DIVERSEVUL: A New Vulnerable Source Code Dataset for Deep Learning Based Vulnerability Detection

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ABSTRACT

We propose and release a new vulnerable source code dataset. We curate the dataset by crawling security issue websites, extracting vulnerability-fixing commits and source codes from the corresponding projects. Our new dataset contains 150 CWEs, 26,635 vulnerable functions, and 352,606 non-vulnerable functions extracted from 7,861 commits. Our dataset covers 305 more projects than all previous datasets combined. We show that increasing the diversity and volume of training data improves the performance of deep learning models for vulnerability detection.

Combining our new dataset with previous datasets, we present an analysis of the challenges and promising research directions of using deep learning for detecting software vulnerabilities. We study 11 model architectures belonging to 4 families. Our results show that deep learning is still not ready for vulnerability detection, due to high false positive rate, low F1 score, and difficulty of detecting hard CWEs. In particular, we demonstrate an important generalization challenge for the deployment of deep learning-based models.

However, we also identify hopeful future research directions. We demonstrate that large language models (LLMs) are the future for vulnerability detection, outperforming Graph Neural Networks (GNNs) with manual feature engineering. Moreover, developing source code specific pre-training objectives is a promising research direction to improve the vulnerability detection performance.

KEYWORDS

datasets, vulnerability detection, deep learning, large language models $\,$

1 INTRODUCTION

Detecting software vulnerabilities is crucial to prevent cybercrimes and economic losses, but to date it remains a hard problem. Traditional static and dynamic vulnerability detection techniques suffer from shortcomings. Given the tremendous success of deep learning in image and natural language applications, it is natural to wonder if deep learning can enhance our ability to detect vulnerabilities [4, 14, 17, 24, 31]. However, as we show in this paper, we still need to overcome many challenges before deep learning can achieve great performance for vulnerable source code detection.

For deep learning to be successful, we need a large dataset of vulnerable source code. We release a new open vulnerability dataset for C/C++, DIVERSEVUL. To curate the dataset, we crawl security issue websites, collect vulnerability reports, extract vulnerability-fixing commits for each vulnerability, clone the corresponding projects,

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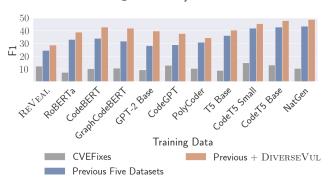


Figure 1: An overview of several of our results. Collecting more data significantly improves performance, collecting more diverse data improves performance, and our new dataset (DIVERSEVUL) yields better models than prior datasets (red bars vs gray bars). If we have enough data, large language models (e.g., NatGen) are superior to previousgeneration models (e.g., REVEAL, a GNN model with manually selected features), but we need large datasets to see these benefits. LLMs are better able to take advantage of larger datasets than previous-generation models. The best LLMs for this task, CodeT5 and NatGen, have been pre-trained with code-specific tasks.

and extract vulnerable and nonvulnerable source code from them. Our dataset contains 26,635 vulnerable functions and 352,606 nonvulnerable functions extracted from 7,861 commits, covering 150 CWEs. This is more than twice the size of the C/C++ data from the previous largest and most diverse dataset CVEFixes [2]. Our dataset is more diverse and covers almost 50% more projects than the combination of all previously published datasets. We will publicly release the DiverseVul dataset to the community.

Our new dataset has enabled us to study the state-of-the-art deep learning methods and gain new insights about promising research directions as well as the challenges for vulnerability detection. In particular, we study several questions. Does more training data help, or are models saturated? Does the model architecture make a big difference? Is it better to use hand-crafted features or generic models? Are larger models better? What are the most promising directions for further improving deep learning for vulnerability detection?

To study the effect of model architectures, we experiment with 11 different deep learning architectures from 4 representative model families: Graph Neural Networks (GNN) [12], RoBERTa [9, 10, 15], GPT-2 [16, 22, 28], and T5 [3, 23, 27]. Much work on deep learning for vulnerability detection used GNNs with hand-crafted features [4, 17, 31]. We also explore applying large language models (LLMs) to vulnerability detection, as LLMs have achieved state-of-the-art results for natural language processing and code understanding, even though they don't use hand-crafted features. We study the performance of these models on three datasets: (1) CVEFixes [2], the largest previously published dataset of C/C++ vulnerabilities; (2) the combination of all previously published datasets (Devign [31], ReVeal [4], BigVul [8], CrossVul [18], CVEFixes [2]), deduplicated; (3) the combination of those previous dataset and our DiverseVul (details in Table 3).

Our experiments show that, when evaluating on prior datasets, the model architecture has little effect and LLMs perform about the same as GNNs. In particular, on CVEFixes, the largest previously released dataset, the ReVeal model (a GNN) achieves 12.3 F1 score, vs F1 scores of 7.4–14.9 for LLMs (see Figure 1). One might be tempted to conclude from this that the exact architecture has little effect. However, with the additional data we collect, we can see that this conclusion is not correct. When evaluating on larger datasets, the conclusion is reversed: LLMs can perform significantly better than GNNs. In particular, when we combine all previously published datasets together with our DIVERSEVUL, the best LLM achieves F1 score of 48.9, vs 28.9 for ReVeal.

These experiments show that we need large datasets to reliably evaluate deep learning approaches to vulnerability detection, as the relative performance of different architectures shifts radically as we increase the amount of training data available. They also show that gathering more data is a promising direction to improving vulnerability detection using deep learning: a 5× increase in the amount of training data (from CVEFixes to all datasets) improved the performance of our best model from 10.5 to 48.9 F1 score. They suggest that LLMs are better able to make use of large datasets than GNNs: larger datasets improve the performance of ReVeal only modestly, but improve the performance of LLMs significantly. Our experiments also suggest that diversity in training data are helpful for improving performance. Our dataset improves diversity by containing vulnerability from 809 different projects, which is over 40% more than the largest previous dataset.

Unfortunately, the state-of-the-art deep learning techniques are still not ready for vulnerability detection yet. Our best model has 48.9% F1 score, 44.4% true positive rate, and 3.5% false positive rate. The false positive rate is still far too high for the model to be practically useful. A project might contain tens of thousands of functions, and this false positive rate corresponds to hundreds of false positives, which is more than most analysts are likely to be willing to wade through [1].

Despite the challenges, Figure 1 shows that large language models (LLMs) are the future for deep learning based vulnerability detection. In previous papers, researchers believe that GNN with manual feature engineering is promising for vulnerability detection [4, 17, 31], since it combines domain knowledge with deep learning. In contrast, our results show that large language models (RoBERTa, GPT-2, and T5 families) significantly outperform GNNs,

especially when training with more data. In particular, CodeT5 models (CodeT5 Small, CodeT5 Base, NatGen) are the best.

Contrary to the common belief that model size is the most important factor for LLMs to perform well, our results show that the most important factor may be how the LLM is trained. Pretraining on code understanding tasks appears to offer large improvements. For example, CodeT5 Small is pretrained to predict variable and function names, and it can achieve an average of 6 percentage points higher F1 score than models that are twice its size but were not pretrained on code. Surprisingly, we found that pretraining tasks that are effective for natural language do not help vulnerability detection much. Instead, it appears we need code-specific pretraining tasks. We think that developing better code-specific pretraining tasks is a promising research direction for improving deep learning based vulnerability detection.

