Vulnerability Mimicking Mutants

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Abstract—With the increasing release of powerful language models trained on large code corpus (e.g. CodeBERT was trained on 6.4 million programs), a new family of mutation testing tools has arisen with the promise to generate more "natural" mutants in the sense that the mutated code aims at following the implicit rules and coding conventions typically produced by programmers. In this paper, we study to what extent the mutants produced by language models can semantically mimic the observable behavior of security-related vulnerabilities (a.k.a. Vulnerability-mimicking Mutants), so that designing test cases that are failed by these mutants will help in tackling mimicked vulnerabilities. Since analyzing and running mutants is computationally expensive, it is important to prioritize those mutants that are more likely to be vulnerability mimicking prior to any analysis or test execution. Taking this into account, we introduce VMMS, a machine learning based approach that automatically extracts the features from mutants and predicts the ones that mimic vulnerabilities. We conducted our experiments on a dataset of 45 vulnerabilities and found that 16.6% of the mutants fail one or more tests that are failed by 88.9% of the respective vulnerabilities. More precisely, 3.9% of the mutants from the entire mutant set are vulnerability-mimicking mutants that mimic 55.6% of the vulnerabilities. Despite the scarcity, VMMS predicts vulnerability-mimicking mutants with 0.63 MCC, 0.80 Precision, and 0.51 Recall, demonstrating that the features of vulnerability-mimicking mutants can be automatically learned by machine learning models to statically predict these without the need of investing effort in defining such features.

I. INTRODUCTION

Research and practice with mutation testing have shown that it is one of the most powerful testing techniques [3], [22], [27], [55]. Apart from testing the software in general, mutation testing has been proven to be useful in supporting many software engineering activities which include improving test suite strength [2], [14], selecting quality software specifications [41], [42], [61], among others. Though, its use in tackling software security issues has received little attention. A few works focused on model-based testing [10], [43] and proposed security-specific mutation operators to inject potential security-specific leaks into models that can lead to test cases to find attack traces in internet protocol implementations. Other works proposed new security-specific mutation operators that aim to mimic common security bug patterns in Java [40] and C [45]. These works empirically showed that traditional mutation operators are unlikely to exercise security-related aspects of the applications and thus, the proposed operators attempt to convert non-vulnerable code to vulnerable by mimicking common real-world security bugs. However, patternbased approaches have two major limitations. On one hand, the design of security-specific mutation operators is not a trivial task since it requires manual analysis and comprehension of the vulnerability classes that cannot be easily expanded to the extensive set of realistic vulnerability types (e.g. they restrict to memory [40] and web application [45] bugs). On the other hand, these mutation operators can alter the program semantics in ways that may not be convincing for developers as they may perceive them as unrealistic/uninteresting [6], thereby hindering the usability of the method.

With the aim of producing more realistic and natural code, a new family of tools based on language models has recently arisen. Currently, language models are employed for code completion [39], test oracle generation [62], program repair [15], among many other software engineering tasks. Particularly, language models are been used for mutant generation yielding to several mutation testing tools such as SemSeed [53] and DeepMutation [63]. While these tools are subject to expensive training on datasets containing thousands of buggy code examples, there is an increasing interest in using pretrained language models for mutant generation [5], [21], [56], e.g. a mutation testing tool $\mu BERT$ [21] uses CodeBERT [24] to generate mutants by masking and replacing tokens with CodeBERT predictions.

Since pre-trained language models were trained on large code corpus (e.g. CodeBERT was trained on more than 6.4 million programs), their predictions are typically considered representative of the code produced by programmers. Hence, we wonder:

Are mutation testing tools using pre-trained language models effective at producing mutants that semantically mimic the behaviour of software vulnerabilities?

A positive answer to this question can be a promising prospect for the use of these security-related mutants to form an initial step for defining security-conscious testing requirements. We believe that these requirements are particularly useful when building regression test suites for security intensive applications.

The task of analyzing the mutants, and writing and executing tests, in general, is considered expensive. Despite a large number of mutants created, it is well known that many of them are of low utility, i.e., they do not contribute much to the testing process [2], [31], [37]. Due to this, several mutant selection techniques have been proposed to make mutation testing more cost-effective [13], [38], [48], [50], [70]. Therefore, to make our approach useful in practice, we need to filter and select only specific mutants that resemble the behavior of security issues, especially vulnerabilities.

Taking this into account, we propose to enable securityconscious mutation testing by focusing on a minimal set of mutants that rather behave similarly to vulnerabilities a.k.a. *Vulnerability-mimicking Mutants*. Such mutants are the ones that semantically mimic the observable behavior of vulnerabilities, i.e., a mutant is vulnerability-mimicking when it fails the same tests that are failed by the vulnerability that it mimics, proving its existence in the software a.k.a. *PoV* (Proof of Vulnerability). Using *Vulnerability-mimicking Mutants* as test requirements can guide testers to design test suites for tackling vulnerabilities similar to the mimicked ones.

We conducted experiments on a dataset of 45 reproducible vulnerabilities, with severity ranging from high to medium, and found that for 40 out of 45 vulnerabilities, (i.e., for 88.9% vulnerabilities) there exists at least one mutant that fails one or more tests that are also failed by the respective vulnerabilities. More precisely, 3.9% of the mutants from the entire mutant set are vulnerability-mimicking. Despite being few in quantity, these *Vulnerability-mimicking Mutants* semantically mimic 55.6% of the vulnerabilities, i.e., these mutants fail the "same" tests that are failed by the respective vulnerabilities that they mimicked.

Since such mutants are very few among the large set of mutants generated, we propose *VMMS*¹, a machine learning based approach that automatically learns the features of *Vulnerability-mimicking Mutants* to identify these mutants *statically. VMMS* is very accurate in predicting *Vulnerability-mimicking Mutants* with 0.63 MCC, 0.80 Precision, and 0.51 Recall. This demonstrates that the features of *Vulnerability-mimicking Mutants* can be automatically learned by machine learning models to statically predict these without the need of investing effort in manually defining any related features. We believe that *Vulnerability-mimicking Mutants* can be curity intensive applications, and can be particularly useful in evaluating and comparing fuzzing or other security testing tools. In summary, our paper makes the following contributions:

- We show that mutation testing tools based on language models can generate mutants that mimic real software vulnerabilities. 3.6% of the mutants semantically mimic 25 out of 45 studied vulnerabilities.
- 2) We also show that for most of the vulnerabilities (40 out of 45) there exists at least one mutant that fails the one test finding the vulnerability (although not mimicking it).
- 3) We propose VMMS, a machine-learning based approach for identifying Vulnerability-mimicking Mutants. Our results show that VMMS is very accurate in its predictions as it obtains 0.63 MCC, 0.80 Precision, and 0.51 Recall.

II. BACKGROUND

A. Mutation Testing

Mutation testing is a popular fault-based testing technique [3], [22]. It works by introducing slight syntactic modifications to the original program, a.k.a., *mutants*. These mutants are artificially seeded faults that aim at simulating bugs present in the software. The tester designs test cases in order to *kill* these mutants, i.e., to distinguish the observable behavior between a mutant and the original program. Thus, selecting specific mutants enables testing specific structures of a given language that the testing process seeks [27]. Due to this flexibility, Mutation Testing is used to guide test generation [51], to perform test assessment [49], to uncover subtle faults [14], and to perform strong assertion inference [41].

B. Vulnerabilities

Common Vulnerability Exposures (CVE) [20] defines a security vulnerability as "a flaw in a software, firmware, hardware, or service component resulting from a weakness that can be exploited, causing a negative impact to the confidentiality, integrity, or availability of an impacted component or components.". The inadvertence of a developer or insufficient knowledge of defensive programming usually causes these weaknesses. Vulnerabilities are usually reported in publicly available databases to promote their disclosure and fix. One such example is National Vulnerability Database, aka NVD [46]. NVD is the U.S. government repository of standards based vulnerability management data. All vulnerabilities in the NVD have been assigned a CVE (Common Vulnerabilities and Exposures) identifier. The Common Vulnerabilities and Exposures (CVE) Program's primary purpose is to uniquely identify vulnerabilities and to associate specific versions of codebases (e.g., software and shared libraries) to those vulnerabilities. The use of CVEs ensures that two or more parties can confidently refer to a CVE identifier (ID) when discussing or sharing information about a unique vulnerability.

C. Vulnerability-mimicking Mutants

The issues related to security, especially vulnerabilities have received less attention in the mutation testing literature. As a result, despite its flexibility, mutation testing has not been used as the first line of defense against vulnerabilities. Also, there is no clear definition of *Vulnerability-mimicking Mutants*, (i.e., mutants that mimic the vulnerability behavior) to focus on, in order to perform mutation testing to guarantee the software under analysis is vulnerability-free. Therefore, for the purpose of this study, we use the following definition:

A mutant is vulnerability-mimicking if it fails exactly the same tests that are failed by the vulnerability it mimics, hence having the same observable behavior as the vulnerability.

