# AI-Based Software Vulnerability Detection: A Systematic Literature Review

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Software vulnerabilities in source code pose serious cybersecurity risks, prompting a shift from traditional detection methods (e.g., static analysis, rule-based matching) to AI-driven approaches. This study presents a systematic review of software vulnerability detection (SVD) research from 2018 to 2023, offering a comprehensive taxonomy of techniques, feature representations, and embedding methods. Our analysis reveals that 91% of studies use AI-based methods, with graph-based models being the most prevalent. We identify key limitations, including dataset quality, reproducibility, and interpretability, and highlight emerging opportunities in underexplored techniques such as federated learning and quantum neural networks, providing a roadmap for future research.

# CCS Concepts: • Security and privacy $\rightarrow$ Software and application security; • General and reference $\rightarrow$ Surveys and overviews.

Additional Key Words and Phrases: Software Vulnerability Detection, AI-Based Software Vulnerability Detection, Source Code Vulnerability Detection, Systematic Literature Review

# **1 INTRODUCTION**

Software vulnerabilities have been an ever-growing problem over the past decades [1], and despite the vast body of work on software vulnerability detection (SVD) techniques (a.k.a. sanitization techniques) [126], new and more effective techniques are still needed in this area. Software vulnerabilities can have large-scale, damaging impacts as demonstrated, among others, by the infamous vulnerabilities in Apache Log4j2 [99, 100] that affected more than 35K Java packages [169]. Such vulnerabilities are often identified and enumerated in databases such as the Common Vulnerabilities and Exposures (CVEs) <sup>1</sup> for individual vulnerabilities, and Common Weakness Enumeration (CWE) <sup>2</sup> for vulnerability categories. According to the CVE database, the number of reported CVEs has grown substantially over time. In 1999, only 321 CVE records were reported, whereas in 2023, the total reported record has increased to 29k [90]. This substantial increase demonstrates, despite decades of research in this area, effective and scalable SVD techniques are still a major need for cybersecurity.

Perhaps unsurprisingly, with the recent significant growth in artificial intelligence (AI)-based techniques and their application to security, AI has been applied to the SVD as well. Transformers, first introduced in 2017, revolutionized the field by enabling AI models to learn patterns in sequential data, such as text or code, and handle tasks like translation or summarization [136]. BERT, introduced in 2018, builds on transformers by understanding the meaning of words within their surrounding context, making it particularly powerful for natural language processing tasks [33]. Large language models (LLMs) have pushed this capability even further, generating human-like text and answering complex questions [16]. Graph Neural Networks (GNNs) [120] provide another dimension by learning from data structured as graphs, such as code dependency networks or social connections,

<sup>&</sup>lt;sup>1</sup>https://cve.mitre.org/

<sup>&</sup>lt;sup>2</sup>https://cwe.mitre.org/

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enabling the detection of intricate patterns and relationships . Self-supervised learning allows AI models to identify useful structures in data without relying on manually labeled examples, making it possible to leverage vast, unlabeled datasets [56]. Automated Machine Learning (AutoML) [43] simplifies the process of building and tuning models, enabling non-experts to harness machine learning's power. Explainable AI (XAI) [115] ensures that the decisions made by AI systems are transparent and understandable, fostering trust and enabling humans to interpret results. Federated Learning (FL) [86], introduced in 2017, offers a privacy-preserving way to train AI models directly on users' devices rather than on centralized data servers, reducing the need to share sensitive information [86].

Although several conventional and systematic literature reviews exist in the SVD domain [40, 58, 75, 84, 94, 123], and were insightful in their time, they do not fully capture this significant, recent body of literature on AI-based SVD. According to Hanif et al. [51], traditional approaches such as static analysis, dynamic analysis, pattern matching, taint analysis, and statistical methods represented roughly 25.6% of the reviewed studies. This share is relatively modest, and since earlier surveys have already addressed these conventional methods [72, 105, 156], our focus is on more recent advancements, particularly those leveraging cutting-edge ML and DL-based SVD techniques.

Recent surveys like [40, 51, 77, 94, 159] exist but not without limitations. Some existing surveys [77, 94, 159] are conventional and do not follow systematic literature review principles. They often lack specific inclusion and exclusion protocols, resulting in missing critical information such as the number of papers reviewed, the year range considered, and potentially overlooking relevant studies. Consequently, these surveys may not provide comprehensive data necessary for drawing robust conclusions. Even for systematic reviews, the number of papers analyzed is small in some cases. For instance, Nazim et al. [94] only examined 10 papers, and thus the data provided, although helpful, might not depict the whole picture.

Another gap in the existing surveys is a systematic taxonomy. Although several existing surveys [40, 45] provided different types of basic categorization, in order to know the current practices and find the gap in the existing research, it is essential to have a comprehensive categorization based on several dimensions such as techniques used, feature representation method used, embedding methods used, etc. A comprehensive taxonomy would allow researchers to grasp the landscape of AI techniques and methodologies, facilitating the identification of trends, innovations, and underexplored areas. Additionally, it provides a structured framework for comparing different approaches, enhancing the clarity and depth of future research endeavors. One existing work worth mentioning is Hanif et al. [51] where the authors provided a detailed taxonomy. However, the perspectives they selected were based on research interest and also the categorization provided for ML-based approaches only cover four basic categories which are insufficient for more comprehensive analysis. Similarly, Harzevili et al. [125] provide a broad taxonomy covering various data types and model categories. However, a more detailed and fine-grained classification is still needed, particularly for deep learning-based approaches. Our three-dimensional analysis-spanning DL techniques, feature representation methods, and embedding strategies-extends prior work by introducing a more structured and comprehensive taxonomy tailored to DL-based vulnerability detection in source code. This framework also enables us to highlight insights and challenges for future research in the field.

Considering these gaps, we conducted a systematic literature review with specific inclusion and exclusion criteria, analyzing **98** recent papers published between 2018 and 2023 focused on **AI-based source code vulnerability detection**. Our initial analysis involved characterizing the approaches along several dimensions: the availability of their data and models, their primary detection objective, whether they aimed solely to classify code as vulnerable or non-vulnerable or pursued fine-grained analysis, the programming languages targeted, and the level of granularity employed in the detection process.

We then created a detailed taxonomy that categorizes the reviewed approaches based on several key factors, including the specific techniques used, such as neural networks or graph-based methods, the ways the key features of code are identified and represented (e.g., as sequences or graphs), and the embedding methods employed to translate the code into numerical formats that can be processed by machine learning models. The chosen time range in this paper, targets the most recent papers in the domain, addressing the rapid advancements in AI-based techniques. Our taxonomy aids in understanding the current approaches, identifying their limitations, and providing future guidelines. Additionally, we systematically characterize dataset information, documenting all datasets used in the collected papers, along with recently released data within this time frame, and highlight dataset issues for future researchers to address. Unlike existing surveys, our approach is more systematic, covering a broad range of recent papers and offering a well-defined taxonomy that aligns with the latest advancements in AI-based techniques for vulnerability detection in source code. Providing this structured overview aims to facilitate future research directions in this area, particularly for emerging researchers in the field. A brief overview of our key contributions include:

- **Comprehensive Taxonomy:** We have developed a comprehensive taxonomy that considers various aspects of applying AI models for the purpose of vulnerability detection, including the techniques used, feature representation methods, and embedding strategies. This taxonomy aids in understanding the application of AI-based approaches highlighting their limitations and guiding future research directions.
- **Systematic Dataset Characterization:** We have investigated and analyzed the datasets used in each of the collected papers. We documented the characteristics of each dataset, including the most recently released ones, and highlighted their potential challenges, such as their limitations and interpretability of the models developed based on these datasets, with the purpose of guiding future research in this domain.
- Focus on Recent Advancements: By focusing on recent years (2018–2023), our review captures the surge in AI-based vulnerability detection techniques and offers a more up-to-date perspective on the field, addressing a gap that was missing in previous literature reviews.
- Identification of Basic Characteristics: We have collected and analyzed key characteristics of existing approaches, including data and model availability, detection outcome, whether the models are designed to classify vulnerable and non-vulnerable code or aim for more fine-grained analysis, the programming languages targeted, granularity levels, and other relevant properties. This detailed examination highlights gaps and limitations in current methods, paving the way for more focused and effective future research.

The research questions explored in this survey paper are:

- *RQ*<sub>1</sub> (Datasets): What datasets are prevalent in current vulnerability detection research and what are their primary characteristics? Identifying prevalent datasets is crucial as it highlights the most commonly used benchmarks in the field. Exploring the essential characteristics of datasets, such as their size, diversity, origin, and format, provides insights into their strengths and limitations. Understanding these attributes can guide researchers in selecting appropriate datasets, ensuring their studies are robust and generalizable.
- RQ<sub>2</sub> (Basic Characteristics): What are the main characteristics of source code-based vulnerability detection approaches?

Understanding the principle characteristics of code-based vulnerability detection approaches, such as their granularity level, programming languages used, type of classifiers (binary or multilabel), and other relevant attributes, provides a foundation for categorizing and comparing multiple solution in this problem domain. This RQ can be further broken down into the following RQs:

- *RQ*<sub>2a</sub> (Data/Model Availability): What is the availability of the datasets and models used in source code-based vulnerability detection approaches?
- *RQ*<sub>2*b*</sub> (**Detection Objective**): Do these approaches focus solely on identifying whether code is vulnerable or do they aim for a more detailed, fine-grained analysis?
- *RQ*<sub>2c</sub> (**Programming Languages Used**): Which programming languages are targeted by these vulnerability detection approaches?
- *RQ*<sub>2d</sub> (Granularity Level): What levels of granularity (e.g., statement-level, function-level, file-level, etc.) are considered in these approaches for the purpose of identifying the vulnerabilities?
- *RQ*<sub>3</sub> (Taxonomy): How can we construct a comprehensive taxonomy of existing source code-based vulnerability detection approaches? Constructing a comprehensive taxonomy of vulnerability detection approaches helps to sys-

tematically categorize and compare different methods. This is important for understanding the landscape of recent techniques, identifying the impact of recent advancements in ML, DL, and AI, and uncovering trends and gaps in the literature.