Lastly, we identify an important generalization challenge for the deployment of deep learning based models, which has not been appreciated in previous papers. To deploy a model we need to detect vulnerabilities from new software projects that do not appear in the training set. We found that deep learning models perform very poorly in this setting. In particular, past work has split data into training and test sets by a random split of the vulnerabilities, without regard to which project each vulnerability appears in. However, in practice, we often want to run a vulnerability detection tool on a new project, so there won't be any vulnerabilities from that project in the training set. To evaluate the performance of deep learning in this setting, we set aside a held-out set of projects, which we call "unseen projects"; we train on vulnerabilities from the other projects ("seen projects"), and then test on vulnerabilities from unseen projects. The performance of all models on unseen projects decreases significantly, from a F1 score of 51% on seen projects to only 10% on unseen projects. The cause is unclear; perhaps the model is overfitting to patterns or coding idioms that are specific to the particular projects that appear in the training set. This generalization failure is likely to be a significant barrier to deploying deep learning vulnerability detection in practice. We hope future research will explore how to address this problem. We suggest a simple intervention to use class weights in the training loss, that takes a small step in this direction, but the gap remains very large and more work is needed.

We make the following contributions in this paper:

- We release DIVERSEVUL, a new C/C++ vulnerable source code dataset. Our dataset is twice the size of the previous largest dataset for C/C++, and the most diverse compared to all previous datasets. We demonstrate that improving training data diversity helps vulnerability detection performance.
- We study 11 model architectures from 4 different model families. Our results show that large language models are the future for deep learning based vulnerability detection, and developing source-code specific pretraining objectives is a promising research direction.
- We identify challenges of deep learning for vulnerability detection. In particular, we highlight the difficulty of generalizing to unseen projects outside the training set.

2 RELATED WORK

In this section, we analyze previous public vulnerable source code datasets for C/C++, their labeling methods, and how they are used by related works on deep learning for vulnerability detection.

Synthetic Datasets: SATE IV Juliet [21] and SARD [20] are common synthetic datasets used by previous papers [14, 17, 24]. SARD expands on Juliet v1.0 test suite and contains test cases for multiple programming languages. The test cases are highly accurate, and contain a variety of CWEs. However, they are constructed in isolation using known vulnerable patterns, which are designed to evaluate static and dynamic analysis tools. They don't fully capture the complexities of vulnerabilities within the real-world projects. The VulDeePecker [14] dataset focuses on only two CWEs. They selected vulnerabilities from 19 projects according to CVE information from the National Vulnerability Database (NVD) [19], and also combined SARD [20] test cases from these two CWEs. Both VulDeePecker and SARD are semi-synthetic datasets.

Static Analyzer Labels: The Draper [24] dataset generated labels by selecting the alert categories from three static analyzers: Clang, Cppcheck, and Flawfinder. Some categories of alerts were labeled as vulnerable, and some are mapped to non-vulnerable. The labeled dataset is at the function granularity. The quality of the label is unknown, but the label accuracy of static analyzers tend to be low. D2A [30] used differential analysis on the static analyzer (Infer) output over six open-source repositories. Given thousands of version pairs for a github repository, if the static analyzer generates an alert for the version before a git commit, but not after the commit, then D2A labels the alert before the commit as fixing a vulnerability. For the remaining alerts, D2A labels them as unrelated to vulnerabilities. Each data sample is a trace in the alert. The authors of D2A manually reviewed 57 randomly selected samples, and they found the D2A label accuracy to be 53%.

Manual Labeling: The Devign [31] dataset was labeled by three security researchers. They first used keywords to find commits that likely fixed vulnerabilities and commits unrelated to vulnerabilities from four repositories. Then, for the first category, three security researchers manually reviewed these commits by majority vote. Given labels for each commit, Devign extracts the changed function before the commit as the data sample. The authors of Devign released the data for two repositories, FFMPeg and Qemu. This dataset has high quality labels, but manual labeling was very expensive, which costed around 600 man-hours.

Security Issues: Previous datasets that utilize security issues generate high quality labels for vulnerability-fixing commits. The Re-Veal [4] dataset was labeled using the patches to known security issues at Chromium security issues and Debian security tracker. ReVeal considers the changed functions before a security patch (commit) as vulnerable, after the patch as non-vulnerable, and all unchanged functions as non-vulnerable. Table 3 shows that DiverseVul has 26K vulnerable functions, which is 16× the size of ReVeal.

BigVul [8], CrossVul [18] and CVEfixes [2] collect vulnerability-fixing commits from Common Vulnerabilities and Exposures (CVE) records in the NVD [19]. In particular, CVEFixes covers all published CVEs up to 27 August 2022. CVEfixes and CrossVul datasets contain multiple programming languages, and we use their C/C++ data in

Dataset	Granularity	Label Method	Label Acc
SATE IV Juliet [21]	Function	Synthetic	High
SARD [20]	Function	Semi-Synthetic	High
VulDeePecker [14]	Slice	Semi-Synthetic	High
Draper [24]	Function	Static Analyzer Category Filter	Low
D2A [30]	Trace	Static Analyzer Diff Analysis	53%
Devign [31]	Function	Manual	High
REVEAL [4]	Function	Security Issues	High
BigVul [8]	Commit	Security Issues	High
CrossVul [18]	Commit	Security Issues	High
CVEfixes [2]	Commit	Security Issues	High
DiverseVul	Commit	Security Issues	High

Table 1: Labeling method of DIVERSEVUL and previous datasets.

this paper. These three datasets cover a wide range of projects and CWEs. In comparions, our dataset contains more projects, more CWEs, and doubles the amount of vulnerability-fixing commits.

A few other vulnerable source code datasets in C/C++ do not provide vulnerable functions, and therefore we did not include them in our experiments. For example, AOSP [5] collected commits fixing CVEs from the security bulletin of Android Open Source Project (AOSP), which contain patchs to vulnerabilities in Android OS, the Linux kernel, and system on chip manufacturers. PatchDB [26] provides patch information, i.e., code diff.

Security issues represent the high quality labels as a results from manual labeling effort from a community of developers, and they represent in-the-wild vulnerabilities in real-world projects. Therefore, we also collect our new dataset DiverseVul by crawling security issues. Compared to all previous datasets, DiverseVul is the most diverse one, covering the most number of projects. In particular, DiverseVul has vulnerabilities from 305 new projects that have not been collected by any of the previous real-world datasets (Table 3).