Since a mutant is a slight syntactic modification to the original program, a large number of mutants are generated during mutation testing which requires analysis and execution with the related test suites. This introduces a problem of identifying

¹Vulnerability Mimicking Mutant Selector (VMMS)

Vulnerability-mimicking Mutants among a huge pile of mutants. In our dataset, *Vulnerability-mimicking Mutants* are 3.9% of the entire lot. To deal with the problem of identification of *Vulnerability-mimicking Mutants*, we introduce *VMMS*, a deep learning based approach that predicts *Vulnerability-mimicking Mutants* without requiring any dynamic analysis.

D. Vul4J

There exist several vulnerability datasets for many programming languages [7], [23], [25]. However, they do not contain bug-witnessing test cases to reproduce vulnerabilities, i.e., Proof of Vulnerability (PoV). Such test cases are essential for this study in order to determine whether generated mutants are Vulnerability-mimicking Mutants, as explained in the section above. In general, it is hard to reproduce exploitation (i.e., PoV) for vulnerabilities. Vul4J [12] is a dataset of real vulnerabilities, with the corresponding fixes and the PoV test cases, that we utilized for this study. Although, due to a few test cases failing even after applying the provided vulnerability-fixes, we had to exclude a few vulnerabilities. In total, we conducted this study on 45 vulnerabilities. In table I, we mention the details of considered vulnerabilities that include CVE ID, CWE ID and description, Severity level (that ranges from 0 to 10, provided by National Vulnerability Database [46]), number of Files and Methods that were modified during the vulnerability fix, and number of Tests that are failed by the vulnerability a.k.a. Proof of Vulnerability (PoV).

E. μ BERT

 $\mu BERT$ [21] is a mutation testing tool that uses a pre-trained language model *CodeBERT* to generate mutants by masking and replacing tokens. $\mu BERT$ takes a Java class and extracts the expressions to mutate. It then masks the token of interest, e.g. a variable name, and invokes CodeBERT to complete the masked sequence (i.e., to predict the missing token). This approach has been proven efficient in increasing the fault detection of test suites [21] and improving the accuracy of learning-based bug-detectors [56] and thus, we consider it as a representative of pre-trained language-model-based techniques. For instance, consider the sequence int total = out.length; taken form Figure 1a, $\mu BERT$ mutates the object field access expression length by feeding CodeBERT with the masked sequence int total = out.<mask>;. CodeBERT predicts the 5 most likely tokens to replace the masked one, e.g., it predicts total, length, size, count and value for the given masked sequence. $\mu BERT$ takes these predictions and generates mutants by replacing the masked token with the predicted ones (per masked token creates five mutants). $\mu BERT$ discards non-compilable mutants and those syntactically the same as the original program (cases in which CodeBERT predicts the original masked token).

III. MOTIVATING EXAMPLES

Figures 1 and 2 show motivating examples of how generated mutants can mimic the behavior of vulnerabilities. Fig. 1 demonstrates the example of high severity (7.5) vulnerability CVE-2018-17201 [18] that allows "Infinite Loop", a.k.a., a loop with unreachable exit condition when parsing input files. This makes the code hang which allows an attacker to perform a Denial-of-Service (DoS) attack. The vulnerable code (Fig. 1a) is fixed with the use of an "if" expression (Fig. 1b) to throw an exception and moves out of the loop in case of such an event. Fig. 1c shows one of *Vulnerability-mimicking Mutants* in which the "if" condition is modified, i.e., the binary operator "<" is modified to "=="." This modification makes the "if" condition never executed, nullifying the fix, and behaving exactly the same as the vulnerable code.

Fig. 2 demonstrates the example of another high severity vulnerability CVE-2018-1000850 [17] that allows "Directory Traversal" that can result in an attacker manipulating the URL to add or delete resources otherwise unavailable to him/her. The vulnerable code (Fig. 2a) is fixed with the use of an "if" expression (Fig. 2b) to throw an exception in case `.' or `..' appears in the "newRelativeUrl" (Fig. 2b). Fig. 2c shows one of *Vulnerability-mimicking Mutants* in which the passed argument is changed from "newRelativeUrl" to "name" which changes the matching criteria, hence nullifying the fix, and introducing same vulnerability behaviour.

IV. APPROACH - VMMS

The main objective of *VMMS* is to predict whether a mutant is likely to be vulnerability-mimicking. In order for our approach to be lightweight in terms of engineering and computational effort, we want *VMMS* to be able to (a) learn relevant features of *Vulnerability-mimicking Mutants* without requiring manual feature definition, and (b) to do so without costly dynamic analysis of mutant executions. To achieve this, we divide our task into two parts: learning a representation of mutants using code embedding technique, and learning to predict based on such embeddings whether or not the represented mutants are *Vulnerability-mimicking Mutants*.

A. Overview of VMMS

Figure 3 shows an overview of *VMMS*. We divide our approach into three steps that we detail later in this section:

- 1) *Building a token representation: VMMS* pre-processes the original code in order to remove irrelevant information and to produce abstracted code, which is then tokenized to form a sequence of tokens. Each mutant is eventually transformed into its corresponding token representation and undergoes the next step.
- Representation learning: We train an encoder-decoder model to generate an embedding, a.k.a. vector representation of the mutant. This step is where VMMS automatically learns the relevant features of mutants without requiring an explicit definition of these features.
- 3) Classification: VMMS trains a classification model to classify the mutants (based on their embeddings) as Vulnerability-mimicking Mutants or not. The true labels used for training the model are obtained by i) replacing the fixed code file with a mutated code file in the project, ii) executing the test suite, iii) checking whether or not

TABLE I: The table records the Vulnerability dataset details that include CVE ID, CWE ID and description, Severity level (that ranges from 0 to 10), number of Files and Methods that were modified during the vulnerability fix, and number of Tests that are failed by the vulnerability a.k.a. Proof of Vulnerability (PoV).

CVE	CWE	CWE description	Severity	# Files	#Methods	Failed Tests
(Vulnerability)		(Common Weakness Enumeration)	(0 - 10)	modified	modified	(PoV)
CVE-2017-18349	CWE-20	Improper Input Validation	9.8	1	1	1
CVE-2013-2186	CWE-20	Improper Input Validation	7.5	1	1	2
CVE-2014-0050	CWE-264	Permissions, Privileges, and Access Controls	7.5	2	5	1
CVE-2018-17201	CWE-835	Loop with Unreachable Exit Condition ('Infinite Loop')	7.5	1	1	1
CVE-2015-5253	CWE-264	Permissions, Privileges, and Access Controls	4.0	1	1	1
HTTPCLIENT-1803	NA	NA	NA	1	1	1
PDFBOX-3341	NA	NA	NA	1	1	1
CVE-2017-5662	CWE-611	Improper Restriction of XML External Entity Reference	7.3	1	2	1
CVE-2018-11797	NA	NA	5.5	1	1	1
CVE-2016-6802	CWE-284	Improper Access Control	7.5	1	1	3
CVE-2016-6798	CWE-611	Improper Restriction of XML External Entity Reference	9.8	1	2	1
CVE-2017-15717	CWE-79	Improper Neutralization of Input During Web Page Generation ('Cross-site Scripting')	6.1	1	2	2
CVE-2016-4465	CWE-20	Improper Input Validation	5.3	1	1	1
CVE-2014-0116	CWE-264	Permissions, Privileges, and Access Controls	5.8	1	4	1
CVE-2016-8738	CWE-20	Improper Input Validation	5.8	1	1	2
CVE-2016-4436	NA	NA	9.8	1	2	1
CVE-2016-2162	CWE-79	Improper Neutralization of Input During Web Page Generation ('Cross-site Scripting')	6.1	1	2	1
CVE-2018-8017	CWE-835	Loop with Unreachable Exit Condition ('Infinite Loop')	5.5	1	2	1
CVE-2014-4172	CWE-74	Improper Neutralization of Special Elements in Output Used by a Downstream Component ('Injection')	9.8	2	2	1
CVE-2019-3775	CWE-287	Improper Authentication	6.5	1	1	1
CVE-2019-5775 CVE-2018-1002200	CWE-22	Improper Limitation of a Pathname to a Restricted	5.5	1	1	1
CVL-2010-1002200	CWL-22	Directory ('Path Traversal')	5.5	1	1	1
CVE-2017-1000487	CWE-78	Improper Neutralization of Special Elements used in an OS Command ('OS Command Injection')	9.8	3	17	12
CVE-2018-20227	CWE-22	Improper Limitation of a Pathname to a Restricted Directory ('Path Traversal')	7.5	1	5	1
CVE-2013-5960	CWE-310	Cryptographic Issues	5.8	1	2	15
CVE-2018-1000854	CWE-510 CWE-74	Improper Neutralization of Special Elements in Output	9.8	1	2	1
CVF 2016 2720	NTA .	Used by a Downstream Component ('Injection')	0.0	1	1	1
CVE-2016-3720	NA OVE (11		9.8	1	1	1
CVE-2016-7051	CWE-611	Improper Restriction of XML External Entity Reference	8.6	1	1	
CVE-2018-1000531	CWE-20	Improper Input Validation	7.5	1	1	1
CVE-2018-1000125	CWE-20	Improper Input Validation	9.8	1	4	
APACHE-COMMONS-001	NA	NA	NA	1	1	
CVE-2013-4378	CWE-79	Improper Neutralization of Input During Web Page Generation ('Cross-site Scripting')	4.3	1	1	1
CVE-2018-1000865	CWE-269	Improper Privilege Management	8.8	1	3	1
CVE-2018-1000089	CWE-532	Insertion of Sensitive Information into Log File	7.4	1	2	1
CVE-2015-6748	CWE-79	Improper Neutralization of Input During Web Page Generation ('Cross-site Scripting')	6.1	1	1	1
CVE-2016-10006	CWE-79	Improper Neutralization of Input During Web Page Generation ('Cross-site Scripting')	6.1	1	1	1
CVE-2018-1000615	NA	NA	7.5	1	1	1
CVE-2017-8046	CWE-20	Improper Input Validation	9.8	2	5	1
CVE-2018-11771	CWE-835	Loop with Unreachable Exit Condition ('Infinite Loop')	5.5	1	1	2
CVE-2018-15756	NA	NA	7.5	1	5	2
CVE-2018-1000850	CWE-22	Improper Limitation of a Pathname to a Restricted Directory ('Path Traversal')	7.5	1	2	3
CVE-2017-1000207	CWE-502	Deservation of Untrusted Data	8.8	1	3	1
CVE-2019-10173	CWE-502 CWE-502	Descrialization of Untrusted Data	9.8	1	7	1
CVE-2019-10175 CVE-2019-12402	CWE-302 CWE-835	Loop with Unreachable Exit Condition ('Infinite Loop')	7.5	1	1	1
CVE-2019-12402 CVE-2020-1953	NA	NA	10.0	1	7	2
0,12,2020,1755	1 1 1 1	1111	10.0	1	'	1 4

