APPENDIX

A SLR METHODOLOGY

A.1 Literature Search and Selection

To collect DL related papers in SE, we identified a search string including several DL related terms frequently appeared in SE papers that make use of DL. We then refined the search string by checking the title and abstract of a small number of relevant papers. After that, we used logical ORs to combine these terms, and the search string is:

("deep learning" OR "neural" OR "Intelligence" OR "reinforcement" OR "NN" OR "nn")

We specified the range the papers are published later: 2006- 2020. Following previous studies [7, 8, 11], we selected 32 widely read journals (10) and conferences (22) listed in Table 13 to conduct a comprehensive literature review. We run the search string on three databases (i.e., ACM digital library [7], IEEE Explore [8], and Web of Science [9]) looking for publications in the 32 publication venues whose meta data (including title, abstract and keywords) satisfies the search string. Our preliminary results search returns 824 relevant papers.

A.2 Literature Filtering

After retrieving studies that match our search string, it is necessary to filter unqualified studies, such as studies with insufficient contents or missing information. To achieve this, we applied our inclusion and exclusion criteria to determine the quality of candidate studies for ensuring that every study we kept implemented and evaluated a full DL approaches to tackle SE tasks.

The following inclusion and exclusion criteria are used:

✔ The paper must be written in English.
✔ The paper must adopt DL techniques to address SE problems.
✔ The length of paper must not be less than 6 pages.
✘ Books, keynote records, non-published manuscripts, and grey literature are dropped.
✘ If a conference paper has an extended journal version, the conference version is excluded.

The literature filtering consisted of three steps and was performed by three researchers with rich experience in software engineering. We first discarded duplicate papers from our preliminary results. After that, we applied the inclusion/exclusion criteria by reading their title, abstract and keywords, and narrow the candidate set to 271 studies. After looking through these 271 studies to ensure their relevance (i.e., if a study used deep learning techniques to address practical problems in software engineering, it will be kept as a primary study.), we retained 250 studies. We invited a third researcher to double-check the inconsistencies between the two researchers in the last two steps to minimize human error.

A.3 Data Extraction and Collection

After removing the irrelevant and duplicated papers, we extracted and recorded the essential data and performed overall analysis for answering our four RQs. Table 14 described the detailed information being extracted and collected from 250 primary studies, where the column *'ExtractedDataItems'* lists the related data items that would be extracted from each primary study, and the column *'RQ'* denotes the related research questions to be answered by the extracted data items on the right. To avoid making mistakes in data collection, two researchers extracted these data items from primary studies together and then another researcher double checked the results to make sure of the correctness of the extracted data.

[7] https://dl.acm.org
[8] https://ieeexplore.ieee.org
[9] http://apps.webofknowledge.com

Table 13. Publication venues for manual search

No.	Acronym	Full name	No.	Acronym	Full name
1.	ICSE	ACM/IEEE International Conference on Software Engineering	23.	TSE	IEEE Transactions on Software Engineering
2.	ASE	IEEE/ACM International Conference Automated Software Engineering	24.	TOSEM	ACM Transactions on Software Engineering and Methodology
3.	ESEC/FSE	ACM SIGSOFT Symposium on the Foundation of Software Engineering/European Software Engineering Conference	25.	ESE	Empirical Software Engineering
4.	ICSME	IEEE International Conference on Software Maintenance and Evolution	26.	JSS	Journal of Systems and Software
5.	ICPC	IEEE International Conference on Program Comprehension	27.	IST	Information and Software Systems
6.	ESEM	ACM/IEEE International Symposium on Empirical Software Engineering and Measurement	28.	ASEJ	Automated Software Engineering
7.	RE	IEEE International Conference on Requirements Engineering	29.	IETS	IET Software
8.	MSR	IEEE Working Conference on Mining Software Repositories	30.	STVR	Software Testing, Verification and Reliability
9.	ISSTA	ACM SIGSOFT International Symposium on Software Testing and Analysis	31.	JSEP	Journal of Software: Evolution and Process
10.	SANER	IEEE International Conference on Software Analysis, Evolution and Reengineering	32.	SQJ	Software Quality Journal
11.	ICST	IEEE International Conference on Software Testing, Verification and Validation			
12.	ISSRE	IEEE International Symposium on Software Reliability Engineering			
13.	COMPSAC	IEEE International Computer Software and Applications Conference			
14.	QRS	IEEE International Conference on Software Quality, Reliability and Security			
15.	SPLC	Software Product Line Conferences			
16.	OOPSLA	ACM SIGPLAN international conference on Object oriented programming systems languages	applications		
17.	PLDI	ACM SIGPLAN Conference on Programming Language Design and Implementation			
18.	AAAI	Proceedings of the AAAI Conference on Artificial Intelligence			
19.	ICML	The International Conference on Machine Learning			
20.	ICLR	International Conference on Learning Representations			
21.	NeurIPS	Annual Conference on Neural Information Processing Systems			
22.	IJCAI	International Joint Conference on Artificial Intelligence			