DL for Vulnerable Source Code Detection: Previous papers have used LSTM [14], CNNs and RNNs [24], Bidirectional RNNS [13], and Graph Neural Networks [4, 17, 31] to detect vulnerable source code. A recent paper from Thapa et al. [25] shows that on the VulDeePecker [14] dataset containing two CWEs, large language models outperforms BiLSTM and BiGRU models. However, they did not compare against Graph Neural Networks (GNN). In particular, to train a GNN model, we need to represent programs as graphs that contain useful domain knowledge for vulnerability detection. ReVeal [4] used features obtained from code property graph [29]; and VulChecker [17] proposed a new enriched program dependence graph. These papers used relatively small datasets such as ReVeal and Juliet. If we train the models with larger datasets, it is not clear

Model Family	Model Architecture	# Parameters
GNN	REVEAL	1.28M
	RoBERTa	125M
RoBERTa	CodeBERT	125M
	GraphCodeBERT	125M
	GPT-2 Base	117M
GPT-2	CodeGPT	124M
	PolyCoder	160M
	T5 Base	220M
T5	CodeT5 Small	60M
	CodeT5 Base	220M
	NatGen	220M

Table 2: The number of parameters for different models.

whether GNN with feature engineering is still effective compared to large language models.

3 DATA COLLECTION

Our goal is to collect high-quality vulnerability labels from a diverse set of real-world projects. We focus on collecting data from security issues, since they reflect high-quality labels from a community of developers and security analysts. We start by identifying 29 security issue websites, and then narrow it down to 2 websites with most git system commits ¹. From these websites, we crawl the issue title, body, and relevant git commit URLs. Then, we parse the git commit URLs to extract the projects and commit IDs.

Next, we clone the projects and extract the commits from these projects. We identify the C/C++ related code files in the commits. Then, we extract all functions that were changed in these commits, and also functions that did not change in the files. Same as Re-Veal [4], we label the before-commit version of a changed function to be vulnerable, and the after-commit version to be non-vulnerable. We label all the unchanged files to be non-vulnerable. In total, we have collected 7,861 commits from 809 projects, which result in 26,635 vulnerable functions and 352,606 non-vulnerable functions, covering 150 CWEs.

For issue titles that mention the CVE number, we query the National Vulnerability Database API to obtain the CWE information for the issue and the corresponding commit. For issues with developer annotated vulnerability category, we manually map them to top 25 most popular CWEs. About 81% of our data can be mapped to 150 CWE categories.

4 EXPERIMENTS

In this section, we study how our new dataset can improve the performance of deep learning based vulnerability detection. We study 11 model architectures from 4 model families. We also discuss insights learned from these experiments.

4.1 Model Architectures

We study 4 model families, where 3 families are transformer-based large language models (LLM). Within each LLM family, there are different variants of the model pretrained using different objectives. Table 2 summarizes the number of parameters for all model architectures.

4.1.1 Graph Neural Network. Within the Graph Neural Network (GNN) family, we choose to reproduce a representative previous work ReVeal [4].

Given a function, the REVEAL model constructs a graph to represent the function, computes the embedding vector of the graph, and classifies the vector as vulnerable or nonvulnerable. Specifically, the graph representation for the function is a code property graph [29] (CPG). CPG combines Abstract Syntax Tree (AST), Control Flow Graph (CFG), Data Flow Graph (DFG), and Program Dependence Graph (PDG). Each node has the corresponding source code and type, and each edge has a type. The embedding of the graph is a sum of embeddings of the nodes in the graph. To learn the node embeddings, ReVeal uses Gated Graph Neural Networks (GGNN) [12] to recursively update the embeddings of the nodes. The initial embedding of a node is a concatenation of Word2Vec embedding of the code and the categorical type vector. Then, the GGNN training procedure uses the message passing mechanism to update each node embedding according to the node's neighbors in the graph. Finally, after training the GGNN, REVEAL adds two fully-connected layers, rebalances the training set, to learn the final classifier. The total number of parameters of the ReVeal model is 1.28M.

4.1.2 RoBERTa Family. We select three model achitectures from the RoBERTa family: RoBERTa [15], CodeBERT [9], and GraphCode-BERT [10]. All of them have 12 layers of Transformer encoders, 768 dimenional hidden states, 12 attention heads, and 125M model parameters in total. The common pretraining objective for this family is masked language modeling (MLM). The MLM pretraining process randomly masks a percentage of tokens within the input tokens, effectively removing them, and the training goal is to predict the missing tokens.

Roberta [15] is an extension of Bert [7] that makes changes to important hyperparameters, including removing the pretraining objective of predicting the next sentence, as well as using larger mini-batches and learning rates during training. Roberta was pretrained on a union of five datasets: BookCorpus, English Wikipedia, CC-News, OpenWebText, and Stories.

CodeBERT [9] pretrains the model using the CodeSearchNet [11] dataset containing 2.3M functions from six programming languages (Go, Java, JavaScript, PHP, Python, and Ruby). CodeBERT performs MLM pretraining and replaced token detection pretraining. During pretraining, each input is a pair of natural language description and source code, where the text describes the meaning of the code. The MLM pretraining in CodeBERT makes sure that tokens from both the natural language part and the source code part are masked out, and the replaced token detection corrupts both parts of the input as

 $^{^{1}\}mathrm{snyk.io}$ and bugzilla.redhat.com.

well. CodeBERT outperforms RoBERTa on two downstream tasks, natural language code search and code documentation generation.

GraphCodeBERT [10] also uses the CodeSearchNet [11] training datasets. In addition to having the natural language description and the source code parts of the input, GraphCodeBERT pretraining also constructs a third part of the input that captures the data flow between variables in the source code. In addition to MLM pretraining, GraphCodeBERT proposes two new pretraining objectives: edge prediction and node alignment. The edge prediction task maximizes the dot product between embeddings of two nodes if there is an edge, and the node alignment task maximize the dot product between embeddings of the code token and variable token if the variable represents the code token. Over benchmark datasets, GraphCodeBERT outperforms CodeBERT and RoBERTa on code clone detection, code translation, and code refinement tasks.

Note that the training dataset of CodeBERT and GraphCodeBERT does not have programs written in C/C++.

4.1.3 GPT-2 Family. We select three model architecures from the GPT-2 family: GPT-2 Base [22], CodeGPT [16], and PolyCoder [28]. They have 12 layers of Transformer decoders, 768 dimentional hidden embeddings, and 12 attention heads. The size of the models are in Table 2, ranging from 117M to 160M. The common pretraining objective for this family is causal language modeling, i.e., next token prediction. How well a model is pretrained on the causal language modeling is measured by perplexity. A lower perplexity value indicates a better model.

GPT-2 [22] was pretrained on an unreleased WebText dataset, which was collected by scraping web page links on Reddit.

CodeGPT [16] uses the same training objective and architecture of GPT-2, but different training data. The authors select Python and Java codes from CodeSearchNet [11] as the training set, and release several variants of the pretrained CodeGPT models. In this paper, we use an adapted version of CodeGPT pretrained on Java codes. The CodeGPT model was initialized from GPT-2 weights, and then pretrained using Java codes from CodeSearchNet using the next token prediction task. Note that there is no C/C++ programs in the training set.

PolyCoder [28] uses the same model architecture and pretrianing objective as GPT-2, but pretrains the model from scratch. The authors pretrained the model with data from GitHub containing both source code and natural language comments within the code files. They cloned a total of 147,095 projects, that are the most popular repositories of 12 popular programming languages with at least 50 stars. Their training data contains over 24K repositories in C/C++. The authors curate an evaluation datasets of codes from unseen repositories. On C programming language, PolyCoder achieves the lowest perplexity value, compared to GPT-Neo, GPT-J, and Codex.