the tests failed, and iv) if yes, then matching whether the failed tests are the same as the vulnerability's failed tests.

It is interesting to note that the mutant representation learned by *VMMS* does not depend on a particular vulnerability. *VMMS* rather aims to learn properties of the mutants (and their surrounding context) that are generally vulnerability mimicking. This is in line with the recent work on contextual mutant selection [13], [27], [35] that aims at selecting highutility mutants for mutation testing. This characteristic makes *VMMS* applicable to pieces of code that it has not seen during training. Our results also confirm the capability of *VMMS* to be effective on projects not seen during training. Certainly,

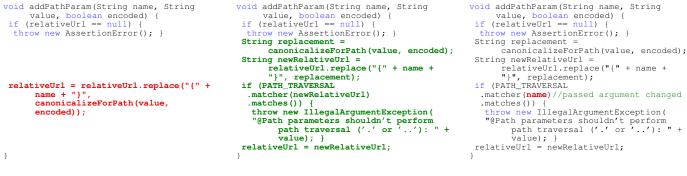
```
private static void decompress
(final InputStream in, final byte[] out)
throws IOException {
                                                                   private static void decompress
                                                                                                                                       private static void decompress
(final InputStream in, final byte[] out)
                                                                      (final InputStream in, final byte[] out)
                                                                     throws IOException {
                                                                                                                                         throws IOException {
                                                                                          = 0;
   int position
                      = 0;
                                                                       int position
                                                                                                                                           int position
                                                                                                                                                               = 0;
                                                                                                                                           final int total = out.length;
while (position < total) {
  final int n = in.read();
      nal int total = out.length;
ile (position < total) {</pre>
                                                                       final int total = out.length;
while (position < total) {</pre>
   final
                                                                       final
                                                                         final
    final int n = in.read();
                                                                                 int n = in.read();
                                                                         if (n < 0) {
  throw new ImageReadException("Error</pre>
                                                                                                                                             if (n == 0) { // `<' modified to `=='
throw new ImageReadException("Error</pre>
                                                                                  decompressing RGBE file"); }
                                                                                                                                                     decompressing RGBE file"); }
                                                                                                                                            if (n > 128) {
    if (n > 128) {
                                                                        if (n > 128) {
      final int value = in.read();
for (int i = 0; i < (n & 0x7f); i++) {
    out[position++] = (byte) value; }</pre>
                                                                         final int value = in.read();
for (int i = 0; i < (n & 0x7f); i++) {
    out[position++] = (byte) value; }
                                                                                                                                              final int value = in.read();
for (int i = 0; i < (n & 0x7f); i++) {</pre>
                                                                                                                                                out[position++] = (byte) value; }
                                                                        } else
    } else {
                                                                                                                                            } else
      for (int i = 0; i < n; i++) {</pre>
                                                                          for (int i = 0; i < n; i++) {</pre>
                                                                                                                                              for (int i = 0; i < n; i++) {</pre>
     out[position++] = (byte) in.read();}
                                                                         out[position++] = (byte) in.read();}
                                                                                                                                              out[position++] = (byte) in.read();}
                                                                     }
```

```
(a) Vulnerable Code (CVE-2018-17201)
```

(b) Fixed Code

(c) Vulnerability-mimicking Mutant

Fig. 1: Vulnerability CVE-2018-17201 (Fig. 1a) that allows "Infinite Loop" making code hang, which further enables Denial-of-Service (DoS) attack is fixed with the conditional exception using "if" expression (Fig. 1b). Vulnerability-mimicking Mutant (Fig. 1c) modifies the "if" condition that nullifies the fix and re-introduces the vulnerability.



(a) Vulnerable Code (CVE-2018-1000850)

(b) Fixed Code

(c) Vulnerability-mimicking Mutant

Fig. 2: Vulnerability CVE-2018-1000850 that allows "Path Traversal", which further enables access to a Restricted Directory (Fig. 2a) is fixed with the conditional exception in case `.' or `..' appears in the "newRelativeUrl" (Fig. 2b). Vulnerability-mimicking Mutant (Fig. 2c) in which the passed argument is changed from "newRelativeUrl" to "name" nullifies the fix and re-introduces the vulnerability.

to make our classifier effective in practice, the selection of the mutant generation technique is important. We use $\mu BERT$ since it produces a sufficiently large set of useful mutants by masking and replacing tokens of the class under analysis. Also, since it employs a pre-trained language model, it proposes code (mutants) similar to the one written by programmers.

B. Token Representation

A major challenge in learning from raw source code is the huge vocabulary created by the abundance of identifiers and literals used in the code [1], [25], [26], [64], [65]. In our case, this large vocabulary may hinder VMMS's ability to learn relevant features of Vulnerability-mimicking Mutants. Thus, we first abstract original (non-mutated) source code by replacing user-defined entities (function names, variable names, and string literals) with generic identifiers that can be reused across the source code file. During this step, we also remove code comments. This pre-processing yields an abstracted version of the original source code, as the abstracted code snippet in Figure 3.

To perform the abstraction, we use the publicly available tool *src2abs* [64]. This tool first discerns the type of each identifier and literal in the source code. Then, it replaces each identifier and literal in the stream of tokens with a unique ID representing the type and role of the identifier/literal in the code. Each ID $\langle TYPE \rangle_{\#}$ is formed by a prefix, (i.e., $\langle TYPE \rangle_{}$) which represents the type and role of the identifier/literal, assigned sequentially while traversing through the code. These IDs are reused when the same identifier/literal appears again in the stream of tokens. Although we use src2abs, any utility that identifiers can be used as an alternative.

Next, to represent a mutant, we annotate the abstracted code with a mutation annotation on the statement next to the operand/operator that has been mutated. These annotations indicate the applied mutation operation, e.g., *BinaryOperator*-

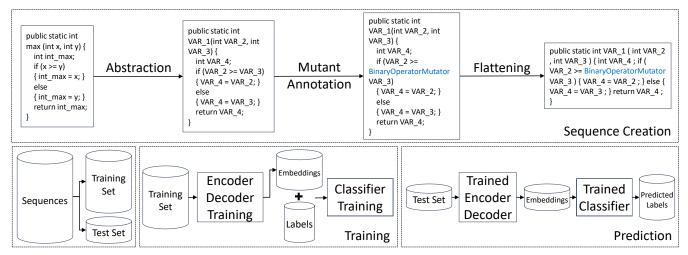


Fig. 3: Overview of *VMMS*: Source code is abstracted and annotated to represent a mutant which is further flattened to create a single-space-separated sequence of tokens. An encoder-decoder model is trained on sequences to generate mutant embeddings. A classifier is trained on these embeddings and their corresponding labels (whether or not the mutants are *Vulnerability-mimicking Mutants*). The trained classifier is then used for label prediction of test set mutants.

