{CT-2, CT-4, CT-5, CT-6\}$, $M_{D,4} = \{CT-1, CT-2, CT-3, CT-4, CT-6, CT-7\}$, and $M_{D,5} = M$. Since the ZigZag-enabled function-level detectors achieve similar results, we consider the ZigZag-enabled “Program Slice + Sequence + BGRU” detector with respect to the 6 instances of $M_D$.

Fig. 7 shows the comparison results. We observe that the ZigZag-enabled detectors using $M_{D,1}$ to $M_{D,5}$ achieve an 11.5% lower FPR, a 47.4% lower FNR, and a 44.1% higher F1 on average, compared with using no code transformations (i.e., $M_{D,0}$). This indicates that introducing known code transformations during training can significantly improve the robustness of DL-based detectors. We also observe that the ZigZag-enabled detectors using $M_{D,1}$ to $M_{D,4}$ and $M_{D,5}$ are very close to each other. Specifically, the former detectors only achieve a 0.4% higher FPR, a 0.9% higher FNR, and a 0.7% lower F1 than the latter on average. This indicates...
Figure 7: Comparing the FPRs, FNRS, and F1s among 6 instances of $M_D$ for the ZigZag-enabled “Program Slice + Sequence + BGRU”

Table 6: The vulnerabilities that are obtained by manipulating the ones in the three real-world software products and detected by the four ZigZag-enabled detectors

Table 7: Comparing the effectiveness of ZigZag-enabled detectors and the vulnerability detectors presented in the literature

4.3 Comparison with Other Vulnerability Detectors (RQ3)

We compare the effectiveness of ZigZag-enabled detectors with other widely-used vulnerability detectors. These vulnerability detectors involve a similarity-based detector VUDDY [9], an open-source rule-based tool Flawfinder [12], a commercial rule-based tool Checkmarx [15], a DL-based function-level detector [34], and a program slice-level detector SySeVR [24]. We choose them because they are widely used to detect vulnerabilities in C programs and they are available to us. We use $M_{D,1}$ available to the defender and use $Q^+$ for test.

Table 7 summarizes the experimental results. We observe that VUDDY [9] has a very high FNR and a low F1 because it can only detect vulnerable functions which are nearly identical to the vulnerable functions in the training programs. Therefore, most code transformations can cause VUDDY to miss vulnerabilities. Flawfinder [12] achieves a high FPR, a high FNR, and a low F1, because it does not use data flow analysis, which causes it to detect vulnerabilities inaccurately. Although Checkmarx [15] adopts data flow analysis, its rules which are defined by human experts are far from perfect, resulting in low effectiveness. The DL-based function-level detector [32] and SySeVR [24] are effective for the original test programs, but their effectiveness drops significantly when applied to the manipulated programs. However, the ZigZag framework can improve their effectiveness significantly. In particular, ZigZag-enabled SySeVR achieves an 8.4% FPR, a 19.2% FNR, and an 81.7% F1 when using $M_{D,1}$, which outperforms all other vulnerability detectors in our experiments. This leads to:

Insight 4. The ZigZag-enabled detectors are much more effective than other kinds of vulnerability detectors when detecting vulnerabilities in manipulated programs.

5 LIMITATIONS AND FUTURE WORK

The present study has some limitations. First, we focus on detecting vulnerabilities in C programs, but the methodology can be adopted or adapted to cope with other programming languages. Experiments need to be conducted for other languages. Second, our experiments only consider 8 code transformations from Tigress, which are sufficient
for demonstrating the feasibility of the attack and the effectiveness of the ZigZag framework. Future studies should investigate all possible code transformations. Third, since existing datasets do not serve our purposes, the effectiveness evaluation is conducted on the dataset we collect from the NVD and SARD, which may raise an external validity issue. We have made our dataset publicly available so that third parties can repeat and validate our experiments. Fourth, the attack against vulnerability detectors incurs a large degree of manipulation to the source code. It is an open problem whether or not ZigZag is effective against adversarial examples generated via small manipulations (assuming it is possible). Fifth, the ZigZag framework uses a pair of classifiers. It is an open problem to investigate whether or not using three or more classifiers would make the resulting detectors more robust.

6 Related Work

Prior studies on detecting vulnerabilities. Our vulnerability detector leverages the static analysis of source code, which is complementary to the dynamic analysis approach [5–8]. Static analysis-based detectors can be further divided into code-similarity-based, rule-based, and machine learning-based detectors. Code similarity-based detectors aim to detect vulnerabilities caused by code clones [9–11]. Rule-based detectors use expert-defined rules to detect vulnerabilities [56], including open-source tools [12–13], commercial tools [15, 16], and academic efforts [17, 18]. Machine learning-based detectors [33] aim to use models learned from expert-defined feature representations of vulnerabilities [19–22] or use DL models without requiring expert-defined feature representations [23–35]. DL-based detectors have received much attention recently. However, the robustness of DL-based detectors is not studied until now.

Prior studies on adversarial examples and training. Adversarial examples have attracted much attention in many domains, such as image processing [56, 57], speech recognition [58], malware detection [59, 60], program analysis [41], and code authorship attribution [44]. To the best of our knowledge, this paper is the first to study adversarial examples in the field of vulnerability detection, which make the DL-based detectors miss the vulnerabilities in the manipulated programs. On the other hand, adversarial training is an important method to improve the robustness of DL-based models in the fields such as image processing [57–59], neural language processing [60, 61], malware detection [62, 63], and source code processing [64–66]. The ZigZag framework proposed in this paper is an innovative adversarial training method for vulnerability detection.

Prior studies on code transformations. Code transformations are widely used for compiler-based optimizations [67–69], program readability and maintainability improvement [70–72], intelligent property protection [73], [74], and program analysis tasks evaluation [75, 76]. Code transformation methods are divided into three classes: semantics-preserving vs. semantics-approximating vs. semantics-changing [76]. There are some code obfuscators or program transformation tools for C programs [50–55]. In this paper, we leverage semantics-preserving transformations to attack DL-based detectors.

7 Conclusion

We studied the robustness of DL-based vulnerability detectors by using experiments to demonstrate that simple attacks can make vulnerabilities evade them. We presented an innovative ZigZag framework to enhance the robustness of DL-based vulnerability detectors. The key insight underlying the framework is to decouple feature learning and classifier learning and make the resulting features and classifiers robust against code transformations. Experimental results show that the ZigZag framework can substantially improve the robustness of DL-based detectors. The limitations discussed in Section 5 offer open problems for future research.

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