4.1.4 T5 Family. We select four model achitectures from the T5 family: T5 Base [23], CodeT5 Base, CodeT5 Small [27], and Nat-Gen [3]. All models have encoder-decoder Transformer layers. CodeT5 Small has 6 encoder layers and 6 decoder layers, 512 dimensional hidden states, 8 attention heads, and 60M parameters. The other models have 12 encoder layers and 12 decoder layers, 768 dimensional hidden states, 12 attention heads, and 220M parameters.

T5 [23] pretrains the model using the masked language modeling objective. In particular, T5 pretraining procedure randomly

masks spans of tokens. The pretraining dataset is C4 (Colossal Clean Crawled Corpus). The authors curate the C4 dataset by processing the Common Crawl dataset to get hundreds of gigabytes of clean English text.

CodeT5 [27] uses the same underlying transformer architecture as T5. We consider two model sizes in our experiments: CodeT5 Base and CodeT5 small. The CodeT5 Small is the smallest LLM, with one third the model size of other T5 based models, and roughly half the model size of RoBERTa and GPT-2 family models. CodeT5 was pretrained on on both CodeSearchNet data and additional C/C# projects from GitHub. In addition to the masked span prediction objective, CodeT5 utilizes the knowledge about whether a token is an identifier (a variabel name or a function name) and designs two new pretraining tasks. The new pretraining tasks are, masked identifier prediction (masking all identifiers) and identifier tagging (predict whether a token is an identifier).

NatGen [3] proposes a new pretraining objective called "naturalizing" pretraining. The naturalizing pretraining is similar to a code editing process, that takes some weird synthetic code and tranform that into developer-readable code. The authors generate un-natural code by semantic preserving code transformations including adding dead code, changing a while loop to a for loop without variable initialization, renaming variables, and inserting confusing code element, etc. Then, the pretraining objective asks the model to naturlize the code to the original developer-friendly form. The NatGen model starts the pretraining from the CodeT5 Base weights, and then continues the pretraining process using their new pretraining objective. Doing well on the naturalizing pretraining objective requires the model to understand the code well. Compared to CodeT5, NatGen improves the performance over various downstream tasks such as code translation, text to code generation, and bug repair.

4.2 Model Performance with More Data

4.2.1 Dataset Setup. Deep learning models perform well when they are trained on a lot of data. Therefore, we combine non-synthetic datasets with high-quality vulnerability labels from real-world projects, including Devign, ReVeal, BigVul, CrossVul, and CVEFixes (discussed in Table 1). We then combine them with DI-VERSEVUL and remove duplicate samples to create the Previous + DIVERSEVUL dataset, as shown in Table 3.

Table 3 presents the statistics for each of the previous five datasets, as well as our dataset, DIVERSEVUL, and the merged datasets. Compared to all previous datasets, DIVERSEVUL includes a larger number of projects, more CWEs, more vulnerable functions, and more vulnerability-fixing commits. Specifically, DIVERSEVUL contains 26,635 vulnerable functions, of which 21,586 have CWE information, more than twice the number in any previous dataset. Having more data associated with CWE information will provide us with a more comprehensive understanding of model prediction results. The last two rows in Table 3 show the unique new data provided by DIVERSEVUL in the merged datasets after deduplicating samples. Comparing Previous and Previous + DIVERSEVUL datasets, we can see that DIVERSEVUL contains 305 new projects that do not exist in any of the previous datasets. Moreover, DIVERSEVUL provides 17,066 unique new vulnerable functions.

Dataset	# Projects	# CWEs	# Functions	# Vul Func	# Vul Func with CWE Info	# Commits
Devign	2 ▽	N/A	26,037	11,888	N/A	N/A
ReVeal	200	N/A	18,169	1,664	N/A	N/A
BigVul	348	91	264,919	11,823	8,783	3,754
CrossVul*	498	107	134,126	6,884	6,833	3,009
CVEFixes*	564	127	168,089	8,932	8,343	3,614
DiverseVul	809	150	379,241	26,635	21,586	7,861
Previous†	640	140	343,400	30,532	14,159	17,956
Previous + DiverseVul	945	155	552,783	47,598	26,458	22,140

^{†:} We aggregate previous five datasets by combining and deduplicating samples from Devign, ReVeal, BigVul, CrossVul, and CVEfixes.

Table 3: Statistics about previous five datasets, DIVERSEVUL, merged Previous dataset, and Previous + DIVERSEVUL.

For our experiments, we randomly select 80% of the samples from the Previous + DiverseVul dataset as the training set, 10% as the validation set, and 10% as the test set. We also contruct the Previous training and validation sets that only contain the previous five datasets, and training and validation sets that only contain CVE-Fixes data. This allows us to train models with different amounts of data and evaluate how much our dataset helps in improving the model's performance to predict the same test set from Previous + DIVERSEVUL.

4.2.2 Results. For each model architecture in Table 2, we train three models, using CVEFixes, Previous, and Previous + DIVERSE-VUL training datasets. We train the REVEAL models from scratch, and we fine tune the large language models (LLMs) for the vulnerability detection task from pretrained model weights. This gives us 33 models in total. The detailed training setups in our experiments can be found in Appendix A.

Table 4 shows the performance of the models over the same test set from Previous + DIVERSEVUL. The following summarizes the results:

Result 1: Adding DIVERSEVUL to the training set improves the test performance. In all 11 model architectures, we demonstrate that training on DIVERSEVUL on top of existing data helps improve the vulnerability detection performance. Adding DIVERSEVUL in the training set improves the F1 score for all models by 6.4% on average, compared to only training with the Previous dataset.

Result 2: Large language models significantly outperform the GNN-based Reveal model. When trained on Previous + DIVERSEVUL, the F1 score of the Reveal model is 28.83, whereas the F1 scores of LLMs range from 34.49 to 48.87. Figure 1 illustrates the difference in performance between the orange bars representing the different models trained on Previous + DIVERSEVUL. However, when the models are trained solely on CVEFixes data, there is no clear advantage of LLMs over GNN-based Reveal model. Interestingly, training on more data significantly improves the performance of LLMs compared to Reveal. Within the LLMs, the T5 family generally outperforms the Roberta family, which in turn is better

than the GPT-2 family. However, even the best-performing model, NatGen, is not yet suitable for deployment in vulnerability detection, with a 3.51% false positive rate and a 48.87% F1 score. The false positive rate is still too high to be practical, and the F1 score is still low. Nevertheless, we believe that large language models hold promise for deep learning-based vulnerability detection, and it is hopeful to further improve their performance.

Result 3: the three base LLM models, RoBERTa, GPT-2 Base, and T5 Base, have similar performance for vulnerability detection. RoBERTa only uses encoders, GPT-2 only uses decoders, and T5 uses encoder-decoder Transformer layers. Despite the architecture differences, all of these base models have not pretrained on code. We do not observe significant differences in the test performance between these base models.