Mutator represents mutation on the binary operator ">=", as shown in figure 3. We repeat the process for every mutant.

Finally, we flatten every mutant (by removing newline, extra white space, and tab characters) to create a single-space-separated sequence of tokens. Using these sequences, we intend to capture as much code as possible around the mutant without incurring an exponential increase in training time [25]–[27], [64], [66]. We found a sequence length of 150 tokens to be a good fit for our task as it does not exceed 18 hours of training time (wall clock) on a Tesla V100 GPU.

C. Embedding Learning with Encoder-Decoder

Our next step is to learn the embedding, a.k.a. vector representation (that is later used to train a classification model) from mutants' token representation. We develop an encoder-decoder model, a neural architecture commonly used in representation learning task [36]. The key principle of our encoder-decoder architecture is that the encoder transforms the token representation into an embedding and the decoder attempts to retrieve the original token representation from the encoded embedding. The learning objective is then to minimize the binary cross-entropy between the original token representation and the decoded one. Once the model training has converged, we can compute the embedding from any other mutant's token representation by feeding the latter into the encoder and retrieving the output embedding.

We use a bi-directional Recurrent Neural Network (RNNs) [9] to develop our encoder-decoder, as previous works on code learning have demonstrated the effectiveness of these models to learn useful representations from code sequences [4], [25]–[27], [60]. We build *VMMS* on top of KerasNLP [68] which is a natural language processing library providing a general purpose *Transformer Encoder-Decoder* architecture following the work of Vaswani et. al [67] which has shown to perform good both in software engineering and other learning tasks [25], [26], [59].

To determine an appropriate number of training epochs for model convergence, we conducted a preliminary study involving a small validation set (independent of both the training and test sets used in our evaluation) where we monitor the model's performance in replicating (as output) the same mutant sequence provided as input. We pursue training the model till the training performance on the validation set does not improve anymore. We found 10 epochs for the sequences up to a length of 150 tokens to be a good default for our validation sets.

D. Classifying Vulnerability-mimicking mutants

Next, we train a classification model to predict whether a mutant, which is represented by the embedding produced by the Encoder, is likely to be Vulnerability-mimicking Mutants. The learning objective here is to maximize the classification performance, which we mainly measure with Matthews Correlation Coefficient (MCC), Precision, and Recall, as detailed in section VI-B. To obtain our true classification labels, we replace the fixed code file with a mutated code file in the project, execute the test suite, and check whether or not the tests failed. If the tests fail, we match if the failed tests are the same as the vulnerability's failed tests to determine whether or not the mutant is a vulnerability-mimicking mutant. For developing the classification model, we rely on random forests [8] because these are lightweight to train and have shown to be effective in solving various software engineering tasks [33], [54]. We used standard parameters for random forests, viz. we set the number of trees to 100, use Gini impurity for splitting, and set the number of features (i.e. embedding logits) to consider at each split to the square root of the total number of features.

Once the model training has converged, we use the random forest to predict whether a mutant (in the testing set) is likely to be *Vulnerability-mimicking Mutants*. We make the mutant go through the preprocessing pipeline to obtain its abstract token representation, then feed this representation into the trained encoder-decoder model to retrieve its embeddings, and input this embedding into the classifier to obtain the predicted label (vulnerability-mimicking or not).

V. RESEARCH QUESTIONS

We start our analysis by investigating how many vulnerabilities in our dataset can be behaviourally mimicked by one or more mutants, i.e., how many mutants fail the same PoVs (tests that were failed by the respective vulnerabilities). Therefore we ask:

RQ1 *Empirical observation I:* How many vulnerabilities can be mimicked by the mutants?

For this task, we rely on Vul4J dataset [41] (section II-D) for obtaining vulnerable projects with vulnerabilities, corresponding fixes, and PoV tests, and on $\mu BERT$ [21] (section II-E) for generating mutants. In the Vul4J dataset, the fixes (for the vulnerabilities) passed the corresponding project's test suite (containing the PoV tests) in 45 cases for which we mention the details in Table I. $\mu BERT$ produces mutants of the fixed code, which are checked for mimicking the corresponding vulnerability by replacing the fixed code file with the mutant and executing the test suite. Apart from checking how many vulnerabilities can be mimicked by the mutants, we also analyze how semantically similar the generated mutants are with the vulnerabilities. We measure the semantic similarity of a mutant with the vulnerability by calculating the Ochiai coefficient [47] as explained in the following section VI-A. Hence, we ask:

RQ2 *Empirical observation II:* How similar are the generated mutants with vulnerabilities?

Next, we analyze if the features of *Vulnerability-mimicking Mutants* can be automatically learned by machine learning models to statically predict these without the need of investing effort in defining such features. We do so by training models as explained in section IV and check the performance of *VMMS* in predicting *Vulnerability-mimicking Mutants*. Hence, we ask:

RQ3 *Prediction Performance:* How effective is *VMMS* in automatically defining and learning the features associated with *Vulnerability-mimicking Mutants*?

VI. EXPERIMENTAL SETUP

A. Semantic similarity

Mutation seeds artificial faults, a.k.a. mutants, by performing slight syntactic modifications to the program under analysis. For instance, in Figure 3, the expression $x \ge y$ can be mutated to x < y. Semantic similarity is usually used to evaluate fault seeding [32], [34], [52], i.e. how similar is a mutant (seeded artificial fault) to the desired (real) fault. In the case of this study, the desired fault is the corresponding vulnerability.

To compute the semantic similarity we resort to dynamic test executions. We use a similarity coefficient, i.e., Ochiai coefficient [47], to compute the similarity of the passing and

failing test cases. This is a common practice in many different lines of work, such as mutation testing [32], [52], program repair [30], and code analysis [29] studies. Since semantic similarity compares the behavior between two program versions using a reference test suite, the Ochiai coefficient approximates program semantics using passing and failing test cases.

The Ochiai coefficient represents the ratio between the set of tests that fail in both versions over the total number of tests that fail in the sum of the two. For instance, let P_1 , P_2 , fTS_1 and fTS_2 be two programs and their respective set of failing tests, then the Ochiai coefficient between programs P_1 and P_2 is computed as:

$$Ochiai(P_1, P_2) = \frac{|fTS_1 \cap fTS_2|}{\sqrt{|fTS_1| \times |fTS_2|}}$$

The Ochiai coefficient ranges from 0 to 1, with 0 in case of none of the failed tests is the same between both versions of the programs, (i.e., a mutant and the vulnerability that it is trying to mimic), and 1 in case of all the failed tests match between both versions. Intuitively, a mutant M mimics vulnerability V, if and only if its semantic similarity is equal to 1, i.e., Ochiai(V, M) = 1. The mutants shown in Figures 1 and 2 have an Ochiai coefficient equal to 1 with their corresponding vulnerability.

B. Prediction Performance Metrics

Vulnerability-mimicking Mutants prediction modeling is a binary classification problem, thus it can result in four types of outputs: Given a mutant is vulnerability-mimicking if it is predicted as vulnerability-mimicking, then it is a true positive (TP); otherwise, it is a false negative (FN). Vice-versa, if a mutant does not mimic the vulnerability and, if it is predicted as vulnerability-mimicking then it is a false positive (FP); otherwise, it is a true negative (TN). From these, we can compute the traditional evaluation metrics such as *Precision* and *Recall*, which quantitatively evaluate the prediction accuracy of prediction models.

$$Precision = \frac{TP}{TP + FP} \quad Recall = \frac{TP}{TP + FN}$$

Intuitively, *Precision* indicates the ratio of correctly predicted positives over all the considered positives. *Recall* indicates the ratio of correctly predicted positives over all the actual positives. Yet, these metrics do not take into account the true negatives and can be misleading, especially in the case of imbalanced data. Hence, we complement these with *Matthews Correlation Coefficient (MCC)*, a reliable metric of the quality of prediction models [25], [69]. It is regarded as a balanced measure that can be used even when the classes are of very different sizes [58], e.g. *3.9% Vulnerability-mimicking Mutants* in total, for 45 vulnerabilities in our dataset (as shown in Table II). *MCC* is calculated as:

$$MCC = \frac{TP \times TN - FP \times FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}}$$

MCC returns a coefficient between 1 and -1. An MCC value of 1 indicates a perfect prediction, while a value of -1 indicates

a perfect inverse prediction, i.e., a total disagreement between prediction and reality. MCC value of 0 indicates that the prediction performance is equivalent to random guessing.