• RQ<sub>4</sub> (Limitations and Future Directions): What are the limitations of current vulnerability detection methodologies, and what recommendations can be proposed to address these shortcomings and guide future research efforts?

Identifying the limitations of current methodologies is essential for recognizing areas needing improvement. By understanding these shortcomings, such as issues with datasets, models, researchers can focus on addressing these challenges. Proposing recommendations and future research directions fosters innovation and guides the development of more effective and efficient vulnerability detection techniques.

The rest of the paper is organized as follows. In Section 2, we discuss the current research work in the SVD domain and differences between these approaches and ours. Section 3 describes our methodology, where we explain how we conducted our survey, including the inclusion and exclusion criteria for selecting papers. Section 4 explains all the detailed characteristics of the existing datasets and answers RQ1. In Section 5, we describe the basic characteristics of the primary studies and answer RQ2. In Section 6, we present a taxonomy of the existing research areas related to code-based detection and and thoroughly examine the research contributions in this category to address RQ3. Section 7 highlights the limitations and challenges of current approaches and outlines future research directions to address RQ4. Finally, we summarize the key findings of our survey in Section 8.

# 2 RELATED WORK

This section provides an overview of related literature reviews and other related studies in this area.

A brief overview is provided in Table 1 where each paper contains the corresponding category, the period for which the study was conducted (if provided by the authors), the total number of papers surveyed (if provided by the authors), and the key concept of the paper. We categorize the existing work into two categories, namely literature reviews and other Analytical and Comparative Approaches, based on their focus and methodology. Each category is described in the following subsections.

# 2.1 Literature Reviews

This subsection includes papers that either conducted systematic literature reviews with defined inclusion and exclusion criteria, paper counts, year ranges, and other specific details, or conventional literature reviews where such statistics are not explicitly provided.

Hanif et al. [51] conducted their literature review based on 90 papers ranging from 2011-2020, where they developed two independent taxonomies. The first taxonomy categorized existing works based on different types of research interests, grouping them into categories with respect to their methods, detection, features, code, and datasets. In essence, this taxonomy reflects how the reviewed studies were structured around these high-level categories of research focus. In the second taxonomy, they categorized ML-based approaches into four main categories namely supervised, unsupervised, ensemble, and deep learning. Additionally, Ghaffarian and Shahriari [45] reviewed ML and data mining techniques in SVD domain and provided a high-level categories, including machine learning and data mining techniques, software metric-based approaches, anomaly detection methods, and others.

Harzevili et al. (2024) [125] recently conducted a comprehensive systematic literature review, offering broad insights into the use of machine learning for software vulnerability detection across diverse data types—including source code, binaries, and commit metadata—over an extended period (2011–2024). In contrast, our work differs in both scope and depth. We focus exclusively on AI-driven techniques for source code vulnerability detection, specifically within the dynamic and rapidly advancing period of DL-based methods from 2018 to 2023. This narrower focus enables us to construct a fine-grained taxonomy across three key dimensions: detection methods, feature representation techniques, and embedding strategies. Additionally, we provide a detailed analysis of dataset characteristics such as programming language, granularity, metadata availability, and detection objectives. As such, our study complements and extends the prior review by delivering a more focused and in-depth classification, along with actionable insights to guide future research in AI-based software vulnerability detection.

Zeng et al. [159] conducted their survey based on four recent efforts which they referred to as "game changer". While their approach identifies critical research directions emerging from these "game changers," their survey is distinct from ours in terms of scope and methodology. They primarily focused on highlighting key innovations from these four papers, offering insights into potential future directions. In contrast, our study aims to create a more systematic literature review, encompassing a broader range of research within the SVD domain.

Additionally, some surveys focus on specific types of attacks, such as the work by Liu et al. [77], which compares and analyzes techniques solely aimed at detecting XSS vulnerabilities.

Compared to the above-mentioned surveys, we provide a more comprehensive analysis. We deliberately target recent advancements in AI within the timeframe of 2018 to 2023 (inclusive), capturing the surge in AI-powered methods that are reshaping the SVD landscape. Furthermore, we contribute a novel and detailed taxonomy that goes beyond the existing classifications. This taxonomy analyzes AI-based approaches from multiple perspectives, considering the techniques used, feature representation methods for vulnerability characterization, and the role of embedding techniques in transforming code for DL models.

# 2.2 Analytical and Comparative Approaches

This section includes papers that are not strictly systematic literature reviews but compare various approaches or conduct studies to gain insights into current methods. While these papers contribute to a deeper understanding of existing approaches, they differ from our work in that their primary

Paper	Category	Period	#Papers	Published	Key Concept
Hanif et al. [51]	Vulnerability Detection	2011-2020	90	2021	Presented two separate taxonomies in SVD based on research interest and approaches
Ghaffarian and Shahriari [45]	Vulnerability Detection	-	-	2017	Provided bassic categorization of efforts in SVD domain
Zeng et al. [159]	Vulnerability Detection	-	-	2020	Identified and discussed four game- changing papers and discussed there impact
Liu et al. [77]	XSS Vulnerabil- ity Detection	-	-	2019	Discussed classification of XSS attack
Lomio et al. [81]	Vulnerability Detection	-	-	2022	Investigated how Machine Learning is assisting developers to detect vulnerabilities
Zhu et al. [176]	Vulnerability Detection	2016-2017	48	2022	Studied how perception gap can be reduced
Chakrobrty et al. [22]	Vulnerability Detection	-	-	2022	Conducted a survey to see how exist- ing DL-based vulnerability detection methods work in a real word dataset
Zheng et al. [171]	-	-	-	2021	The authors studied how ML strate- gies influence vulnerability detec- tion in source code
Harzevili et al.[125]	Vulnerability Detection	2011- Jun'24	138	2024	Studied ML-based approaches to un- cover publication trend, understand the dataset, along with representa- tion, provide architectural classifica- tion of models, discover popular vul- nerability type explored etc.
This work	Vulnerability Detection	2018- 2023	98	TBD	Using a systematic approach, docu- ments basic characteristics of exist- ing datasets, provides a comprehen- sive taxonomy of the recent source code based vulnerability approaches

Table 1. A Brief Overview of Related Literature Reviews

goal was not to conduct a more systematic literature review with specific inclusion and exclusion criteria for a defined range.

For example, Lomio et al. [81] investigated how the existing ML-based SVD mechanism supports the developers in commit-level detection by considering only 9 projects, a selection whose justification is not well explained. [176] conducted a study to re-execute a set of DL-based methods and reported a significant drop in their performance compared to their original experimental results. They referred to this as a perception gap and explored ways to reduce it. Similarly, Chakraborty et al. [22] conducted a study to evaluate the effectiveness of existing DL-based vulnerability detection methods on real-world datasets. Their major finding is that the existing DL-based vulnerability detection methods, while promising in controlled settings, often struggle to maintain their effectiveness when applied to real-world datasets.

Zheng et al. [171] conducted an experiment to evaluate the impact of various ML strategies on vulnerability detection outcomes. The results indicated that the attention mechanism played a crucial role in detecting vulnerabilities, while transfer learning did not improve model performance.

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Fig. 1. Basic workflow of the proposed approach based on PRISMA method

Their analysis revealed that composite code representations achieved the best results. In contrast to our work, their study had a more specific focus, analyzing the effects of different ML strategies within the SVD domain.

# 3 METHODOLOGY

We followed the widely used PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) [91] principle to conduct the systematic literature review. PRISMA contains a set of guidelines designed to help researchers report systematic reviews thoroughly, ensuring reproducible reporting of the review process. It has emerged as a widely adopted methodology for conducting surveys, with the paper being cited in over 12,000 articles at the time of writing this paper.

According to the original PRISMA statement, there are four primary phases in a systematic review process, namely *identification*, *screening*, *eligibility*, and *included* phase. The identification phase involves searching for potential studies from various sources (e.g., databases, reference lists). During screening duplicate records are removed, and the remaining studies are assessed based on predefined inclusion and exclusion criteria, typically focusing on titles and abstracts. Full-text articles of studies that passed the screening phase are reviewed in detail, during the eligibility phase, to confirm their relevance and compliance with the study criteria. The final phase lists the studies that meet all criteria and are included in the systematic review for further detailed analysis and synthesis.

In the revised PRISMA methodology<sup>3</sup>, the "eligibility" phase is integrated into the screening process. We have adopted this updated version for our study for simplicity and clarity. The detailed steps of our methodology are illustrated in Figure 1. In the Figure, Step 1 illustrates the PRISMA **identification** phase, where we collected a total of 1,806 papers.

We began this phase by systematically documenting a set of **inclusion criteria** for our search below:

- Search Keywords: Since we are only interested in papers on source-code-based software vulnerability detection, we formulated the keywords: *software vulnerability detection* and *source code vulnerability detection* based on our experience. We additionally experimented with additional keywords, including *software vulnerability identification* and *software vulnerability discovery*; however, they did not identify any new relevant papers that were not already included in our existing pool.
- **Timeframe:** We focused on papers published in the past six years (2018–2023) to capture recent efforts, given the rapid advancements in AI-based approaches.
- Databases: For each keyword, we searched three databases ACM, IEEE, and Google Scholar that are also used in other surveys [11, 40, 51, 121, 122]. These databases are well-regarded

<sup>&</sup>lt;sup>3</sup>https://www.eshackathon.org/software/PRISMA2020.html

Keyword	IEEE	GScholar	ACM	Removing	Removing
SVD	624	515	372	Duplicate	Exclusion
SCVD	102	147	46	640	08
Total		1,806		049	70

Table 2. Statistics of the total number of papers

in the research community for their comprehensive coverage of high-quality, peer-reviewed literature.

As shown in Figure 1, we initiated the process by downloading papers from the three specified databases for each keyword. For each database, the search concluded when no further relevant papers could be identified based on their titles. The list of papers selected during this search is presented in Table 2. The initial search yielded a total of 1,806 papers across all three databases, with a detailed breakdown by keyword and database also provided in the table.

Once collected the papers from all three resources, we removed the duplicates using Mendeley [88], an open-source reference management tool. This removed 1,157 papers, resulted in 649 remaining papers. We then read the abstract, and introduction.