Result 4: Pretraining on code does not lead to significant improvements in vulnerability prediction, if we only use natural language pretraining tasks. The code models CodeBERT, GraphCodeBERT, CodeGPT, PolyCoder are not significantly better than the corresponding text models RoBERTa and GPT-2 Base. Specifically, when trained on the Previous dataset, CodeBERT and GraphCodeBERT perform similarly to RoBERTa. When trained on the Previous + DIVERSEVUL dataset, CodeBERT and GraphCode-BERT improve the F1 score by around 3% compared to RoBERTa. On the other hand, when trained on Previous dataset, CodeGPT and PolyCoder have up to 2.7% higher F1 scores than GPT-2; but when trained on Previous + DIVERSEVUL, CodeGPT and PolyCoder perform worse than GPT-2. Our findings suggest that pretraining models on code using MLM or next token prediction techniques does not yield significant improvements in detecting C/C++ vulnerabilities. While CodeBERT, GraphCodeBERT, and CodeGPT have not pretrained on C/C++, PolyCoder has pretrained over C/C++ code for next token prediction, which still does not help detecting C/C++ vulnerabilities.

Result 5: Code-specific pretraining tasks on C/C++ make a big difference in improving vulnerability detection performance. The two CodeT5 models and the NatGen model have the best F1 scores. They are pretrained using code-specific pretraining

^{*:} CVEfixes and CrossVul are multi-language datasets. We report numbers for C/C++ code.

^{▼:} Devign authors released data from two repositories: FFMPeg+Qemu. ♦: Chromium and Debian packages.

Model	Model	Pretrain	Pretrain	Code-Specific	Turkuku a Cat	Test on Prev + DIVERSEVUL (%)				
Family	Arch	on Code	on C/C++	Pretrain Task	Training Set	Acc	Prec	Recall	F1	FPR
					CVEFixes	82.54	10.80	14.33	12.31	11.08
GNN	ReVeal				Previous	87.88	23.21	26.31	24.66	7.10
					Prev + DiverseVul	84.90	22.37	40.55	28.83	11.48
					CVEFixes	91.05	32.89	4.17	7.41	0.80
	RoBERTa				Previous	90.51	41.89	27.35	33.09	3.56
					Prev + DiverseVul	90.83	45.45	34.13	38.99	3.84
RoBERTa					CVEFixes	90.95	34.49	6.07	10.33	1.08
RODERTA	CodeBERT	/			Previous	90.59	42.69	28.15	33.93	3.55
					Prev + DiverseVul	89.89	41.61	44.15	42.84	5.82
					CVEFixes	91.11	38.67	6.26	10.78	0.93
	GraphCodeBERT	/		~	Previous	91.05	45.93	24.27	31.76	2.68
					Prev + DiverseVul	89.36	39.46	44.82	41.97	6.45
					CVEFixes	90.79	30.05	5.52	9.33	1.21
	GPT-2 Base				Previous	91.21	47.14	20.30	28.38	2.14
					Prev + DiverseVul	90.73	44.97	35.72	39.81	4.10
GPT-2					CVEFixes	90.20	27.21	8.50	12.95	2.13
GP 1-2	CodeGPT	/			Previous	91.02	45.05	21.40	29.02	2.45
					Prev + DiverseVul	90.77	44.83	32.72	37.83	3.78
					CVEFixes	90.52	27.55	6.43	10.43	1.59
	PolyCoder	/	'		Previous	90.73	42.93	24.33	31.06	3.04
					Prev + DiverseVul	91.12	46.98	27.24	34.49	2.89
					CVEFixes	90.95	32.49	5.12	8.85	1.00
	T5 Base				Previous	91.50	50.84	28.10	36.20	2.55
					Prev + DiverseVul	91.57	51.35	33.23	40.35	2.95
					CVEFixes	90.24	29.59	9.95	14.89	2.22
	CodeT5 Small	/	/	~	Previous	91.28	48.91	36.79	41.99	3.61
T5					Prev + DiverseVul	91.71	52.20	40.33	45.50	3.47
					CVEFixes	90.79	34.38	8.10	13.11	1.45
	CodeT5 Base	~	/	~	Previous	91.49	50.53	37.02	42.74	3.40
					Prev + DiverseVul	91.99	54.16	43.12	48.01	3.43
					CVEFixes	91.01	35.85	6.11	10.45	1.03
	NatGen	~	/	~	Previous	91.65	51.88	37.57	43.58	3.27
					Prev + DiverseVul	92.03	54.32	44.42	48.87	3.51

Table 4: Adding DiverseVul to the training set improves the test performance. We evaluate the models on the same test set from Previous + DiverseVul. For every model architecture, training on Previous + DiverseVul improves the test performance compared to only training on the Previous dataset. There isn't a big difference between model performance across different architectures if we only train on the CVEFixes dataset. However, if we train on larger datasets, large language models significantly outperform the GNN-based ReVeal model. Among them, CodeT5 Small, CodeT5 Base, and NatGen models have the highest F1 scores (in bold). Pretraining the model using code specific pretraining task over C/C++ is very effective.

tasks on C/C++. CodeT5 models use identifier-aware pretraining tasks: masked identifier prediction and identifier tagging. NatGen does additional code naturalizing pretraining on top of CodeT5, such as removing dead code and renaming variables. These pretraining tasks ask the model learn about basic code understanding, which significantly improves the fine-tuned model performance for vulnerability detection task. Note that GraphCodeBERT also does

some code-specific pretraining to learn embeddings from a pair of variables with data flow to have large dot product value. However, since it did not train on C/C++ data, it is unknown whether such pretraining task is effective for vulnerability prediction.

Result 6: Code-specific pretraining task is more important than the model size. Among the best three models with performance numbers in bold in Table 4, the CodeT5 Small model

Percentage	Train	Validation	Previous	Previous + DiverseVul
10%	44,222	5,527	~	/
20%	88,445	11,055	✓	✓
30%	132,667	16,583	✓	✓
40%	176,890	22,111	✓	✓
50%	221,113	27,639	✓	✓
60%	265,335	33,166		✓
70%	309,558	38,694		✓
80%	353,780	44,222		✓
90%	398,003	49,750		✓

Table 5: We set up a more diverse training / validation set by randomly sampling from the training and validation sets in Previous + DiverseVul, and a less diverse training / validation set by only sampling from Previous. The percentage column denotes data volume as a percentage of full training / validation sets in Previous + DiverseVul. Since the size of the Previous data is smaller than Previous + DiverseVul, we only sample it up until 50%.

has only 60M parameters, half of the size of RoBERTa models and GPT-2 models, and less than one third the size of other T5 models. However, CodeT5 Small performs very similar to the largest CodeT5 Base and NatGen models, and it performs better than all the other models. Contrary to the belief that larger models tend to produce better performance, our results show that code-specific pretraining task is more important than the model size for vulnerability detection.

4.3 Dataset Diversity

4.3.1 Dataset Setup. We want to measure the effect of data diversity on model performance for vulnerability detection. We want to compare models trained on two datasets with the same volume, where one is less diverse with only the previous datasets, and one is more diverse with the addition of our dataset DIVERSEVUL.

We run the following experiment ten times. For each run, we randomly split the Previous + DiverseVul into training, validation, and test sets. Then, we simulate the effect of different data volume and diversity by subsampling the training and validation sets. Specifically, we randomly sample a percentage of the training and validation data from the full training and validation data of Previous + DiverseVul, as well as the merged Previous dataset. Then, we train the models, and evaluate them on the same original test set without subsampling.