C. Experimental Procedure

To answer our RQs, we first execute the test suite for every mutant produced by $\mu BERT$ and analyze which mutants fail the same tests that were failed by the vulnerability to determine *Vulnerability-mimicking Mutants*. In total, $\mu BERT$ produces *16,409* mutants for the fixed versions of the 45 projects (for which the 45 corresponding vulnerabilities are mentioned in Table I). We repeated the test suite execution process for every project to label *Vulnerability-mimicking Mutants* that mimic the corresponding vulnerability.

Once the labeling is complete, to answer *RQ1*, we perform an exact match of the mutant's failed tests with the vulnerability's failed tests to determine how many vulnerabilities are mimicked by the generated mutants. To answer RQ2, we rely on the Ochiai similarity coefficient (elaborated in Section VI-A) to measure how similar the generated mutants are with the vulnerabilities. We calculate the Ochiai coefficient to compute the similarity of the passing and the failing test cases of every vulnerability with all the corresponding project's mutants. To answer RQ3, we train models on Vulnerabilitymimicking Mutants and perform k-fold cross-validation (where k = 5) at project level (our dataset has only 1 vulnerability per project) where each fold contains 9 projects. So, we train on mutants of 36 projects (4 training folds) and test on mutants of the remaining 9 projects (1 test fold). Once we get the predictions for all 45 subjects, we compute the Prediction Performance Metrics (elaborated in Section VI-B) for VMMS in order to show its learning ability.

VII. EXPERIMENTAL RESULTS

A. Empirical observation I (RQ1)

 $\mu BERT$ generates 16,409 mutants in total, for all projects in our dataset. Out of 16,409 mutants, 646 mutants are *Vulnerability-mimicking Mutants* mimicking 25 out of 45 vulnerabilities, i.e., at least one or more mutants behave the same as 25 vulnerabilities. Overall, 3.9% of the generated mutants mimicked 55.6% of the vulnerabilities in our dataset. Table II shows the project-wise distribution of *Vulnerabilitymimicking Mutants* including the total number of mutants generated and the number (and percentage) of mutants that mimic the vulnerabilities. These results are encouraging and evidence the potential value of using *Vulnerability-mimicking Mutants* as test requirements in practice for security-conscious testing, leading to test suites that can tackle similar mimicked vulnerabilities. TABLE II: RQ1: The table records the *Vulnerability-mimicking Mutants* distribution details that include the total number of generate mutants across all the projects with vulnerabilities, and the number and percentage of *Vulnerability-mimicking Mutants* among them. Overall, 3.9% of the generated mutants mimic 55.6% of the vulnerabilities.

CVE	# Total	Vulnerability-mimicking			
(Vulnerability)	π nutants	mutants			
(vullet usinty)	mutunts	(#)	(%)		
CVE-2017-18349	286	0	0%		
CVE-2013-2186	191	0	0%		
CVE-2014-0050	456	0	0%		
CVE-2018-17201	375	8	2.13%		
CVE-2015-5253	257	0	0%		
HTTPCLIENT-1803	553	5	0.9%		
PDFBOX-3341	2169	308	14.2%		
CVE-2017-5662	511	86	16.83%		
CVE-2018-11797	266	1	0.38%		
CVE-2016-6802	338	16	4.73%		
CVE-2016-6798	441	19	4.31%		
CVE-2017-15717	437	77	17.62%		
CVE-2016-4465	48	0	0%		
CVE-2014-0116	167	0	0%		
CVE-2016-8738	50	0	0%		
CVE-2016-4436	74	0	0%		
CVE-2016-2162	169	1	0.59%		
CVE-2018-8017	738	17	2.3%		
CVE-2014-4172	212	12	5.66%		
CVE-2019-3775	9	0	0%		
CVE-2018-1002200	177	0	0%		
CVE-2017-1000487	586	0	0%		
CVE-2018-20227	18	3	16.67%		
CVE-2013-5960	112	1	0.89%		
CVE-2018-1000854	9	2	22.22%		
CVE-2016-3720	387	0	0%		
CVE-2016-7051	387	0	0%		
CVE-2018-1000531	158	2	1.27%		
CVE-2018-1000125	155	14	9.03%		
APACHE-COMMONS-001	144	1	0.69%		
CVE-2013-4378	189	0	0%		
CVE-2018-1000865	432	2	0.46%		
CVE-2018-1000089	205	7	3.41%		
CVE-2015-6748	989	0	0%		
CVE-2016-10006	356	1	0.28%		
CVE-2018-1000615	67	38	56.72%		
CVE-2017-8046	12	0	0%		
CVE-2018-11771	1754	12	0.68%		
CVE-2018-15756	274	0	0%		
CVE-2018-1000850	307	2	0.65%		
CVE-2017-1000207	29	0	0%		
CVE-2019-10173	1658	10	0.6%		
CVE-2019-12402	246	1	0.41%		
CVE-2020-1953	11	0	0%		

Answer to RQ1: $\mu BERT$ -generated 646 out of 16,409 mutants mimicked 25 out of 45 vulnerabilities, i.e., 3.9% of the generated mutants mimicked 55.6% of the vulnerabilities. This evidence that pre-trained language models can produce test requirements (mutants) that behave the same as vulnerabilities, making security-conscious mutation testing feasible.

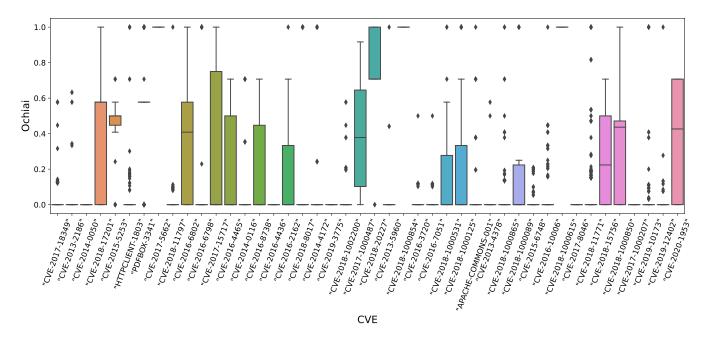


Fig. 4: RQ2: Distribution of the mutant-vulnerability similarity in terms of Ochiai similarity coefficient across all the vulnerabilities when compared for similarity with the generated mutants. Overall, 16.6% of the mutants fail one or more tests that were failed by 88.9% of the respective vulnerabilities.

B. Empirical observation II (RQ2)

In addition to 646 mutants mimicking 25 vulnerabilities, i.e., 646 mutants failed by exactly the same tests as the respective 25 vulnerabilities of the corresponding projects, 2,720 mutants achieved the Ochiai similarity coefficient greater than 0 with 40 vulnerabilities of the corresponding projects. This shows that 2,720 mutants, i.e., 16.6% of the mutants fail one or more tests (of the corresponding projects) that were failed by 40 respective vulnerabilities, i.e., 88.9% of the vulnerabilities in our dataset. Figure 4 provides an overview of the mutant-vulnerability similarity in terms of Ochiai similarity coefficient distribution across all the vulnerabilities in our dataset when compared for similarity with the generated mutants.

Despite not behaving exactly the same as the vulnerability, there are many mutants that share some vulnerable behaviors which can help testers to identify the cause of the vulnerability. Moreover, vulnerability-similar mutants can help to design more thorough and complete suites to tackle vulnerabilities.

Answer to RQ2: $\mu BERT$ -generated 2,720 out of 16,409 mutants achieved an Ochiai similarity coefficient greater than 0 with 40 out of 45 vulnerabilities, i.e., *16.6%* of the generated mutants fail one or more tests (of the corresponding projects) that were failed by 88.9% of the respective vulnerabilities.

C. Prediction Performance (RQ3)

Despite the class imbalance, VMMS effectively predicts Vulnerability-mimicking Mutants with a prediction performance of 0.63 MCC, 0.80 Precision, and 0.51 Recall outperforming a random selection of *Vulnerability-mimicking Mutants* (i.e., MCC equals 0). These scores indicate that the features of *Vulnerability-mimicking Mutants* can be automatically learned by machine learning models to statically predict these without the need of investing effort in defining such features. Indeed, any improvement in the mutation testing tools or the pre-trained language models that allow producing better *Vulnerability-mimicking Mutants*, can leverage *VMMS* to select a more complete set of security-related test requirements.