We then reviewed the abstract and introduction of each remaining paper to assess whether it should be filtered based on our exclusion criteria. In

cases, when we were uncertain about the paper's relevance from the abstract alone, we read the entire paper for further assessment. The **exclusion criteria** for our work are outlined below:

- Papers outside the scope of our study, primarily were related to network vulnerabilities, embedded and/or IoT vulnerabilities, cloud computing vulnerabilities, Android vulnerabilities, web vulnerabilities, smart contract vulnerabilities, binary-based vulnerabilities, and fuzzing-based approaches, and the one those addressed SVD using conventional approaches rather than DL or ML.
- Papers that were not peer-reviewed were excluded because their validity could not be verified, with the exception of VulDeePecker paper [71]. Although this paper was not peer-reviewed, it has garnered 977 citations at the time of writing, indicating its significant impact on the community.
- Work-in-progress papers, vision papers, posters, and case study papers were excluded due to incomplete results or insufficient data for further analysis.
- Papers lacking clarity or containing ambiguous explanations. Some papers could not be fully evaluated due to missing basic information (e.g., dataset, programming language, granularity level, methodology) resulting from unclear or vague descriptions.
- We identified 66 papers that were literature reviews, study papers, or papers that compared multiple approaches/techniques in the SVD domain. Although relevant, these papers were excluded from our primary list because they did not introduce new techniques. However, we examined these papers to extract valuable insights, concerns, and useful statistics, which were incorporated into our analysis and were previously shared in Section 2.2.
- Papers not written in English.

Following the exclusion criteria, 541 papers were removed, leaving a total of **98** papers for further review. A summary of these statistics is presented in Table 2. We captured the year-wise distribution of the remaining papers, as illustrated in Figure 2, revealing an upward trend. Notably, in 2018, only five papers met our selection criteria, while this number has increased to 37 in 2023.

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#### 4 DATASETS

In this section, we address **RQ1** by documenting *reused datasets* identified in the papers we studied. By reused datasets, we refer to those that have been employed in more than one paper. Datasets used only once by their original authors and those not made publicly available were excluded from our analysis. While we have not listed the excluded datasets here due to space constraints, a comprehensive list of all datasets is provided in our supplementary material <sup>4</sup>.

Our analysis resulted in the identification of eight reused datasets introduced within the timeframe of our study. Additionally, we included datasets utilized by these reused datasets, arriving at a total of 27 datasets for inclusion.

Table 3 lists these datasets, providing a basic description, granularity level, language support, and download link for each dataset. This table enables an analysis of key dataset characteristics. For instance, it conveys that 16 out of 27 datasets are specifically designed for C/C++ code, 7 support multiple languages, 3 of them contain Java code and the remaining 1 focuses on JavaScript code. Regarding granularity, 15 datasets offer function-level analysis, 5 utilize code gadget/code slice granularity, referring to code segments, which directly influence (or are influenced by) a specific computation or variable of interest or perform a specific task, 1 employs statement-level granularity, and 2 provide multi-level analysis, 3 focus on commit-level code.

Datasets marked with an asterisk (\*) contain not only the standard labels that indicate whether a given sample is vulnerable or safe, but also they provide information about the specific type of vulnerability associated with each sample, such as CVE or CWE identifiers—that categorizes the nature of the vulnerability. Having this additional information allows researchers and practitioners to better understand the exact security issues present in the data and tailor their detection and remediation strategies accordingly.

Description	Granularity	Language	Download Link
Manually labeled dataset	Function	C/C++	https://sites.google.com/
from FFmpeg and QEMU			view/devign
used in CodexGlue [82]			
leaderboard containing			
12,460 vulnerable and			
14,858 safe functions			
	DescriptionManually labeled datasetfrom FFmpeg and QEMUused in CodexGlue [82]leaderboard containing12,460 vulnerable and14,858 safe functions	DescriptionGranularityManually labeled datasetFunctionfrom FFmpeg and QEMUused in CodexGlue [82]leaderboard containing12,460 vulnerable and14,858 safe functionsused in CodexGlue [82]	DescriptionGranularityLanguageManually labeled datasetFunctionC/C++from FFmpeg and QEMUused in CodexGlue [82]leaderboard containing12,460 vulnerable and14,858 safe functions

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<sup>4</sup>https://drive.google.com/drive/folders/1QY1iLadRe9YYwW7bAQMIH4y\_I8aO6QPf?usp=sharing

Name	Description	Granularity	Language	Download Link
VulDeePecker*	Based on NVD, contains	Code Gad-	C/C++	https://github.com/CGCL-
[71]	17,725 vulnerable and	get		codes/VulDeePecker
	43,913 not vulnerable code			
NU //D*	gadgets	<u>c1:</u>	N 10 1	1 // 1 /
NVD	database maintained by US	Slice	Multiple	https://nvd.nist.gov/
	government			
CVE*	Publicly disclosed cyberse-	Slice	Multiple	https://cve_mitre_org/
	curity vulnerability list that		r	F
	contains relevant informa-			
	tion about vulnerabilities.			
Reveal [21]	Labeled dataset from	Function	C/C++	https://github.com/
	Chromium and Debian			VulDetProject/ReVeal
	projects. Labeling was			
	done with the help of issue			
Duranal at al*	tracking system	Franction		https://acfic/d45hm/
Russel et al.	Debian Linux distribution	Function	C/C++	https://osi.io/d45bw/
[110]	public Git repositories on			
	GitHub (labeling was done			
	by static analyzers), also la-			
	beled synthetic data from			
	Juliet test suite			
Juliet/ SARD*	Contains production soft-	Function	Multiple	https://samate.nist.gov/
	ware applications with			SARD/test-suites
	known vulnerabilities.			
	Artifacts contain designs,			
VulDeel ocator	Source code, and binaries	Function	C/C++	https://github.com/
[69]	NVD and SARD Labeling	1 unction	0/0++	VulDeeLocator/
[0)]	of NVD records were done			VulDeeLocator
	by their <i>"diff"</i> files before			
	and after patches. The			
	dataset contains 14,511			
	programs, including 2,182			
	real-world programs			
	and 12,329 synthetic and			
<b>11</b> 77 <b>1 1 *</b>	academic programs	<b>F</b> ('	0/0	
wang et al.	based on CVE and SAPD	Function	C/C++	https://github.com/
[137]	Labeling is done using a set			Huantwang/FUNDED_MISE
	of predictive models or ex-			
	perts.			
Project KB*	Collected both from NVD	Statement	Java	https://github.com/SAP/
[106]	and from project-specific			project-kb/tree/main/
	Web resources that the au-			MSR2019
	thors monitored on a con-			
	tinuous basis			

Table 3. Characteristics of datasets used in papers (source code-based detection) (continued)

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Table 3. Characteristics of datasets used in papers (source code-based detection) (continued)

Name	Description	Granularity	Language	Download Link
SySeVR* [70]	Contains data from NVD and SARD	Slice	C/C++	https://github.com/SySeVR/ SySeVR
Lin et al.* [74]	contained manually labeled 457 vulnerable functions and collected 32,531 non- vulnerable functions from 6 open-source projects based on CVE and NVD	Function	C/C++	https://github.com/ DanielLin1986/ TransferRepresentationLearning
Cao et al.* [20]	Covers 13 common memory-related vulnerabil- ities based on SARD and CVE. Labeling was done automatically using "diff" files	Statement	C/C++	https://github.com/ MVDetection/MVD
ApacheCrypto- API-Bench [3]	Consists of 86 real vulner- abilities from 10 Apache open-source projects	Snippet	Java	https://github.com/ CryptoAPI-Bench/
Kluban et al.* [62]	Dataset is curated based on Snyk vulnerability database [59] and Google VulnCode- DB project [2]	Function	Javascript	https://github.com/Marynk/ JavaScript-vulnerability- detection
Alves et al.* [10]	Data is collected based on 2875 security patches of Linux Kernel, Mozilla, Xen Hypervisor, httpd and glibc	Function, File, Class	C/C++	https://eden.dei.uc.pt/%E2% 88%BCnmsa/metrics-dataset
Cao et al.* [19]	Based on NVD and Github, they labeled function based on " <i>diff</i> " file. Contains 3867 vulnerable and 92,058 vul- nerable functions	Function	C/C++	https://github.com/ SicongCao/BGNN4VD
Ponta et <sup>*</sup> al.[106]	Maps 624 publicly disclosed vulnerabilities affecting 205 distinct open-source Java projects	Commit level	Java	https://github.com/eclipse/ steady
Reis and Abreu <sup>*</sup> [113]	The authors scrapped the CVE details database for GitHub references and augmented the data with 3 other security-related datasets (Bigvul, Secbench [111, 112], Pontas et al. [106]). The dataset con- tains natural language artifacts (commit messages, commits comments, and summaries), meta-data, and code changes	Commit level	20 lan- guages	https://github.com/TQRG/ security-patches-dataset

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Name	Description	Granularity	Language	Download Link
Tian et al.* [135]	Based on SARD. Contains 264,822 labeled synthetic functions, where 166,641 are non-vulnerable and 98,181 are vulnerable across 118 CWE-IDS.	Function	C/C++	https://github.com/XUPT- SSS/TrVD
Bhandari et al.* [13]	Contains vulnerable and corresponding patched code, Programming lan- guage used, five levels of abstraction-commit-, file-, and function levels, repository- and CVE levels. In total, this dataset con- tains 18,249 files and 50,322 methods	Commit, file, function	Independent	https://github.com/secureIT- project/CVEfixes
Big-Vul <sup>*</sup> [41]	Extracted from 348 Github projects, BigVul data con- tains functions before and after fixing the vulnerabil- ity. In total, there are 11,823 vulnerable and 253,096 non- vulnerable functions in this dataset	Function	C/C++	https://github.com/ ZeoVan/MSR_20_Code_ Vulnerability_CSV_Dataset
xVDB* [55]	Contains 12,432 CVE patches from repositories and issue trackers, and 12,458 insecure posts from O&A sites	Commit	C, C++, Java, JavaScript, Python and Go	https://iotcube.net/
Cross-vul* [97]	File-level granularity dataset that contains a) The directory with all source code files, b) A JSON file containing commit and file information associated with CVE IDs and CWE IDs, c) the commit message dataset that consists of three separate CSV files. Contains 13,738 vulnerable and 13,738 non-vulnerable files	Function	40 pro- gramming languages	https://doi.org/10.5281/ zenodo.4734050, https://doi. org/10.5281/zenodo.4741963

Table 3. Characteristics of datasets used in papers (source code-based detection) (continued)

Continued on next page

Name	Description	Granularity	Language	Download Link
D2A [172]	Contains a) Bug Reports (Trace), b) Bug function source code (Function), c) Bug function source code, trace functions source code, and bug function file URL (Code). Labeled by static analysis and differential analysis	Function	C/C++	https://github.com/IBM/ D2A
NVD-new* [169]	Obtained patch files from the reference links to the NVD, and commits on the Github repository. Func- tions before and after the fixing patches are generated by VulnDBGen. Contains 9947 and 9947 non vulnera- ble functions	Function	C/C++	https://github.com/CGCL- codes/DissectVulDetection/ tree/main/Dataset
DiverseVul* [24]	Contains 18,945 vulner- able functions spanning 150 CWEs and 330,492 non-vulnerable functions extracted from 7,514 commit records	Function	C/C++	https://github.com/wagner- group/diversevul

# 5 PRIMARY CHARACTERISTICS OF CODE-BASED DETECTION

In this section, we analyze and document the key characteristics of the reviewed papers to address **RQ2**. Our focus includes, but is not limited to, identifying the detection objectives, exploring the granularities of vulnerability detection, and examining the targeted programming languages. Understanding these characteristics is essential for identifying trends and gaps in current research, providing insights to guide future studies in enhancing model design and implementation.