Table 5 shows the different sizes of subsets we sample from Previous and Previous + DiverseVul. From 10% to 50% volumes of all data, we can sample from both Previous + DiverseVul and Previous. They represent a more diverse training data setting and a less diverse one, when the data volume is the same. Note that the full Previous dataset size is about 62% of the full Previous + DiverseVul, so we don't subsample Previous training data more than 50%. For each run, we training models with different subsets of data under different diversity, and we also train models with the

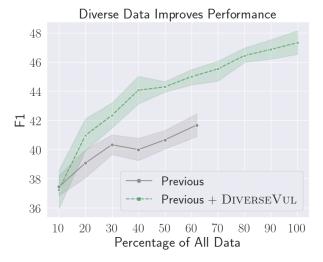


Figure 2: Deep learning for vulnerability source code detection needs more diverse data. We fine-tune CodeT5 Small models on different amounts of vulnerable source code data with different diversity and report the test F1 score. We run each dataset setup 10 times. The lines are the average, and the region denotes 95% confidence interval. This figure shows that, (1) given the same amount of data, the more diverse training set (Previous + DiverseVul) improves the test F1 score on vulnerability detection: the green region has better detection performance compared to the grey region. (2) Training on more data helps the performance even further, and there may potentially be more performance improvement if we collect more data. Note that the size of Previous is only 62% of Previous + DiverseVul, so the data volume for Previous stops at 62% of all data.

full training set from Previous and Previous + DIVERSEVUL. Then, we repeat the experiment ten times.

4.3.2 Results. We fine tune 160 CodeT5 Small models on different dataset setups from 10 experiment runs. Within each run, we evaluate the models on the same final test set from the Previous + DIVERSEVUL, and train 16 models by using different percentages of training and validation data. For each percentage and sample source (✔ in Table 5), we randomly subsample the training and validation sets, and fine tune CodeT5 Small models. Figure 2 plots the average and 95% confidence interval for the test F1 score, when a model is fine tuned from a corresponding dataset setup.

Result 7: Increasing the diversity of the training dataset helps vulnerability detection. Increasing the volume of the training dataset helps too. Our results show that training on a more diverse dataset can improve the test performance by up to 4% F1 score, averaged across 10 runs. If we analyze the region where the dataset volume allows us to sample from both Previous and Previous + DIVERSEVUL (10% to 50%), the green region (Previous + DIVERSEVUL) has better F1 scores than the grey region (Previous) in general.

Moreover, increasing the volume of the training data can also improve the test performance of the model. If we look at the entire

curve and region for Previous + DIVERSEVUL, there is an upward trend of better test F1 score as the volume of training data increases. We suspect that the effect of data volume has not saturated yet, and collecting more data might further improve the performance on vulnerability detection.

4.4 Generalization

Dataset	Total	Train	Validation	Test
Previous	640	545	545	95
Previous + DIVERSEVUL	945	850	850	95

Table 6: Seen and unseen projects split for Previous and Previous + DiverseVul datasets. We randomly reserve 95 projects as unseen test projects. Then, we randomly sample 90% of data from Previous as the training set, and 10% as the validation set. This gives our 545 seen projects in training and validation sets of Previous dataset. We also randomly sample 90% and 10% from Previous + DiverseVul data as the training and validation sets. The training / Validation projects from Previous + DiverseVul are supersets of those from Previous.

4.4.1 Dataset Setup. In a real-world deployment scenario, a vulnerability detection model needs to predict vulnerable source code in new developer projects that it has not been trained on. Therefore, we would like to test a model's performance on unseen projects.

We randomly select 95 unique projects from the merged Previous dataset as the unseen projects test set, to evaluate all models in this experiment. Then, the remaining projects are treated as seen projects in both training set and validation set. For both Previous and Previous + DIVERSEVUL datsets, we randomly sample 90% of the seen projects as the training set, and 10% remaining projects are the validation set. The training and validation sets of Previous + DIVERSEVUL are supersets of these from Previous. Table 6 shows the number of projects in different sets.

4.4.2 Results. We train ReVeal and fine tune each LLM on the seen projects training set from Previous and Previous + DiverseVul, resulting in 22 models in total. We make sure that these models have been trained well, since they have achieved validation performance similar to training performance. Table 7 shows the test performance of these models over unseen projects.

The F1 scores of all models on unseen projects are very low. We highlighted the highest five F1 scores in bold in Table 7. The best models are CodeT5 Base models trained on either training set, and CodeT5 Small, NatGen, ReVeal models trained on Previous + DiverseVul seen projects. The generalization performance of ReVeal is better than Roberta and GPT-2 models, but not as good as the CodeT5 Base models.

Result 8: There is a significant challenge for deep learning models to generalize to unknown test projects on the vulnerability detection task. A popular use case of AI for Code is the GitHub CoPilot, where the AI model suggests ways to complete the code to developers when they are writing code. If AI for deep

learning detection is also a coding assistant, it needs to suggest potential vulnerable functions a developer is writing, in a new project it has not been trained on. Alternatively, static analyzers can be used to examine vulnerabilities in different projects. In a similar use case, deep learning based detection model needs to analyze a new project (after development) it has not seen before. Both of these use cases require the deep learning model to have strong generalization performance to new projects, and it is an open research problem for the community to tackle.

4.5 Weighting

In this section, we investigate whether three simple weighting schemes can potentially improve the model's generalization performance to unseen test projects. The weighting schemes are the following.

4.5.1 Project Balanced Batch Sampler. Our idea is to make the model perform equally well on different projects. Therefore, we propose a batch sampler that is equally likely to sample from any project in the training set. If a project is picked, it then randomly sample from all functions belonging to the project.

4.5.2 Weighted Soft F1 Loss. Since we care about F1 score as the final performance metric, we would like explore if a different loss function helps with improving the generalization performance. We use normalized prediction probabilities (between 0 and 1) from the training samples to calculate true positives, true negatives, false positives, and false negatives, as in floating point numbers. Then, we use these to compute two F1 scores of predicting the positive label (vulnerable function) and the negative label (nonvulnerable functions) separately. The loss for the positive label is 1 - positive F1 score, and the loss for the negative label is 1 - negative F1 score. Finally, we give a higher weight to the first loss value, proportional to the ratio of nonvulnerable to vulnerable functions in the data. Then, we choose the corresponding loss value according to the ground truth class label as the final training loss.

4.5.3 Class Weights for Cross Entropy Loss. In this scheme, we still use cross entropy loss for training. We upweighting the loss value for the positive class (vulnerable class), proportional to the ratio of nonvulnerable samples over vulnerable samples. We use the same loss value for the negative class.

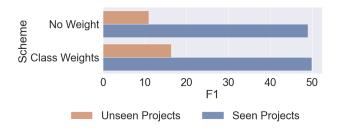


Figure 3: Using class weights in the training loss function improves the generalization performance over unseen projects for CodeT5 Small, and it slightly improves the performance on seen projects as well. The test F1 score on unseen projects is still quite low.