Answer to RQ3: *VMMS* achieves a prediction performance of 0.63 MCC, 0.80 Precision, and 0.51 Recall in predicting *Vulnerability-mimicking Mutants*. This indicates that the features of *Vulnerability-mimicking Mutants* can be automatically learned by machine learning models to statically prioritize these prior to any analysis or execution.

VIII. THREATS TO VALIDITY

External Validity: Threats may relate to the vulnerabilities we considered in our study. Although our evaluation expands to vulnerabilities of severity ranging from high to low, spanning from single method fix to multiple methods modified during the fix (as shown in Table I, the results may not generalize to other vulnerabilities. We consider this threat of low importance since we verify all the vulnerabilities and also their fixes by executing tests provided in the Vul4J dataset [12]. Moreover, our predictions are based on the local mutant context, which has been shown to be a determinant of mutants' utility [27], [35]. Other threats may relate to the mutant generation tool, i.e., $\mu BERT$ that we used. This choice was made since $\mu BERT$ relies on CodeBERT to produce mutations that look natural and are effective for mutation tesing. We consider this threat of low importance since one can use a better mutant generation tool that can produce more *Vulnerability-mimicking Mutants*, which will help *VMMS* in achieving better prediction performance. Nevertheless, in case other techniques produce different predictions, one could retrain, tune and use *VMMS* for the specific method of interest, as we did here with $\mu BERT$ mutants.

Internal Validity: Threats may relate to the restriction that we impose on sequence length, i.e., a maximum of 150 tokens. This was done to enable reasonable model training time, approximately 18 hours to learn mutant embeddings on Tesla V100 gpu. Other threats may be due to the use of Transformer Encoder-Decoder following the work of Vaswani et. al [67] for learning mutant embeddings. This choice was made for simplicity to use the related framework out of the box similar to the related studies [25], [59]. Other internal validity threats could be related to the test suites we used and the mutants considered as vulnerability mimicking. We used well-tested projects provided by the Vul4J dataset [12]. To be more accurate, our underlying assumption is that the extensive pool of tests including the Proof-of-Vulnerability (PoV) available in our experiments is a valid approximation of the program's test executions, especially the proof of a vulnerability and its verified fix.

Construct Validity: Threats may relate to our metric to measure the semantic similarity of a mutant and a vulnerability, i.e., the Ochiai coefficient. We relied on the Ochiai coefficient because it is widely known in the fault-seeding community as a representative metric to capture the semantic similarity between a seeded and real fault. In the context of this study, the seeded fault is a mutant and the real fault is a vulnerability. We consider this treat of low importance as the Ochiai coefficient takes into consideration the failed tests of a mutant and a vulnerability (as explained in section VI-A) representing the observable behavior and serving its purpose for this study.

IX. RELATED WORK

The unlikelihood of standard PIT [16] operators to produce security-aware mutants was observed by Loise et al. [40] where the authors designed pattern based operators to target specific vulnerabilities. They relied on static analysis for validation of generated mutants to have similarities with their targeted vulnerabilities.

Fault modeling related to security policies was explored by Mouehli et al. [44] where they designed new mutation operators corresponding to fault models for access control security policies. Their designed operators targeted modifying user roles and deleting policy rules to modify application context, specifically targeting the implementation of access control policies. Mutating high-level security protocol language (HLPSL) models to generate abstract test cases was explored by Dadeau et al. [19] where their proposed mutations targeted to introduce leaks in the security protocols. They relied on the automated validation of Internet security protocols and applications tool set to declare the mutated protocol unsafe and capable of exploiting the security flaws.

Targeting black box testing by mutating web applications' abstract models was explored by Buchler et al. [11] where they produced model mutants by removing authorization checks and introducing noisy (non-sanitized) data. They relied on model-checkers to generate execution traces of their mutated models for the creation of intermediate test cases. Their work was focused on guiding penetration testers to find attacks exploiting implementation-based vulnerabilities (e.g., a missing check in a RBAC system, non-sanitized data leading to XSS attacks).

Similar to Loise et al., Nanavati et al. [45] also show that traditional mutation operators only simulate some simple syntactic errors. Hence, they designed memory mutation operators to target memory faults and control flow deviation. They focused on programs in C language and rely on memory allocation primitives in specific to C. Similarly, Shahriar and Zulkernine [57] and Ghosh et al. [28] also defined mutation operators related to the memory faults. Their designed operators also exploited memory manipulation in C programs (such as buffer overflows, uninitialized memory allocations, etc.), which security attacks may exploit. These works also focused on programs in C language.

Unlike the above-mentioned related works, we do not target a specific vulnerability pattern/type. Also, since we rely on a pre-trained language model (employed by $\mu BERT$), we do not require to design specific mutation operators to target specific security issues. Additionally, our validation of vulnerabilitymimicking mutants is not based on a static analysis, but rather a dynamic proof as our produced/predicted vulnerabilitymimicking mutants fails tests that were failed by respective vulnerabilities, a.k.a., Proof-of-vulnerability (PoV).

X. CONCLUSION

In this study, we showed that language model based mutation testing tools can produce *Vulnerability-mimicking Mutants*, i.e., mutants that mimic the observable behavior of vulnerabilities. Since these mutants are a few, i.e., 3.9% of the entire mutant set, there is a need for a static approach to identify such mutants. To achieve this, we presented *VMMS*, a method that learns to select *Vulnerability-mimicking Mutants* from given mutant's code context. Our experiments show that *VMMS* identified *Vulnerability-mimicking Mutants* with 0.63 MCC, 0.80 Precision, and 0.51 Recall, which indicates that the features of *Vulnerability-mimicking Mutants* can be automatically learned by machine learning models to statically predict these without the need of investing effort in defining such features.

REFERENCES

- [1] Uri Alon, Shaked Brody, Omer Levy, and Eran Yahav. code2seq: Generating sequences from structured representations of code. In 7th International Conference on Learning Representations, ICLR 2019, New Orleans, LA, USA, May 6-9, 2019. OpenReview.net, 2019.
- [2] Paul Ammann, Márcio Eduardo Delamaro, and Jeff Offutt. Establishing theoretical minimal sets of mutants. In Seventh IEEE International Conference on Software Testing, Verification and Validation, ICST 2014, March 31 2014-April 4, 2014, Cleveland, Ohio, USA, pages 21–30. IEEE Computer Society, 2014.
- [3] Paul Ammann and Jeff Offutt. Introduction to Software Testing. Cambridge University Press, 2008.
- [4] Dzmitry Bahdanau, Kyunghyun Cho, and Yoshua Bengio. Neural machine translation by jointly learning to align and translate. In 3rd International Conference on Learning Representations, ICLR 2015, San Diego, CA, USA, May 7-9, 2015, Conference Track Proceedings, 2015.
- [5] Patrick Bareiß, Beatriz Souza, Marcelo d'Amorim, and Michael Pradel. Code generation tools (almost) for free? A study of few-shot, pre-trained language models on code. *CoRR*, abs/2206.01335, 2022.
- [6] Moritz Beller, Chu-Pan Wong, Johannes Bader, Andrew Scott, Mateusz Machalica, Satish Chandra, and Erik Meijer. What it would take to use mutation testing in industry - A study at facebook. In 43rd IEEE/ACM International Conference on Software Engineering: Software Engineering in Practice, ICSE (SEIP), pages 268–277. IEEE, 2021.
- [7] Guru Prasad Bhandari, Amara Naseer, and Leon Moonen. Cvefixes: automated collection of vulnerabilities and their fixes from open-source software. In Shane McIntosh, Xin Xia, and Sousuke Amasaki, editors, *PROMISE '21: 17th International Conference on Predictive Models and Data Analytics in Software Engineering, Athens Greece, August 19-20, 2021*, pages 30–39. ACM, 2021.
- [8] Leo Breiman. Random forests. Mach. Learn., 45(1):5-32, 2001.
- [9] Denny Britz, Anna Goldie, Minh-Thang Luong, and Quoc V. Le. Massive exploration of neural machine translation architectures. *CoRR*, abs/1703.03906, 2017.
- [10] Matthias Büchler, Johan Oudinet, and Alexander Pretschner. Security mutants for property-based testing. In Martin Gogolla and Burkhart Wolff, editors, *Tests and Proofs - 5th International Conference*, *TAP@TOOLS 2011, Zurich, Switzerland, June 30 - July 1, 2011. Proceedings*, volume 6706 of *Lecture Notes in Computer Science*, pages 69–77. Springer, 2011.
- [11] Matthias Büchler, Johan Oudinet, and Alexander Pretschner. Semiautomatic security testing of web applications from a secure model. In Sixth International Conference on Software Security and Reliability, SERE 2012, Gaithersburg, Maryland, USA, 20-22 June 2012, pages 253– 262. IEEE, 2012.
- [12] Quang-Cuong Bui, Riccardo Scandariato, and Nicolás E. Díaz Ferreyra. Vul4j: A dataset of reproducible java vulnerabilities geared towards the study of program repair techniques. In 19th IEEE/ACM International Conference on Mining Software Repositories, MSR 2022, Pittsburgh, PA, USA, May 23-24, 2022, pages 464–468. ACM, 2022.
- [13] Thierry Titcheu Chekam, Mike Papadakis, Tegawendé F. Bissyandé, Yves Le Traon, and Koushik Sen. Selecting fault revealing mutants. *Empir. Softw. Eng.*, 25(1):434–487, 2020.
- [14] Thierry Titcheu Chekam, Mike Papadakis, Yves Le Traon, and Mark Harman. An empirical study on mutation, statement and branch coverage fault revelation that avoids the unreliable clean program assumption. In Proceedings of the 39th International Conference on Software Engineering, ICSE 2017, Buenos Aires, Argentina, May 20-28, 2017, pages 597–608. IEEE / ACM, 2017.
- [15] Zimin Chen, Steve Kommrusch, Michele Tufano, Louis-Noël Pouchet, Denys Poshyvanyk, and Martin Monperrus. Sequencer: Sequence-tosequence learning for end-to-end program repair. *IEEE Trans. Software Eng.*, 47(9):1943–1959, 2021.
- [16] Henry Coles, Thomas Laurent, Christopher Henard, Mike Papadakis, and Anthony Ventresque. Pit: A practical mutation testing tool for java (demo). In *Proceedings of the 25th International Symposium on Software Testing and Analysis*, ISSTA 2016, page 449–452, New York, NY, USA, 2016. Association for Computing Machinery.
- [17] Cve-2018-1000850. https://nvd.nist.gov/vuln/detail/ CVE-2018-1000850, (accessed January 10, 2023).
- [18] Cve-2018-17201. https://nvd.nist.gov/vuln/detail/CVE-2018-17201, (accessed January 10, 2023).