# 5.1 Data Availability

To address **RQ2a**, we assessed the availability of code and data in the collected papers. As shown in the pie chart in Figure 3(a), artifacts were available for around 50% of the papers. The lack of available artifacts in the remaining papers can hinder future model improvements and dataset utilization. Please note that availability does not guarantee reproducibility, raising further questions about replicating the results.

# 5.2 Detection Objective/Outcome

Accurately identifying software vulnerabilities is a important step in improving code security. To address RQ2b, depending on the chosen approach, detection efforts may focus on broad classifications of code as vulnerable or non-vulnerable, or they may focus on pinpointing specific lines of code that contribute to security issues. Each of them is described in the following subsections.

5.2.1 *Classification-Based Detection.* The primary goal of the efforts in this category is to determine whether a code segment, such as a code snippet, function, or file is vulnerable. Models in this category perform a binary (vulnerable/non-vulnerable) or multi-label classification at various levels of granularity, such as file-level, function-level, or slice-level. Classification-based detection is well-suited for scanning large codebases, quickly identifying areas of potential concern, and helping security teams prioritize further investigation. Although



Fig. 3. Characteristics of source code-based classification approaches

efficient, this method often provides limited insight into the exact location or cause of vulnerabilities, as it only labels code segments as a whole. As demonstrated in the pie chart in Figure 3(b), in our analysis, the vast majority of papers (95 out of 98) employed this approach. Among those papers, 92 developed a binary classifier where the main objective was to detect security flaws irrespective of vulnerability type. We found 3 papers that developed multi-class classifiers for specific types of vulnerability. These particular efforts, while capable of identifying specific types of vulnerabilities, were limited in scope, addressing only a small number of known vulnerability categories.

*5.2.2 Fine-Grained Detection.* Compared to the previous set of approaches, fine-grained detection seeks to pinpoint the exact statements or lines within a code snippet that lead to vulnerabilities. By highlighting these specific elements, fine-grained approaches allow developers to quickly focus their attention on the root causes of security bugs. Only 3 papers followed this path in our analysis, which indicates that pinpointing vulnerability in a specific code segment is yet to be explored more thoroughly.

### 5.3 Programming Languages

To address **RQ2c**, we analyzed the programming languages targeted for vulnerability detection in the reviewed studies. In most cases, the models were programming language specific. The pie chart in Figure 3(c) illustrates that C/C++ dominated, being the focus of 91 papers. Java was the target in 4 papers while only 3 studies addressed multiple languages (e.g. C/C++, Java, Swift, PHP at the same time).

### 5.4 Code Granularity

To address **RQ2d**, we identified, granularity levels of the solution proposed in each paper, such as file, function, line, and code gadget-based levels.

As demonstrated in the pie chart in Figure 3(d), 59 papers focused on function-level granularity, making it the most common granularity level. The second most common level of granularity being used was code snippet/code gadget/program slice (23 papers), collectively referred to as "snippet." At this granularity level, the released dataset did not include a specific function but rather several lines of code, which could be either consecutive or non-consecutive, with the authors detecting whether each particular code snippet is vulnerable or not. Six papers examined code vulnerabilities at the granularity level of line or statement , one at file level, six papers considered multi-level granularity such as both function and statement levels, and finally three papers considered other levels of granularity, such as commit-level, component-level, multiple functions and minimum intermediate representation (simplified version of the code).

#### 6 TAXONOMY: CODE-BASED DETECTION

In this section, we propose a taxonomy developed based on the papers reviewed for code-based software vulnerability detection, addressing **RQ3**. The taxonomy is depicted in Figure 4. At the first level of the hierarchy, the existing approaches are categorized into two main groups: Machine Learning (ML)-based approaches, and Deep Learning (DL)-based approaches.

Among the papers analyzed, a substantial majority (96%, or 94 papers) employed DL techniques, such as graph neural network and transformer-based models. In contrast, only 4% (4 papers) utilized solely ML-based approaches, such as those using code metrics as features for classification purposes. We begin by presenting several examples of existing alternative approaches to ML- and DL-based methods, followed by a discussion of ML- and DL-based approaches. Finally, we provide a detailed taxonomy of DL-based approaches in Section 6.2.

#### 6.1 Other Approaches

While ML- and DL-based models dominate the field of vulnerability detection, several alternative methods are also employed, encompassing both static and dynamic analysis techniques. A few examples of the static approaches include **Code Similarity-Based Methods**, such as clone matching [4, 15], which identifies vulnerable code clones by tracing patch files and utilizing graph-based components; pattern-based similarity matching [62, 92, 168], which leverages pattern recognition and textual similarity to detect vulnerabilities in real-world applications; and graph-based similarity matching [30, 142], which compares function-level graphs and code property graphs to assess vulnerabilities. Another example is **Rule and Logic-Based Methods**, such as rule-based techniques [109], which rely on predefined detection rules to identify cryptographic and SSL/TLS API misuses, and propositional functions [49], which categorize software vulnerabilities using logical models based on CWE classification. In contrast, dynamic approaches, such as **Data Flow and Program Analysis-Based Methods**, analyze runtime behaviors, such as taint analysis [60] which tracks how tainted data propagates through programs and representing vulnerability signatures as traces of inter-procedural data dependencies.

# 6.2 DL-based Approaches

Although DL-based methods were used in most of the efforts, basic ML-based approaches were also used in 4 papers gathered in our study. These efforts used different software metrics to detect vulnerabilities in source code. For instance, Medeiros et al. [87] aimed to understand how the information provided by software metrics, such as Cyclomatic Complexity, Lines of Code, and Coupling Between Objects, can be utilized by ML-based approaches, including decision tree (DT), random forest (RF), extreme gradient boost (EGB), and linear support vector machine (SVM), to differentiate between vulnerable and non-vulnerable code. Similarly, Zagane et al. [157] employed code metrics, such as the number of total lines, cyclomatic complexity, and the number of distinct operators, to quantify extracted pieces of code. This quantification provided insights into the presence of vulnerabilities at a fine granularity level, using random forest (RF), decision trees (DT), and K-nearest neighbor (KNN) approaches. Salimi et al. [119] introduced the concept of vulnerable slices, referring to vulnerable code units, to measure software using both structure-based and statement-based metrics.



Fig. 4. Taxonomy of source code-based vulnerability detection methods. Each colored rectangle contains classification based on different aspects and thus classifies the same papers based on different characteristics



Fig. 5. Year-wise distribution of the techniques of papers for DL-based detection

These newly measured metrics were subsequently used to characterize vulnerable codes, with SVM-based classification applied for vulnerability detection.

Some other approaches used AST-Based clustering methods for the identification of vulnerabilities in code. For instance, Debeyan et al. [6] compared AST-based approaches with existing metric-based approaches using SVM, RF, and naive Bayes (NB) classifiers. They found that AST-based approaches achieved higher predictive performance, particularly in multiclass classification tasks, by leveraging AST n-grams as features.

Out of a total of 98 papers, 94 papers utilized DL-based techniques for detecting software vulnerabilities. As illustrated in Figure 4, we further categorized these papers according to three key aspects. First, the **DL** technique employed (represented by the blue rectangle), second, the feature representation technique used (indicated by the green rectangle), and third, the embedding methods utilized to feed data into the neural network (shown in the yellow rectangle). Each rectangle corresponds to a distinct classification criterion, with papers being grouped according to their approach for each aspect.

It is important to note that if a paper employs more than one approach, it is placed into all relevant subcategories. As a result, the total number of papers in the main category may be smaller than the sum of papers across all sub-categories within each rectangle. This classification structure provides a more comprehensive understanding of the diverse ways in which DL techniques, feature representations, and embedding methods are applied in the context of software vulnerability detection.