Model	Model	Pretrain	Pretrain	Code-specific	Training Set	Test on Unseen Projects (%)					
Family	Arch	on Code	on C/C++	Pretrain task	Pretrain task		Prec	Recall	F1	FPR	
GNN	ReVeal				Previous	82.88	5.06	20.85	8.14	14.78	
GININ	REVEAL				Prev + DiverseVul	84.8	6.56	24.05	10.31	12.91	
	RoBERTa				Previous	94.69	6.20	3.23	4.25	1.85	
	RODERTA				Prev + DiverseVul	94.37	3.61	2.12	2.67	2.14	
RoBERTa	CodeBERT				Previous	94.94	9.53	4.57	6.17	1.64	
	COUCDERT				Prev + DiverseVul	94.56	4.52	2.45	3.18	1.96	
	GraphCodeBERT	·		_	Previous	95.32	4.64	1.45	2.21	1.12	
	Grapheodebliki				Prev + DiverseVul	94.28	6.46	4.23	5.11	2.32	
	GPT-2 Base				Previous	94.92	6.19	2.78	3.84	1.60	
	Gr 1-2 base				Prev + DiverseVul	94.16	4.53	3.01	3.61	2.40	
GPT-2	CodeGPT			Previous	94.32	5.98	3.79	4.64	2.25		
	Coucorr				Prev + DiverseVul	94.43	5.10	3.01	3.78	2.11	
	PolyCoder	PolyCoder /			Previous	95.41	8.54	2.67	4.07	1.08	
	1 ory coder				Prev + DiverseVul	93.90	6.23	4.79	5.42	2.73	
	T5 Base				Previous	95.67	20.21	6.35	9.66	0.95	
	15 base				Prev + DiverseVul	95.05	13.90	6.90	9.23	1.62	
	CodeT5 Small	·	V		Previous	95.02	12.21	5.90	7.96	1.60	
T5	Code13 Siliali				Prev + DiverseVul	94.56	13.53	9.13	10.9	2.21	
	CodeT5 Base	·	V	_	Previous	95.41	20.65	9.13	12.66	1.33	
	Code13 base				Prev + DiverseVul	94.63	14.04	9.24	11.15	2.14	
	NatGen	\ \	/		Previous	95.48	17.86	6.68	9.72	1.16	
	Natoch				Prev + DiverseVul	94.68	13.06	8.13	10.02	2.05	

Table 7: We randomly choose 95 projects as unseen projects for testing. The remaining projects are used for training. We train each model on seen projects and test them on unseen projects. We highlight the best five F1 scores in bold. Overall, the F1 scores show that these models have poor generalization performance on unseen projects.

Scheme	Train on Seen Projects Test on Unseen Projects (%)					Train on Random Samples Test on Random Samples (%)				
	Acc	Prec	Recall	F1	FPR	Acc	Prec	Recall	F1	FPR
No Weighting	94.56	13.53	9.13	10.90	2.21	91.71	52.20	40.33	45.50	3.47
Project Balanced Batch Sampler	94.20	9.48	6.90	7.99	2.49	89.72	39.60	37.80	38.68	5.41
Weighted Soft F1 Loss	96.33	47.17	5.57	9.96	0.24	90.37	42.67	35.63	38.83	4.49
Class Weights for Cross Entropy Loss	91.36	12.59	23.05	16.29	6.05	88.00	37.99	63.12	47.43	9.67

Table 8: Using class weights for cross entropy loss improves the CodeT5 Small model's performance. In the first case, training on seen projects and testing on unseen projects, class weights improves the test F1 score from 10.9% to 16.29%. In the second case, training and testing on samples drawn from the same distribution, class weights improves the test F1 score from 45.5% to 47.43%.

4.5.4 Results. We follow the same project split dataset setup described in Section 4.4. We fine tune CodeT5 Small models over the seen projects training set from Previous + DIVERSEVUL dataset, and test them on 95 unseen projects. We use four schemes to fine tune four models: no weighting, project balanced batch sampler,

weighted soft F1 loss, and class weights for cross entropy loss. In addition, we fine tune another four models using these schemes over a different data split, the random data split described in Section 4.2.

Result 9: Using class weights for cross entropy loss can improve the model's generalization performance to unseen projects, but there is a lot of room for further improvements.

CWE	Train (%)	Test #	TPR (%)	FPR (%)	
CWE-125	12.99	250	32.40	3.43	Out-of-bounds Read
CWE-190	5.01	104	16.35	3.43	Integer Overflow or Wraparound
CWE-200	5.15	135	31.85	3.43	Exposure of Sensitive Information to an Unauthorized Actor
CWE-20	11.27	238	38.66	3.43	Improper Input Validation
CWE-22	1.11	20	20.00	3.43	Path Traversal
CWE-241	0.33	6	0.00	3.43	Improper Handling of Unexpected Data Type
CWE-269	1.12	22	9.09	3.43	Improper Privilege Management
CWE-276	0.18	2	0.00	3.43	Incorrect Default Permissions
CWE-284	3.38	77	28.57	3.43	Improper Access Control
CWE-287	0.61	8	0.00	3.43	Improper Authentication
CWE-288	0.08	3	0.00	3.43	Authentication Bypass Using an Alternate Path or Channel
CWE-295	0.89	22	9.09	3.43	Improper Certificate Validation
CWE-310	2.00	37	29.73	3.43	Cryptographic Issues
CWE-352	0.11	1	0.00	3.43	Cross-Site Request Forgery (CSRF)
CWE-362	2.64	55	14.55	3.43	Race Condition
CWE-369	1.24	31	32.26	3.43	Divide By Zero
CWE-399	5.60	109	39.45	3.43	Resource Management Errors
CWE-400	2.38	28	0.00	3.43	Uncontrolled Resource Consumption
CWE-401	1.83	40	30.00	3.43	Missing Release of Memory after Effective Lifetime
CWE-415	2.28	61	27.87	3.43	Double Free
CWE-416	5.74	112	12.50	3.43	Use After Free
CWE-434	0.07	1	0.00	3.43	Unrestricted Upload of File with Dangerous Type
CWE-476	7.09	148	14.86	3.43	NULL Pointer Dereference
CWE-502	0.05	3	33.33	3.43	Deserialization of Untrusted Data
CWE-522	0.07	0	N/A	3.43	Insufficiently Protected Credentials
CWE-611	0.09	3	0.00	3.43	Improper Restriction of XML External Entity Reference
CWE-61	0.39	4	0.00	3.43	UNIX Symbolic Link (Symlink) Following
CWE-703	6.36	125	11.20	3.43	Improper Check or Handling of Exceptional Conditions
CWE-787	19.73	424	16.67	3.43	Out-of-bounds Write
CWE-78	0.39	6	29.72	3.43	OS Command Injection
CWE-79	1.59	40	30.00	3.43	Cross-site Scripting
CWE-798	0.01	0	N/A	3.43	Use of Hard-coded Credentials
CWE-862	0.28	2	0.00	3.43	Missing Authorization
CWE-89	0.33	5	40.00	3.43	SQL Injection
CWE-918	0.02	3	0.00	3.43	Server-Side Request Forgery (SSRF)
CWE-94	0.68	12	0.00	3.43	Improper Control of Generation of Code ('Code Injection')

Table 9: We evaluate the prediction performance of the CodeT5 Base model across top-25 CWEs and 8 most popular CWEs in DIVERSEVUL. We highlight the 10 highest training sample percentages and 10 highest TPR numbers in bold. Having more training samples for a specific CWE does not necessarily improve the model's prediction performance, and some CWEs are harder to learn than others. Most CWEs with 0% TPR have under 10 samples in the test set.