- [19] Frédéric Dadeau, Pierre-Cyrille Héam, Rafik Kheddam, Ghazi Maatoug, and Michaël Rusinowitch. Model-based mutation testing from security protocols in HLPSL. *Softw. Test. Verification Reliab.*, 25(5-7):684–711, 2015.
- [20] Definition of vulnerability. https://www.cve.org/ResourcesSupport/ Glossary/#, (accessed January 10, 2023).
- [21] Renzo Degiovanni and Mike Papadakis. μbert: Mutation testing using pre-trained language models. In 15th IEEE International Conference on Software Testing, Verification and Validation Workshops ICST Workshops 2022, Valencia, Spain, April 4-13, 2022, pages 160–169. IEEE, 2022.
- [22] Richard A. DeMillo, Richard J. Lipton, and Frederick G. Sayward. Hints on test data selection: Help for the practicing programmer. *Computer*, 11(4):34–41, 1978.
- [23] Jiahao Fan, Yi Li, Shaohua Wang, and Tien N. Nguyen. A C/C++ code vulnerability dataset with code changes and CVE summaries. In Sunghun Kim, Georgios Gousios, Sarah Nadi, and Joseph Hejderup, editors, MSR '20: 17th International Conference on Mining Software Repositories, Seoul, Republic of Korea, 29-30 June, 2020, pages 508– 512. ACM, 2020.
- [24] Zhangyin Feng, Daya Guo, Duyu Tang, Nan Duan, Xiaocheng Feng, Ming Gong, Linjun Shou, Bing Qin, Ting Liu, Daxin Jiang, and Ming Zhou. Codebert: A pre-trained model for programming and natural languages. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: Findings, EMNLP, volume EMNLP 2020 of Findings of ACL, pages 1536–1547. Association for Computational Linguistics, 2020.
- [25] Aayush Garg, Renzo Degiovanni, Matthieu Jimenez, Maxime Cordy, Mike Papadakis, and Yves Le Traon. Learning from what we know: How to perform vulnerability prediction using noisy historical data. *Empir. Softw. Eng.*, 27(7):169, 2022.
- [26] Aayush Garg, Renzo Degiovanni, Facundo Molina, Mike Papadakis, Nazareno Aguirre, Maxime Cordy, and Yves Le Traon. Assertion inferring mutants. *CoRR*, abs/2301.12284, 2023.
- [27] Aayush Garg, Milos Ojdanic, Renzo Degiovanni, Thierry Titcheu Chekam, Mike Papadakis, and Yves Le Traon. Cerebro: Static subsuming mutant selection. *IEEE Transactions on Software Engineering*, pages 1–1, 2022.
- [28] Anup K. Ghosh, Tom O'Connor, and Gary McGraw. An automated approach for identifying potential vulnerabilities in software. In *Security* and Privacy - 1998 IEEE Symposium on Security and Privacy, Oakland, CA, USA, May 3-6, 1998, Proceedings, pages 104–114. IEEE Computer Society, 1998.
- [29] Nicolas E. Gold, David W. Binkley, Mark Harman, Syed S. Islam, Jens Krinke, and Shin Yoo. Generalized observational slicing for treerepresented modelling languages. In Eric Bodden, Wilhelm Schäfer, Arie van Deursen, and Andrea Zisman, editors, Proceedings of the 2017 11th Joint Meeting on Foundations of Software Engineering, ESEC/FSE 2017, Paderborn, Germany, September 4-8, 2017, pages 547–558. ACM, 2017.
- [30] Claire Le Goues, ThanhVu Nguyen, Stephanie Forrest, and Westley Weimer. Genprog: A generic method for automatic software repair. *IEEE Trans. Software Eng.*, 38(1):54–72, 2012.
- [31] Yue Jia and Mark Harman. Higher order mutation testing. *Inf. Softw. Technol.*, 51(10):1379–1393, 2009.
- [32] Yue Jia and Mark Harman. Higher order mutation testing. *Information and Software Technology*, 51(10):1379–1393, 2009. Source Code Analysis and Manipulation, SCAM 2008.
- [33] Matthieu Jimenez, Renaud Rwemalika, Mike Papadakis, Federica Sarro, Yves Le Traon, and Mark Harman. The importance of accounting for real-world labelling when predicting software vulnerabilities. In Proceedings of the 2019 27th ACM Joint Meeting on European Software Engineering Conference and Symposium on the Foundations of Software Engineering, ESEC/FSE 2019, page 695–705, New York, NY, USA, 2019. Association for Computing Machinery.
- [34] René Just, Darioush Jalali, Laura Inozemtseva, Michael D. Ernst, Reid Holmes, and Gordon Fraser. Are mutants a valid substitute for real faults in software testing? In Shing-Chi Cheung, Alessandro Orso, and Margaret-Anne D. Storey, editors, Proceedings of the 22nd ACM SIGSOFT International Symposium on Foundations of Software Engineering, (FSE-22), Hong Kong, China, November 16 - 22, 2014, pages 654–665. ACM, 2014.
- [35] René Just, Bob Kurtz, and Paul Ammann. Inferring mutant utility from program context. In Proceedings of the 26th ACM SIGSOFT Interna-

tional Symposium on Software Testing and Analysis, Santa Barbara, CA, USA, July 10 - 14, 2017, pages 284–294, 2017.