Category	# Unique Papers	Models (Total Papers)	Most Popular Model
Sequential models	26	LSTM (6), BiLSTM (19), tree-LSTM (1), RNN (1), BiRNN (1), GRU (1), BiGRU (2), SeqGAN (1)	BiLSTM (19)
Graph-based models	34	GNN (13), GGNN (5), RGCN (2), GCN (3), SAR- GIN (1), behavior graph (1), GAT (1), BGNN (1), DGCNN (1), HetGNN (1), context-aware graph (1), hierarchical embedded (1), jump GAT (1), UCPG (1)	GNN (13)
Transformer-based models	14	BERT (4), RoBERTa (1), transformer-Based LM (1), HGT (1), transformer (2), dubbed VulD- transformer (1), SAT (1), hierarchical compres- sion EM (1), CodeBERT (1), LLM (1)	BERT (4)
Convolutional neu- ral networks (CNN)	17	basic CNN (13), DGCNN (1), TextCNN (2), con- volutional pooling layers (1), AlexNet (1), Lenet (1), Tcnn (1)	basic CNN (13)
Other	17	Quantum neural network (1), MTLF (1), Hierar- chical attention neural network (1), serialization- based NN (1), MLP (3), Serialization-based (1), Se- quence & structure Fusion (1), curriculum learn- ing (1), horizontal federated learning (1), meta- learning (1), PU learning (1), IGS (1), pathfinding & pruning (1), path-flow based (1), attention neu- ral network (1)	MLP (3)

#### Table 4. Models used in DL-based techniques

*6.2.1* **Method/Technique**. This section classifies the papers based on the deep learning (DL) model employed in their work. We categorize them into five major groups: sequential models, graph-based models, transformer-based models, convolutional neural networks (CNN), and others. For each major category, we further refine the classification into more specific subcategories based on the specific architecture in the neural model. Table 4 provides an overview of each major category along with their subcategories and the number of related papers in each subcategory. The following sections describe each category in detail:

(1) Sequential Models: In this category, models are specifically designed to process sequential data, typically one element at a time, which makes them particularly effective for tasks involving natural language or time series data. Out of the 94 papers utilizing DL-based approaches, 25 studies employed sequential models as the foundation for vulnerability detection. Several distinct models with a wide variety of neural

network architectures were identified. For instance, Long short-term memory (LSTM) is a type of recurrent neural network (RNN) capable of capturing long-term dependencies in sequential data, and it was used in several efforts [18, 31, 57, 117, 149, 178]. Similarly, Bidirectional long short-term memory (BiLSTM) is an extension of the LSTM model that processes input in both forward and backward directions, and it was utilized in many technique [23, 25, 36, 48, 57, 67, 70, 71, 73, 74, 78, 79, 85, 95, 133, 149, 164, 178, 179]. In addition, Tree-structured long short-term memory (Tree-LSTM) is a variant of LSTM designed to process hierarchical or syntactic structures, such as trees in abstract syntax trees (ASTs), making it particularly suitable for tasks involving structural data [138]. On the other hand, Basic RNN focuses on simple sequential data processing but is limited by vanishing gradients in long sequences, and it was utilized in only one work in our survey [116]. Furthermore, Bidirectional RNN (BiRNN) captures contextual information by processing data in both directions and was used in one effort [69]. Moreover, Gated recurrent unit (GRU) is a simplified version of LSTM that reduces computational complexity while retaining performance, and it was employed in two studies [57, 149]. Likewise, Bidirectional gated recurrent unit (BiGRU) extends GRU to process input in both forward and backward directions and was utilized in two additional studies [42, 57]. Finally, SeqGAN is a generative adversarial network tailored for sequential data generation and evaluation, and it was employed in one study [80].

As presented in Table 4, BiLSTM emerged as the most extensively utilized sequential model, appearing in 19 studies. Following this, standard LSTM models were the second most frequently employed model, featured in 6 studies.

Figure 5 illustrates the year-wise distribution of models based on the techniques employed. As shown in the figure, sequential models reached their peak usage in 2021, with a total of 7 studies. However, by 2023, their adoption had declined, with only 3 studies utilizing these models. This trend indicates a potential shift in research focus towards integrating sequential models with other architectures and exploring strategies to enhance their performance in vulnerability detection tasks.

(2) Graph-based Models: This category includes models specifically designed to analyze source code in the form of graph-structured data. A total of 35 papers employed graph-based approaches to detect vulnerabilities in software systems.

**Basic Graph Neural Networks (GNNs)** are models designed to understand relationships between nodes in a network, much like identifying connections within a web of friends. In the context of source code analysis, GNN-based models have been utilized in 13 studies, where the source code is represented through various graph or tree-based structures [20, 32, 38, 54, 64, 83, 96, 127, 130, 146, 158, 163, 175]. These models effectively capture structural dependencies within the code, facilitating vulnerability detection. Expanding on basic GNNs, **Gated Graph Sequence Neural Networks (GGNNs)** are a specialized variant that focuses on processing information over sequences. This approach is comparable to tracking messages exchanged among friends over time to understand evolving relationships. GGNN-based vulnerability detection models have been developed in five studies, where gated mechanisms are explored to enhance graph processing and improve detection performance [118, 137, 141, 143, 153].

Another important variant is the **Relational Graph Convolutional Network (RGCN)**, which aims to analyze different types of relationships between graph nodes. This can be likened to understanding various social connections, such as family, work, and friendship networks within a community. In our review, RGCN-based models were incorporated in two studies to capture and leverage complex node relationships for vulnerability detection [35, 170].

Similarly, **Graph Convolutional Networks (GCNs)** are a streamlined variant of GNNs, focusing on simplifying and strengthening relationships within a graph. An example of this would be identifying closely connected clusters in a map of cities. Our analysis revealed that GCNs were employed in three studies, primarily for static vulnerability detection tasks [27, 108, 138].

In contrast, the **Self-Attention Readout Graph Isomorphism Network (SAR-GIN)** is a more advanced GNN variant that emphasizes the most critical parts of the network. This approach is analogous to identifying the most influential individuals in a social group. Among the papers we reviewed, this model was utilized in only one study, reflecting its niche but potentially impactful role in vulnerability detection [148].

Beyond these commonly used models, there are **Other Graph-Based Models** that were each employed in a single study. These include the Behavior Graph Model [155], Graph Attention Network [160], Bidirectional Graph Neural Network (BGNN) [19], Deep Graph Convolutional Neural Network (DGCNN) [104], Heterogeneous Graph Neural Network (HetGNN) [26], Context-Aware Graph-Based Model [68], Hierarchical Embedded Graph Model [52], Jump Graph Attention Network [161], and the Unified Code Property Graph (UCPG) [65]. Although these models are less frequently applied, they showcase the diversity of graph-based techniques being explored for vulnerability detection.

As shown in Table 4, basic GNNs were the most popular graph-based approach, utilized in 13 out of 35 papers. Figure 5 highlights that graph-based methods first emerged in 2019 and have seen a steady increase in usage over time, with a peak in 2023 when 17 papers adopted this approach for software vulnerability detection.

(3) Transformer-based Models: This category leverages the transformer architecture, renowned for its effectiveness in processing sequential and structured data. Below, we summarize the specific transformer-based models employed in the reviewed efforts:

**BERT** is a widely used model for capturing bidirectional context in text data and has been applied in several studies [34, 61, 144, 178]. Building on BERT, **CodeBERT** is a pre-trained model specifically designed for source code analysis and was employed in one study [108]. Similarly, **RoBERTa**, an optimized variant of BERT, has been utilized to enhance performance in vulnerability detection tasks [50]. Another significant model is the **Transformer-based Language Model**, which leverages transformers to understand and predict text patterns, as demonstrated in [145].

In addition to these models, the **Heterogeneous Graph Transformer (HGT)** is designed to process heterogeneous graph-structured data, capable of handling different types of nodes and relationships, such as mapping a city's roads and landmarks. This model was developed in one study within our review [152]. Furthermore, the **Transformer/VulD-transformer** is a flexible architecture for understanding data patterns, with a specialized version tailored for vulnerability detection [167].

The **Structure-Aware Transformer (SAT)** goes a step further by incorporating the structural aspects of data, similar to understanding the layout of a building blueprint, and was featured in one study [151]. Additionally, the **Hierarchical Compression Encoder Model** is a specialized transformer designed for compressing and processing hierarchical information in a structured format, and its application was proposed in one work [76].

Finally, the **Large Language Model (LLM)** represents a highly advanced class of AI models trained on vast datasets to understand and generate human-like language. LLMs were employed for vulnerability detection in one study [107].

Among the 14 transformer-based works, BERT was the most widely used, appearing in four of the studies, as shown in Table 4. The other models were each utilized in a single paper.

From Figure 5, we observe that transformer-based approaches first emerged in the SVD domain in 2021, with three works incorporating these models. Their adoption has grown steadily, reaching a peak in 2023 with seven primary studies employing transformer-based techniques.

(4) Convolutional Neural Networks (CNN): CNNs have also been employed in SVD tasks. CNNs, a type of deep learning model, are specifically designed to process data with a grid-like structure, such as images or sequences. They excel in identifying and learning hierarchical patterns through their architecture, which typically includes convolutional layers that apply filters to detect features, pooling layers that reduce dimensionality while retaining critical information, and fully connected layers that integrate these features for classification.

**Basic Convolutional Neural Networks (CNNs)** are fundamental deep learning models designed to scan data, such as code sequences, to identify patterns that help classify vulnerable and non-vulnerable components. This model has been widely adopted in several studies [14, 18, 66, 80, 89, 102, 116, 131, 139, 147, 162, 163, 165]. Expanding on basic CNNs, the **Dynamic Graph Convolutional Neural Network (DGCNN)** is specifically designed for graph-structured data, enabling it to dynamically learn relationships within the graph. This model was developed for vulnerability detection [150].

Similarly, the **Text Convolutional Neural Network (TextCNN)** is optimized for processing text data, such as code snippets, to uncover patterns in sequential data, as demonstrated in [17, 36]. To further enhance the performance of CNNs, **Convolutional Pooling Layers** combine convolution and pooling operations, allowing the model to focus on the most critical features [161].

In addition to these models, **AlexNet**, a classic CNN architecture originally designed for image classification, has been adapted for code vulnerability detection [149]. Alongside AlexNet, **LeNet**, one of the earliest CNN models known for its simplicity and effectiveness in pattern detection, has also been applied in the same study [149]. Moreover, the **Task-specific CNN (TCNN)** is tailored specifically for software vulnerability detection, further demonstrating its utility [149].

This range of CNN-based models highlights the versatility of convolutional architectures in addressing different aspects of vulnerability detection, from basic pattern recognition to sophisticated graph and text analysis.

Among all CNN-based approaches, the basic CNN model was the most widely adopted, appearing in 13 primary studies as shown in Table 4. Figure 5 indicates that CNNs were first introduced in SVD tasks in 2018 within the scope of our reviewed efforts. In 2023, CNN-based approaches were employed by 9 studies, making CNNs the second most popular technique after graph-based approaches.