Class weights also improve the model's performance if training / testing samples are drawn from the same distribution. Table 8 shows the evaluation results of modeled fine tuned with different schemes. For the seen / unseen projects experiment, the baseline no weighting scheme has 10.9% F1 score. The project balanced batch sampler and weighted soft F1 loss do not help with generalization, which actually result in decreased test F1 score. Using class weights for cross entropy loss is effective at increasing the F1 score from 10.9% to 16.29%.

Figure 3 shows the gap between validation F1 score and test F1 score for two CodeT5 Small models, fine tuned with no weighting scheme and class weights for cross entropy loss. The validation

set contains the same set of known projects in the training set, whereas the test set contains unknown projects. From the bars, we observe that using class weights reduces the gap between validation F1 and unknown projects test F1 scores, with slightly improved validation F1 score. This means that, using class weights improves the performance of the model over samples drawn from the same distribution as well as from a different distribution of new projects. However, there is still a large gap between 49.9% validation F1 and 16.29% test F1. As future research directions of the generalization problem, there is a lot of potential to further improve the model's performance over unknown projects.

4.6 Performance on CWEs

To understand the difficulty of learning different CWEs, we select 33 CWEs to examine the CodeT5 Base model's prediction performance when it is trained on Previous + DiverseVul. The 33 CWEs include top-25 CWEs according to MITRE [6], and eight most popular CWEs in DiverseVul outside the top 25. We select vulnerable functions belonging to these 33 CWEs and all nonvulnerable functions from the Previous + DiverseVul test set obtained from the random split in Section 4.2.

Result 10: Some CWEs are easier to learn than others regardless of the training data size. Table 9 shows the CodeT5 Base model's prediction performance across the 33 CWEs. We have highlighted the 10 most prevalent CWEs in the training set and 10 highest True Positive Rate (TPR) numbers in bold. Note that all CWEs have the same False Positive Rate (FPR) since FPR is only related to nonvulnerable functions. We observe that having more samples for a particular CWE in the training set does not necessarily result in the model learning it better than CWEs with fewer training samples. Moreover, some CWEs with very few training samples are well-detected by the model. For example, CWE-369, CWE-401, CWE-502, CWE-78, CWE-79, CWE-89, all of which account for less than 2% of the training data, have the highest TPRs. This suggests that some CWEs are easier to learn and do not require a large amount of training data, while others are more challenging to learn, even with more training samples. For instance, CWE-416 had 5.74% of the training samples, but its TPR was only 12.5%.

For some CWEs, we do not have enough test samples, resulting in extremely low TPR numbers. The "Test #" column shows the number of vulnerable functions belonging to that CWE in the test set. For CWEs with 0% TPR, most have less than 10 samples in the test set

DIVERSEVUL includes 21,586 vulnerable functions with CWE information. We hope that our dataset will encourage future research into studying hard-to-detect CWEs.

5 LIMITATION

Our dataset, DIVERSEVUL, provides high quality labels for commits that fix vulnerabilities as we source data from security issue websites where security experts have vetted these commits. However, some label noise may be present for vulnerable functions extracted from these commits. To label vulnerable functions, we follow the methodology used in REVEAL [4], BigVul [8], CrossVul [18], and CVEFixes [2], which considers a function vulnerable if it was changed by the vulnerability-fixing commit. Although our labeling technique is state-of-the-art and can scale effectively, we cannot guarantee that every function changed by the commit is vulnerable. Label noise is a common limitation for many security datasets, and we hope that releasing our dataset will enable the community to explore methods to remediate the effects of label noise in the future.

6 CONCLUSION

This paper presents a new dataset, DIVERSEVUL, for detecting software vulnerabilities using deep learning. The dataset contains 150 CWEs, 26,635 vulnerable functions, and 352,606 nonvulnerable functions extracted from 7,861 commits, which is more diverse

and twice the size of the previous largest and most diverse dataset, CVEFixes. We use this new dataset to study the effectiveness of various deep learning architectures in detecting vulnerabilities. We have experimented with 11 different deep learning architectures from four model families: Graph Neural Networks (GNN), RoBERTA, GPT-2, and T5. The results have shown that increasing the diversity and volume of training data is beneficial for vulnerability detection, especially for large language models. Adding the new DIVERSEVUL dataset to the training set improves the performance even further. We have found that developing code-specific pretraining tasks is a promising research direction for deep learning based vulnerability detection, whereas the main challenge is to generalize the deep learning models to unknown projects. We will release the DIVERSEVUL dataset to the community.

ACKNOWLEDGMENTS

This research was supported by the NSF under grant CNS-2154873, by C3.AI's Digital Transformation Institute, and by the Center for AI Safety Compute Cluster. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the sponsors.

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A MODEL TRAINING SETUPS

A.1 REVEAL Setup

We use Joern on GitHub ² to obtain the Code Property Graphs. This is a newer version than what ReVeal used, because if we use the same old version of Joern as in the ReVeal paper, almost half of the functions in all datasets cannot be extracted into graphs.

For the Gated Graph Neural Network, we set maximum training epochs to be 100 and pick the model with the best validation F1 score, for experiments in Section 4.2. We set maximum training

²After commit a6aa08ee9842eedb52e149695e3a34500b6ceab0 on Oct 11, 2022.

epochs to be 60 for experiments in Section 4.4. We follow the original setting in ReVeal source code to use Adam optimizer with learning rate 0.0001, and weight decay 0.001.

To train the classification layers in ReVeal, we set the maximum number of epochs to be 100 in all experiments, and also pick the model with the best validation F1 score after every epoch. We follow the original setting in ReVeal source code to use Adam optimizer with learning rate 0.001, and no weight decay.

A.2 Fine Tuning Setup

To fine tune LLM models, we apply a linear classification head over the Tranformer model, following standard methods. For RoBERTa, CodeBERT, and GraphCodeBERT, we apply the linear layer over the embedding that represents the first token ([CLS]). For GPT-2-Base, CodeGPT, and PolyCoder, we apply the linear layer over the embedding of the last token. For the T5 Base, CodeT5 Small, CodeT5 Base, and NatGen, we apply the linear layer over the embeddings of the last decoder state.

We use training batch size 32, learning rate 2e-5, Adam optimizer, and train for 10 epochs. We use a linear learning rate decay with warm up of 1,000 steps. We check the model's validation performance every 1,000 steps, and save the model with the best validation performance for testing. We use the same learning rate for all models and all training data setups with one exception. When we train Roberta on Previous + DiverseVul from the random data split (in Section 4.2), we use learning rate 1e-5, since a larger learning rate results in a degenerate model that always predicts a function as nonvulnerable.