- [36] Nal Kalchbrenner and Phil Blunsom. Recurrent continuous translation models. In Proceedings of the 2013 Conference on Empirical Methods in Natural Language Processing, EMNLP 2013, 18-21 October 2013, Grand Hyatt Seattle, Seattle, Washington, USA, A meeting of SIGDAT, a Special Interest Group of the ACL, pages 1700–1709. ACL, 2013.
- [37] Marinos Kintis, Mike Papadakis, and Nicos Malevris. Evaluating mutation testing alternatives: A collateral experiment. In 17th Asia Pacific Software Engineering Conference, APSEC 2010, Sydney, Australia, November 30 - December 3, 2010, pages 300–309. IEEE Computer Society, 2010.
- [38] Bob Kurtz, Paul Ammann, Jeff Offutt, Márcio Eduardo Delamaro, Mariet Kurtz, and Nida Gökçe. Analyzing the validity of selective mutation with dominator mutants. In Thomas Zimmermann, Jane Cleland-Huang, and Zhendong Su, editors, Proceedings of the 24th ACM SIGSOFT International Symposium on Foundations of Software Engineering, FSE 2016, Seattle, WA, USA, November 13-18, 2016, pages 571–582. ACM, 2016.
- [39] Fang Liu, Ge Li, Yunfei Zhao, and Zhi Jin. Multi-task learning based pre-trained language model for code completion. In *Proceedings of* the 35th IEEE/ACM International Conference on Automated Software Engineering, page 473–485, New York, NY, USA, 2021. Association for Computing Machinery.
- [40] Thomas Loise, Xavier Devroey, Gilles Perrouin, Mike Papadakis, and Patrick Heymans. Towards security-aware mutation testing. In 2017 IEEE International Conference on Software Testing, Verification and Validation Workshops, ICST Workshops 2017, Tokyo, Japan, March 13-17, 2017, pages 97–102. IEEE Computer Society, 2017.
- [41] Facundo Molina, Marcelo d'Amorim, and Nazareno Aguirre. Fuzzing class specifications. In 44th IEEE/ACM 44th International Conference on Software Engineering, ICSE 2022, Pittsburgh, PA, USA, May 25-27, 2022, pages 1008–1020. ACM, 2022.
- [42] Facundo Molina, Pablo Ponzio, Nazareno Aguirre, and Marcelo F. Frias. Evospex: An evolutionary algorithm for learning postconditions. In 43rd IEEE/ACM International Conference on Software Engineering, ICSE 2021, Madrid, Spain, 22-30 May 2021, pages 1223–1235. IEEE, 2021.
- [43] Tejeddine Mouelhi, Franck Fleurey, Benoit Baudry, and Yves Le Traon. A model-based framework for security policy specification, deployment and testing. In Model Driven Engineering Languages and Systems, 11th International Conference, MoDELS 2008, Toulouse, France, September 28 - October 3, 2008. Proceedings, volume 5301 of Lecture Notes in Computer Science, pages 537–552. Springer, 2008.
- [44] Tejeddine Mouelhi, Yves Le Traon, and Benoit Baudry. Mutation analysis for security tests qualification. In *Testing: Academic and Industrial Conference Practice and Research Techniques - MUTATION* (TAICPART-MUTATION 2007), pages 233–242, 2007.
- [45] Jay Nanavati, Fan Wu, Mark Harman, Yue Jia, and Jens Krinke. Mutation testing of memory-related operators. In *Eighth IEEE International Conference on Software Testing, Verification and Validation, ICST 2015 Workshops, Graz, Austria, April 13-17, 2015*, pages 1–10. IEEE Computer Society, 2015.
- [46] National vulnerability database. https://nvd.nist.gov, (accessed January 10, 2023).
- [47] Akira OCHIAI. Zoogeographical studies on the soleoid fishes found in japan and its neighhouring regions-ii. NIPPON SUISAN GAKKAISHI, 22(9):526–530, 1957.
- [48] A. Jefferson Offutt, Ammei Lee, Gregg Rothermel, Roland H. Untch, and Christian Zapf. An experimental determination of sufficient mutant operators. ACM Trans. Softw. Eng. Methodol., 5(2):99–118, 1996.
- [49] Mike Papadakis, Christopher Henard, Mark Harman, Yue Jia, and Yves Le Traon. Threats to the validity of mutation-based test assessment. In Proceedings of the 25th International Symposium on Software Testing and Analysis, ISSTA 2016, Saarbrücken, Germany, July 18-20, 2016, pages 354–365. ACM, 2016.
- [50] Mike Papadakis, Marinos Kintis, Jie Zhang, Yue Jia, Yves Le Traon, and Mark Harman. Chapter six - mutation testing advances: An analysis and survey. Adv. Comput., 112:275–378, 2019.
- [51] Mike Papadakis and Nicos Malevris. Automatic mutation test case generation via dynamic symbolic execution. In *IEEE 21st International Symposium on Software Reliability Engineering, ISSRE 2010, San Jose, CA, USA, 1-4 November 2010*, pages 121–130. IEEE Computer Society, 2010.

- [52] Mike Papadakis, Donghwan Shin, Shin Yoo, and Doo-Hwan Bae. Are mutation scores correlated with real fault detection?: a large scale empirical study on the relationship between mutants and real faults. In Proceedings of the 40th International Conference on Software Engineering, ICSE 2018, Gothenburg, Sweden, May 27 - June 03, 2018, pages 537–548, 2018.
- [53] Jibesh Patra and Michael Pradel. Semantic bug seeding: a learningbased approach for creating realistic bugs. In Diomidis Spinellis, Georgios Gousios, Marsha Chechik, and Massimiliano Di Penta, editors, ESEC/FSE 2021, pages 906–918. ACM, 2021.
- [54] Gustavo Pinto, Breno Miranda, Supun Dissanayake, Marcelo d'Amorim, Christoph Treude, and Antonia Bertolino. What is the vocabulary of flaky tests? In *Proceedings of the 17th International Conference on Mining Software Repositories*, MSR '20, page 492–502, New York, NY, USA, 2020. Association for Computing Machinery.
- [55] Stuart Reid. Software fault injection: Inoculating programs against errors, by jeffrey voas and gary mcgraw, wiley, 1998 (book review). *Softw. Test. Verification Reliab.*, 9(1):75–76, 1999.
- [56] Cedric Richter and Heike Wehrheim. Learning realistic mutations: Bug creation for neural bug detectors. In 2022 IEEE Conference on Software Testing, Verification and Validation (ICST), pages 162–173, 2022.
- [57] Hossain Shahriar and Mohammad Zulkernine. Mutation-based testing of buffer overflow vulnerabilities. In Proceedings of the 32nd Annual IEEE International Computer Software and Applications Conference, COMPSAC 2008, 28 July - 1 August 2008, Turku, Finland, pages 979– 984. IEEE Computer Society, 2008.
- [58] Martin J. Shepperd, David Bowes, and Tracy Hall. Researcher bias: The use of machine learning in software defect prediction. *IEEE Trans. Software Eng.*, 40(6):603–616, 2014.
- [59] Apeksha Shewalkar, Deepika Nyavanandi, and Simone A. Ludwig. Performance evaluation of deep neural networks applied to speech recognition: Rnn, LSTM and GRU. J. Artif. Intell. Soft Comput. Res., 9(4):235–245, 2019.
- [60] Ilya Sutskever, Oriol Vinyals, and Quoc V. Le. Sequence to sequence learning with neural networks. In Advances in Neural Information Processing Systems 27: Annual Conference on Neural Information Processing Systems 2014, December 8-13 2014, Montreal, Quebec, Canada, pages 3104–3112, 2014.
- [61] Valerio Terragni, Gunel Jahangirova, Paolo Tonella, and Mauro Pezzè. Evolutionary improvement of assertion oracles. In ESEC/FSE '20, USA, November 8-13, 2020, pages 1178–1189. ACM, 2020.
- [62] Michele Tufano, Dawn Drain, Alexey Svyatkovskiy, and Neel Sundaresan. Generating accurate assert statements for unit test cases using pretrained transformers. In *IEEE/ACM AST@ICSE 2022, Pittsburgh, PA, USA, May 21-22, 2022*, pages 54–64. ACM/IEEE, 2022.
- [63] Michele Tufano, Jason Kimko, Shiya Wang, Cody Watson, Gabriele Bavota, Massimiliano Di Penta, and Denys Poshyvanyk. Deepmutation: A neural mutation tool. In *ICSE: Companion Proceedings*, ICSE '20, page 29–32, New York, USA, 2020. ACM.
- [64] Michele Tufano, Jevgenija Pantiuchina, Cody Watson, Gabriele Bavota, and Denys Poshyvanyk. On learning meaningful code changes via neural machine translation. In *ICSE 2019, May 25-31, 2019*, pages 25–36. IEEE / ACM, 2019.
- [65] Michele Tufano, Cody Watson, Gabriele Bavota, Massimiliano Di Penta, Martin White, and Denys Poshyvanyk. An empirical study on learning bug-fixing patches in the wild via neural machine translation. ACM Trans. Softw. Eng. Methodol., 28(4):19:1–19:29, 2019.
- [66] Michele Tufano, Cody Watson, Gabriele Bavota, Massimiliano Di Penta, Martin White, and Denys Poshyvanyk. Learning how to mutate source code from bug-fixes. In 2019 IEEE ICSME 2019, Cleveland, OH, USA, September 29 - October 4, 2019, pages 301–312. IEEE, 2019.
- [67] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Lukasz Kaiser, and Illia Polosukhin. Attention is all you need. In NIPS 2017, December, 2017, pages 5998–6008, 2017.
- [68] Matthew Watson, Chen Qian, Jonathan Bischof, François Chollet, et al. Kerasnlp. https://github.com/keras-team/keras-nlp, 2022.
- [69] Jingxiu Yao and Martin J. Shepperd. Assessing software defection prediction performance: why using the matthews correlation coefficient matters. In EASE '20, April 15-17, 2020, pages 120–129. ACM, 2020.
- [70] Lingming Zhang, Milos Gligoric, Darko Marinov, and Sarfraz Khurshid. Operator-based and random mutant selection: Better together. In ASE 2013, Silicon Valley, CA, USA, November 11-15, 2013, pages 92–102. IEEE, 2013.