(5) Other Approaches encompass a diverse set of models utilized in vulnerability detection, each leveraging unique methodologies to address specific challenges. One example is the **Quantum Neural Network**, which harnesses quantum computing principles to enhance computational efficiency and tackle complex patterns [173]. Another notable approach is the **Metric Transfer Learning Framework (MTLF)**, which applies transfer learning techniques to adapt metric-based features from one domain to another, thereby improving vulnerability detection performance [79]. Additionally, the **Hierarchical Attention Network** captures hierarchical relationships within data and assigns attention weights to various information levels, facilitating precise vulnerability identification [47].

Moreover, the **Cross-Modal Feature Enhancement and Fusion** method integrates features from different modalities, such as code structure and textual information, to improve detection accuracy [132]. Approaches like **Serialization-Based and Graph-Based Neural Networks** transform source code into serialized or graph-based representations for more effective analysis, with serialization-based techniques [130] and graph-based methods [134]. The **Multi-Layer Perceptron (MLP**), a simple yet powerful feedforward neural network, has also been applied for vulnerability detection through dense source code representations in three studies [8, 146, 165].

In addition, **Sequence and Structure Fusion-Based Models** enhance detection capabilities by combining sequential and structural features of code [134], while **Curriculum Learning** introduces tasks in an incremental manner, starting from simple to complex, to optimize model training [37]. To address privacy concerns, **Horizontal Federated Learning** enables multiple parties to collaboratively train models without sharing raw data [163]. Furthermore, **Meta-Learning** focuses on training models to adapt quickly to new tasks with minimal data, improving detection efficiency [129].

For handling imbalanced datasets, **Positive and Unlabeled (PU) Learning** utilizes only positive and unlabeled examples during training [140]. Enhancing model interpretability, **Integrated Gradients Enhanced with Saliency (IGS)** combines integrated gradients with saliency maps to explain and improve model predictions [103]. Additionally, **Pathfinding and Heuristic-Based Pruning** employs pathfinding algorithms alongside heuristic pruning to streamline code analysis for vulnerabilities [44], while **Path-Flow-Based Models** analyze execution flow paths within code to detect potential security issues [28].

Lastly, the **Attention Neural Network** applies attention mechanisms to focus on the most relevant parts of the input data, enhancing vulnerability detection performance [39]. Collectively, these models highlight the diversity and innovative approaches adopted in the field of software vulnerability detection.

This category encompasses a diverse range of models that do not fit neatly into the previously defined categories. As we can observe from Table 4, among these models, MLP stands out as a widely used approach. As depicted in Figure 5, there is a trend of increasing popularity in this category over recent years. This suggests that researchers are increasingly exploring a variety of techniques, indicating potential for future improvements in vulnerability detection methodologies.

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Fig. 6. Year-wise distribution of feature representation techniques in DL-based papers

*6.2.2* **Feature Representation**. In this subsection, we categorize existing DL-based works based on the feature representation techniques employed. Source code can be represented in multiple ways, including structurally, semantically, or through intermediate representations. Accordingly, we divide feature representation techniques into three major categories. Figure 6 illustrates the year-wise distribution of papers for each subcategory, highlighting the usage trends. Table 5 provides a detailed list of models within each category and their respective paper counts.

(1) Graph-Based Representations: In this category, source code is represented as structures such as graphs or trees to capture dependencies, control flows, and program behaviors. One of the foundational techniques in this category is the Control Flow Graph (CFG), which captures the control flow within a program, illustrating how the execution moves between different code segments [19, 27, 34, 64, 104, 119, 141, 146, 153]. Complementing CFGs, the **Program Dependence Graph (PDG)** models dependencies between program statements, providing insights into both control and data relationships within the code [20, 44, 54, 67, 68, 70, 89, 102, 103, 119, 129, 132, 138, 139, 141, 144, 147, 151, 158, 162, 167, 179].

Building upon these, the **Code Property Graph (CPG)** integrates multiple representations, including abstract syntax trees (ASTs), control flow graphs, and program dependence graphs, to form a comprehensive code analysis structure [17, 23, 26, 35, 39, 44, 48, 76, 127, 149, 150, 160, 161, 163, 165, 166]. Additionally, specialized models like the **Control Dependence Graph (CDG)** and the **Data Dependence Graph (DDG)** focus on representing control and data dependencies, respectively [152]. The **Program Control Dependence Graph (PCDG)** further integrates both types of dependencies to provide a holistic view of program behavior [137].

To track the movement of data within applications, the **Data Flow Graph (DFG)** is employed, mapping the flow of data across different program components [19, 64, 153], while the **Execution Flow Graph (EFG)** captures the runtime execution paths of programs [138]. For behavior-specific analysis, the **Behavior Graph** focuses on identifying distinct behavioral patterns within the code [155].

The **Abstract Syntax Tree (AST)** is the most widely adopted representation, structuring the syntactic elements of code in a hierarchical tree format to facilitate both syntax and semantic analysis [31, 38, 42, 44, 47, 52, 69, 70, 73, 74, 78–80, 85, 118, 132, 134, 135, 137, 138, 146, 148, 152, 153, 166, 175]. Variations like the **Control Flow Abstract Syntax Tree (CFAST)** combine control flow information with AST structures for enhanced code representation [164], while the **Binary AST** adapts AST techniques for binary-level code analysis [14, 19].

Further extensions include the **Slice Property Graph (SPG)**, which integrates program slicing with graph representations to isolate relevant code segments for analysis [170], and the **Attributed Control Flow Graph** (**ACFG**), which enriches CFGs with additional attributes to capture more granular program details [134]. The **Unified Code Property Graph (UCPG)** consolidates multiple code representations into a unified analytical structure [65], while models like **Path-Flow** focus specifically on tracing execution paths [28].

Lastly, the **Natural Code Sequence (NCS)** approach treats source code as sequences of natural language tokens, enabling the application of natural language processing techniques for code analysis [127, 153]. Among these models, AST is the most widely adopted, appearing in 26 studies. Additionally, as depicted in Figure 6,

graph and tree-based representations have maintained consistent popularity, with 30 papers employing these methods in 2023.

Among these, the Abstract Syntax Tree (AST) is the most widely adopted model, appearing in 26 papers. Figure 6 indicates that Graph/Tree-based representations have been consistently popular, with 30 papers using this method in 2023.

(2) Token-Based Representations: Here, source code is treated as a sequence of tokens, focusing on semantic properties while disregarding structural elements. Code Representations in vulnerability detection vary based on the level of abstraction and the specific analysis goals. One of the simplest forms is using the Source Code directly, without converting it into any structural format, treating it as a plain text sequence. This approach allows for straightforward processing and has been applied in several studies [18, 95, 116, 140, 178]. Moving to more granular representations, the Code Gadget focuses on small, functional segments of code that are often used to analyze specific vulnerabilities. This method enables targeted analysis and has been employed in many studies [37, 61, 71, 107, 108, 131, 173].

Another commonly used representation is the **Code Slice**, which extracts specific portions of the code based on defined slicing criteria, such as data or control dependencies. This method helps isolate relevant code fragments for vulnerability detection and has been utilized in multiple efforts [8, 32, 57, 130, 133, 143, 145]. In contrast, the **Code Snippet** represents small, contiguous segments of code, often extracted for focused analyses on particular code regions [36].

Finally, at the most atomic level, the **Token** representation treats individual code tokens as discrete units of analysis, ignoring their placement within the overall code structure. This approach facilitates fine-grained analysis [25, 50, 117]. Collectively, these representations provide diverse perspectives for analyzing source code, enabling a wide range of techniques for vulnerability detection.

Token-based representations are less popular compared to Graph/Tree-based methods, as reflected in Table 5. However, specific techniques like Code Gadgets and Code Slices have seen broader utilization. Figure 6 shows a steady rise in the use of token-based methods, though their total adoption remains limited.

(3) Intermediate Representation-Based: This category centers on representations used during the intermediate stages of code analysis, providing a simplified and abstract view of the source code. These techniques are designed to transform source code into formats that facilitate more in-depth and comprehensive analysis.

One widely used form of intermediate representation for source code analysis is the **LLVM Intermediate Representation (LLVM IR)**, which is a low-level, platform-independent format designed to facilitate program analysis and transformations. This representation enables detailed examination of program behavior and has been utilized in one effort [69]. In contrast, the **Source-Level Intermediate Representation (SIR)** operates at a higher level, preserving semantic information from the original source code, making it effective for analyses that require a closer connection to source-level constructs [127].

For more compact representations, the **Minimum Intermediate Representation (MIR)** is employed. MIR focuses on reducing redundancy while maintaining the essential features of the program, providing an efficient format for vulnerability detection tasks [66]. Finally, at the lowest level, **Assembly** representation is used, which offers a detailed view of the code close to machine instructions. This representation is particularly useful for low-level security analyses and has been applied in one effort [132].

Together, these intermediate representations provide diverse perspectives for analyzing software, from high-level semantic structures to low-level machine-oriented details, enabling comprehensive approaches to vulnerability detection.

Intermediate representation-based approaches are the least adopted, with only four papers leveraging these methods.

Table 5 provides a concise overview of the models used for each feature representation technique, along with the corresponding paper count for each model. Notably, the AST emerges as the most widely utilized model in the Graph/Tree-based category, appearing in 26 papers. Furthermore, Figure 6 presents the year-wise

distribution of each feature representation technique, highlighting the sustained popularity of graph/treebased representations throughout the survey period. In 2023, for instance, 30 papers adopted graph/tree-based structures for feature representation.

In comparison, the Token-based approach appears less prevalent, as evident by the data in Table 5. However, terms like "code gadget," "code slice," and "code snippet" are frequently used interchangeably to describe non-consecutive code segments, with both code gadgets and code slices being widely employed in several studies. As shown in Figure 6, while the number of papers employing text-based feature representation techniques has gradually increased over time, the overall paper count remains considerably lower than that of studies using graph/tree-based techniques.

Category	# Unique	Models (Total Papers)	Most Popular
	Papers		Model
Graph/Tree Based	70	CFG (9), PDG (23), CPG (13), CDG (1), DDG (1), PCDG (1), DFG (3), EFG (1), behavior graph (1), AST (26), CFAST (1), binary AST (2), slice prop- erty graph (1), value-flow path (1), abstract graph (1), graph (1), attributed control flow graph (1), CG (1), IG (1), NCS (2), unified code	AST (26)
Text-based	23	code gadget (7), code slice (7), source code (5), code snippet (1), token (3)	code gadget (7), code slice (7)
Intermediate representa- tion based	4	LLVM IR (1), SIR (1), minimum intermediate representation (1), assembly (1)	-

Table 5. realure representation methods used in DL-based technique	Гable 5.	eature representati	on methods us	ed in DL-based	l technique
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Table 6. E	mbedding methods used in DL-based techniques	

Category	# Unique	Models (Total Papers)	Most Popular
	Papers		Model
Text-based	73	word2Vec (44), gloVe (3), doc2Vec (5), CBoW (3), sent2vec (6), GRU (1), FastText (3), PACE (1), n-gram (1), Keras library (1), one hot encoding (2)	word2Vec (44), own (12)
BERT Based	13	BERT (4), CodeBERT (8), RobertA (1)	CodeBERT (8)
Graph based	7	node2vec (2), knowledge graph embedding (1), graphToVec (1), struct2vec (1),label-GCN (1), GPT-GNN (1), graph embedding (1)	node2vec (2)
Other	4	<ul><li>large language model embedding (1), MPNet</li><li>(1), value flow path embedding (1), code2vec</li><li>(1)</li></ul>	-

6.2.3 **Embeddings**. Embeddings are essential for converting raw code into continuous vector representations, enabling the code to be effectively input into deep learning models. In this section, we classify the existing deep learning-based approaches according to the embedding techniques used for code representation. The embedding methods identified in the literature are outlined below:

(1) Text-based Embedding: This category includes text-based embedding methods where various versions of source code are passed through embedding models to generate vector representations.

One of the most commonly used methods is **Word2Vec**, which learns vector representations of words by predicting the context in which words appear, effectively capturing semantic relationships. This technique has been extensively utilized in numerous studies [17–19, 23, 25, 26, 32, 35–37, 42, 47, 48, 57, 64, 69, 71, 73, 74,

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Fig. 7. Year-wise distribution of the embedding techniques used in DL-based papers

78, 79, 102, 116, 118, 127, 131–134, 137, 143–145, 148–150, 152, 153, 160, 161, 163, 170, 179]. Complementing Word2Vec, **GloVe** generates word embeddings by factoring a word co-occurrence matrix, capturing global statistical information, and has been applied in three studies [57, 67, 165].

Further extending embedding capabilities, **doc2Vec** learns fixed-length vector representations for entire documents or code snippets, preserving context across longer code fragments [20, 23, 27, 57, 65]. Another related method, the **Continuous Bag of Words (CBoW)**, predicts a target word based on its surrounding context, effectively representing words through their neighboring tokens [66, 73, 74]. For capturing semantic meaning at the sentence or code fragment level, **Sent2Vec** has been employed, which generates continuous vector representations that reflect the overall context [57, 89, 104, 139, 147, 151].

In addition to traditional embeddings, recurrent models like the **Gated Recurrent Unit (GRU)** are used to learn sequential dependencies within code, leveraging gated mechanisms to control information flow [67]. **FastText**, an extension of Word2Vec, represents words as bags of character n-grams, allowing it to capture subword-level information and handle rare words more effectively [23, 57, 167]. Moreover, character-level embedding methods such as **Position-Aware Character Embedding (PACE)** focus on the positional information of characters within code fragments, enhancing syntax-related feature learning [38].

Other notable techniques include **n-gram Based Embedding**, which captures local dependencies in the code by embedding sequences of consecutive words or characters [8], and the **Keras Library Embedding**, a custom embedding approach implemented using the Keras framework to generate vector representations based on specific code patterns [117]. Simpler approaches like **One-Hot Encoding** represent tokens as binary vectors, indicating the presence or absence of specific elements in the vocabulary [37, 161].

Finally, several studies have proposed **Custom Embedding Methods** tailored to specific code analysis tasks, leveraging novel techniques to transform source code into meaningful vector representations [14, 23, 31, 52, 70, 76, 85, 95, 135, 146, 173]. Collectively, these embedding methods form the foundation for feature extraction in source code analysis, enabling machine learning models to perform effective vulnerability detection.

Table 6 provides a summarized overview of all the embedding methods mentioned. Notably, Word2Vec stands out as the most widely used technique among text-based methods, incorporated in 44 studies. Figure 5 shows the year-wise distribution of embedding techniques used in the studies included in our survey. Text-based embedding methods have consistently been popular, with 21 papers employing them in 2023 alone.

(2) BERT-Based Embedding: Techniques in this category leverage models pre-trained on large corpora of text data, which are then fine-tuned for specific downstream tasks, including vulnerability detection in source code. One of the most widely used models in this category is **BERT**, a transformer-based architecture that captures deep contextual relationships by analyzing bidirectional dependencies within the data. This model has been effectively applied to code analysis in several studies [34, 61, 164, 178]. Building on the success of BERT, **CodeBERT** was introduced as a variant specifically designed for programming languages. Pre-trained on a large corpus of source code, CodeBERT has been fine-tuned for various tasks, including vulnerability detection, and has demonstrated strong performance in multiple studies [54, 96, 103, 108, 130, 140, 155, 166].

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In addition to BERT and CodeBERT, **RoBERTa** represents a robustly optimized version of BERT. By employing a larger batch size, longer training periods, and more extensive datasets, RoBERTa has achieved improved performance across a range of NLP and code-related tasks, including vulnerability detection [50]. Collectively, these BERT-based embedding models offer advanced capabilities for understanding both natural language and programming code, making them highly effective tools for software vulnerability analysis.

Table 6 offers an overview of the embedding methods discussed. BERT-based models have become increasingly popular in recent studies due to their powerful representation capabilities. The table clearly shows that, among BERT-based embedding techniques, CodeBERT is the most widely used method, appearing in eight papers. Furthermore, Figure 5 illustrates that BERT-based models were first introduced in SVD in 2021, and since then, the number of papers utilizing BERT-based embeddings has steadily increased, although it remains significantly lower compared to the adoption of text-based methods.

(3) Graph-based Embedding: These techniques leverage graph representations of code to capture complex relationships between different elements and structures within a program. These approaches model code as graphs, where nodes represent entities such as functions or variables, and edges denote relationships like dependencies or control flows.

One widely used technique in this category is **Node2vec**, which learns vector representations for nodes by optimizing a neighborhood-preserving objective, allowing it to effectively capture local graph structures [138, 162]. Complementing this, **Knowledge Graph Embedding** maps knowledge graphs into vector spaces, enabling the model to capture semantic relationships between entities and their attributes, which is particularly useful for code analysis tasks [20].

For capturing the overall structure of code, **GraphToVec** is employed to learn fixed-size vector representations of entire graphs, facilitating the analysis of code interactions and structural patterns [158]. Similarly, **Struct2vec** focuses on encoding structural information by considering the global context of nodes and edges within the graph, thereby enhancing the representation of code hierarchies [162]. Additionally, **Label-GCN**, a variant of the graph convolutional network (GCN), incorporates label information into the graph learning process, improving code representation and vulnerability detection performance [68].

Another notable model is **GPT-GNN**, which combines the language modeling capabilities of GPT with the relational learning power of graph neural networks, effectively capturing both sequential code patterns and graph-based relationships for task-specific applications [129]. Finally, **Graph Embedding** refers to general techniques that map graph structures, such as control flow graphs or program dependence graphs, into continuous vector spaces, enabling downstream analysis for tasks like vulnerability detection [141].

Collectively, these graph-based embedding methods provide robust frameworks for representing code in a way that captures both syntactic and semantic relationships, facilitating more accurate and comprehensive vulnerability analysis.

Table 6 indicates that several graph-based embedding methods were utilized, with node2vec appearing in two papers, while the remaining approaches were each used in just one paper. As shown in Figure 5, graph-based embeddings are less popular than text-based methods, although their use has gradually increased over time. In 2023, a total of five papers employed graph-based embedding techniques.

(4) Other Embedding Techniques: This category encompass a variety of approaches that do not fit directly into traditional categories but offer unique advantages for source code representation and vulnerability detection.

One such technique is **LLM Embedding**, which leverages large pre-trained language models to generate rich, contextual embeddings for source code, capturing deep semantic relationships and code patterns [107]. Complementing this, **MPNet** is a transformer-based model designed to generate embeddings by learning contextual relationships within code snippets, enhancing the understanding of code semantics and dependencies [83].

Another notable method is **Value Flow Path Embedding**, which focuses on capturing the flow of values through a program, encoding these paths into representations that can be effectively utilized for downstream tasks such as vulnerability detection [28]. Additionally, **Code2Vec** offers a distinctive approach by learning

code embeddings based on abstract syntax trees (ASTs), mapping source code into continuous vector spaces for more effective and interpretable representations [44].

Collectively, these embedding techniques broaden the scope of code representation methods, offering specialized solutions that enhance the performance of code analysis models in various software engineering tasks.

# 7 INSIGHTS, CHALLENGES, AND FUTURE DIRECTIONS

In the preceding sections, we analyzed and summarized key characteristics of existing vulnerability detection techniques based on the selected literature. Building on this analysis, thid section explores the core insights, challenges, limitations, and open problems in software vulnerability detection, while also outlining potential directions for future research—thereby addressing **RQ4**.

#### 7.1 Datset Issues

Issues related to datasets are pivotal concerns in vulnerability detection, particularly with the advent of ML and DL-based approaches, which demand substantial data for effective training. While several datasets exist, as discussed in Section 4, certain limitations persist among them. These limitations impact the performance of recent vulnerability detection models, as they are directly influenced by the quality and characteristics of the datasets utilized. The major dataset issues are outlined below.

7.1.1 Lack of Real-World, Large-Scale data. A significant challenge with current datasets is the scarcity of real-world data suitable for training purposes. For instance, the widely used SARD dataset<sup>5</sup> generates synthetic samples that may not accurately reflect real-world scenarios. For example, Chakrabarty et al. [21] demonstrated, with some examples, that real-world examples are more complex than the synthetic ones. It is worth mentioning that although another public dataset NVD<sup>6</sup> contains around 220K records, only a limited number of samples are usable after applying the pre-processing on data [124].

7.1.2 *Imbalanced Data.* The current datasets contain more non-vulnerable records than vulnerable ones as we observed in the primary papers used in our work in Table 3. The same observation is also mentioned by Ghaffarian and Shahriar [46] where they worked with different sets of papers. When a model is trained on such an imbalanced dataset, it is biased towards non-vulnerable examples [21]. One proposed solution by Chakraborty et al. [21] is to use synthetic minority oversampling technique (SMOTE) where we super sample the minority class until all classes have the same frequency.

*7.1.3 Inaccurate Labels.* According to Croft et al. [29], existing datasets suffer from inaccurate labeling. Their analysis of 70 random samples reveals that accuracy values for real-world datasets Devign, Big-Vul, and D2A are 0.80, 0.543, and 0.282 respectively.

7.1.4 Lack of Uniqueness. Croft et al. [29] also mention that over 94% of data in the D2A dataset contains type-1 code clones. The uniqueness values for Devign, Big-Vul, D2A, and Juliet were 0.899, 0.830, 0.021, and 0.163 respectively. In another study, Chakraborty et al. [21] demonstrated, semi-synthetic datasets like NVD, SARD, and Juliet result in a large number of duplicates (more than 60%). If the model is not trained on a dataset that contains unique samples, that can have an impact on the overall performance of the model. Both inter-set and intra-set duplicate samples can lead to improper performance measurement [21].

7.1.5 Lack of Multi-Language Datasets. The current datasets are mostly derived from C/C++ language as we noticed in Table 3. The recent efforts therefore focus mainly on C/C++ as we can see from the pie chart in Figure 3(c). More datasets are required in multiple languages to facilitate work on other programming languages.

*7.1.6 Coarse Granularity Levels.* As shown in Table 3 and Figure 3, most datasets—and consequently, recent research efforts—focus primarily on the function level granularity. However, finer-grained datasets are essential to support techniques capable of precisely pinpointing vulnerabilities.

<sup>&</sup>lt;sup>5</sup>https://samate.nist.gov/SARD

<sup>&</sup>lt;sup>6</sup>https://nvd.nist.gov/

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7.1.7 *Limited Vulnerability Type Coverage.* Our analysis shows that most existing techniques are either vulnerability-type agnostic or narrowly focused on a limited set of vulnerability types. This is inadequate for real-world applications, where practitioners must address a wide range of vulnerabilities, and the specific type being detected is crucial context for effective remediation.

#### 7.2 Unavailability of Data/Model

One of the major issues we identified is the lack of publicly available models or datasets. As shown in Figure 3(a), over 50% of the reviewed efforts do not provide access to either, making reproducibility a significant challenge. This observation aligns with findings by Nong et al. [98], who analyzed 55 papers for adherence to open-science principles, including availability, executability, reproducibility, and applicability. Their study found that only 25.5% of the papers released their tools publicly, and of those, 54.5% lacked proper documentation. Additionally, 27.3% had incomplete or non-functional implementations, rendering them effectively unreproducible. Even among functional tools, only 87.5% were reproducible, and just 14.3% remained replicable when tested on different datasets. Reproducibility is critical not only for validating published results but also for fostering a continuous, self-correcting research process [7].

#### 7.3 Language Dependency

Another key observation is that most existing models are language-specific. As noted in our discussion of dataset limitations, these constraints often carry over into the models trained on them. C/C++ is by far the most commonly used language, while other programming languages remain significantly underrepresented. Moreover, few efforts have produced language-agnostic models. To support the development of more versatile and adaptable solutions, there is a clear need for language- and platform-independent approaches capable of addressing vulnerabilities across a wider range of software systems.

#### 7.4 Insufficient Comparative Analysis Across Approaches

In this work, we introduced a taxonomy for source-code-based vulnerability detection (SVD) methods. Future research could build upon this framework by systematically evaluating and comparing the performance of techniques in various categories. While some comparative studies exist [93, 128, 169], the field still lacks comprehensive and consistent benchmarking.

For example, Zhang et al.[169] found that certain models performed well on real-world datasets but underperformed on manually crafted ones, highlighting the sensitivity of model performance to dataset characteristics. Moreover, there remains a lack of clarity regarding the relative effectiveness of different neural network architectures within SVD[177]. For instance, Convolutional Neural Networks (CNNs) are generally better suited for local feature extraction, whereas Bidirectional LSTM (BiLSTM) networks are more effective at capturing long-range dependencies [177].

Embedding and feature representation techniques also significantly influence model performance. According to Zhu et al. [177], a BiLSTM model performed poorly when using GloVe or Doc2Vec embeddings compared to Word2Vec and FastText. Interestingly, CodeBERT embeddings also underperformed relative to Word2Vec and FastText, despite outperforming GloVe and Doc2Vec. Code2Vec, trained specifically on source code, captured richer semantic information and outperformed the other general-purpose embeddings.

These variations suggest a need for deeper investigation into the interplay between model architectures and embedding techniques. Future research should aim to identify optimal combinations or, at the very least, understand the trade-offs involved in different design choices. Our proposed taxonomy offers a structure for guiding such studies, enabling researchers to systematically test various configurations and identify the most effective strategies for vulnerability detection.

# 7.5 Lack of Interpretability

A growing trend in vulnerability detection is the adoption of deep learning (DL)-based approaches over traditional or classical machine learning (ML) methods. While this shift is promising, DL models are inherently black-box in nature [115], meaning their decision-making processes are often opaque. This lack of transparency poses a significant challenge for the SVD domain, where interpretability is critical—not only for understanding why a vulnerability was detected but also for effectively addressing and resolving it.

Among the studies we reviewed, only a few explicitly addressed interpretability. For example, Li et al. [67] utilized GNNExplainer[154], an interpretable graph neural network framework that helps explain the model's predictions. Similarly, Gu et al. [47] introduced a model with attention mechanisms at both the line and token levels, offering more insight into how the model processes source code.

Despite these efforts, most existing DL-based models remain largely uninterpretable. Greater attention should be directed toward integrating explainable AI techniques or human-in-the-loop methods to enhance model transparency. Improving interpretability will be essential for building trust in automated vulnerability detection systems and supporting effective remediation strategies.

#### 7.6 Granularity Limitations

One significant limitation we observed is that most existing models are not designed for fine-grained vulnerability detection. As highlighted in the pie charts in Figure 3, the majority of current approaches operate at the function level. While a few studies have explored finer-grained detection, such as identifying vulnerabilities at the line or statement level, these efforts remain limited in number.

Fine-grained detection is necessary for providing developers with precise insights into vulnerable code segments. By pinpointing the exact statements responsible for vulnerabilities, such models can greatly assist in efficient debugging and remediation. Therefore, future research should focus on developing and promoting fine-grained approaches to better support practical vulnerability mitigation.

#### 7.7 Greater Adoption of Emerging Deep Learning Techniques is Needed

An analysis of our taxonomy reveals that several emerging DL techniques remain underutilized in the SVD domain, often grouped under the "Other" category. Among these, federated learning (FL) stands out as a promising but largely unexplored approach.

Originally introduced by Google in 2017, FL enables the training of machine learning models across decentralized devices or servers while keeping data localized and private. Although FL has been successfully applied in various cybersecurity domains—including intrusion detection [63, 110], anomaly detection [9], malicious attack detection [53], and malware detection [114]—its application in the SVD domain remains minimal. To date, we identified only a single study [163] that applied FL for vulnerability detection. Given its ability to preserve privacy while leveraging distributed data, FL represents a highly relevant and underexplored direction for future SVD research.

Another emerging approach that has seen limited application in this field is quantum neural networks (QNNs). QNNs integrate the principles of quantum computing with neural network architectures, offering enhanced computational power and potential improvements in learning capacity. They have already demonstrated promise in a range of security-focused areas, including network anomaly detection [5], supply chain attack detection [5], intrusion detection [59], objectionable content filtering [101], and hardware security [12]. However, in the context of software vulnerability detection, their application is nearly nonexistent, with only one known study [173] exploring this avenue.

Given the demonstrated success of both FL and QNNs in related security domains, further exploration of these techniques in SVD is warranted. Leveraging these emerging technologies could significantly enhance the scalability, privacy, and accuracy of future vulnerability detection models.

#### 7.8 Poor Performance on Real-World Data

One of the major challenges in software vulnerability detection (SVD) is the poor generalization of existing models to real-world scenarios. Chakraborty et al. [21] conducted experiments using several widely adopted vulnerability detection models and found a significant performance drop when these models were applied to real-world datasets. Specifically, they observed that when a pre-trained model was directly tested on real-world data, its performance dropped by approximately 70%. Even after retraining the models with real-world data, the performance decline remained substantial—around 54%.

For instance, the VulDeePecker model [71] originally reported a precision of 87%. However, when evaluated on real-world data using the pre-trained model, the precision dropped drastically to 11%. Even after retraining, the precision only reached 18%, which is still considered low and inadequate for practical deployment.

To address this issue, future work should focus on strategies that enhance model robustness and adaptability. Potential approaches include data augmentation, transfer learning, fine-tuning with diverse real-world data, and the integration of explainable AI techniques to improve model interpretability and generalization.

#### 8 CONCLUSION

This study provides a comprehensive review of recent advancements in software vulnerability detection (SVD) using AI-based techniques. By systematically analyzing research published between 2018 and 2023, we developed a detailed taxonomy that captures key dimensions of source-code-based SVD approaches, including detection techniques, feature representation methods, and embedding strategies. In addition to this taxonomy, we documented the core characteristics of existing datasets and models, highlighted current limitations, and proposed future research directions to advance the field.

Our analysis shows that over 96% of the reviewed studies employed deep learning (DL) methods, with graph-based techniques emerging as the most commonly used for both feature extraction and embedding generation. Despite notable advancements, several critical challenges persist, including limited datasets, reproducibility issues, granularity limitations, and a lack of interpretability. Granularity limitations are particularly problematic; without detailed, fine-grained information, practitioners struggle to effectively identify and remediate vulnerabilities. Addressing these challenges should be a primary focus of future research in this field. We also identified a need for greater exploration of emerging approaches, such as federated learning and quantum neural networks, which have shown promise in other security domains.

By addressing these gaps and embracing innovative methodologies, the research community can significantly improve the robustness, scalability, and practical applicability of vulnerability detection systems.

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