B BA: WHAT ARE THE TRENDS IN THE PRIMARY STUDIES ON USE OF DL IN SE?

We analyzed the basic information of primary studies to comprehend the trend of DL techniques used in SE in terms of the publication date, publication venues, and main contribution types of primary studies.

Table 14. Data Collection for Research Questions

RQs	**Extracted data items**
RQ1	Basic information of each primary study (i.e., title, publication year, authors, publication venue)
RQ1	The type of main contribution in each study (e.g., empirical study, case study, survey, or algorithm)
RQ2	DL techniques used in each study
RQ2	Whether and how the authors describe the rationale behind techniques selection
RQ3	Dataset source (e.g., industry data, open source data, or collected data)
RQ3	Dataset name
RQ3	The generation method of ground-truth for training/testing/validation sets
RQ3	Data type (e.g., source code, nature language text, and pictures)
RQ3	The process that datasets are transformed into input sets suitable for DNNs
RQ3	Presence / absence of replication package
RQ4	The practical problem that a SE task tries to solve
RQ4	The SE activity in which each SE task belongs
RQ4	The approach used for each SE task (e.g., regression, classification, ranking, and generation)
RQ5	Whether and what optimization techniques are used
RQ5	What measures are used to evaluate the DL model

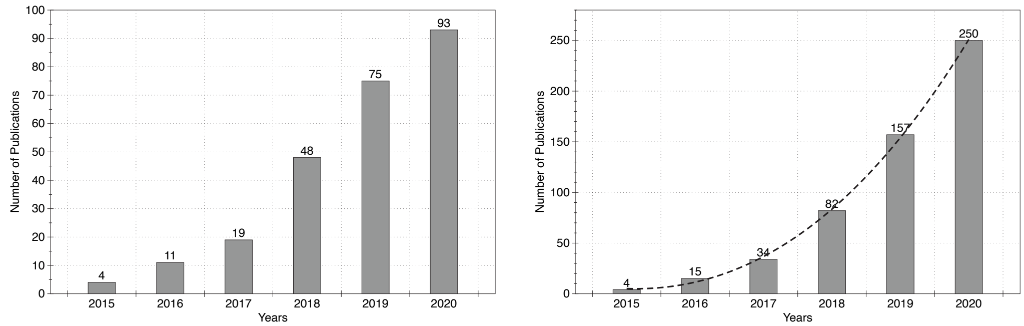
B.1 Publication trends of DL techniques for SE

We analyzed the publication trends of DL-based primary studies published between 2006 and 2020. Although the concept of "Deep Learning" has been proposed in 2006 and DL techniques had been widely used in many other fields in 2009, we did not find any studies using DL to address SE tasks before 2015. Fig. 5(a) shows the number of relevant studies published in predefined publication venues since 2020. It can be observed that the number of publications from 2015 to 2020 shows a significant increase, with the number researching 93 papers in 2020. Besides, another trend among DL studies is that a growing number of papers turn the research direction into using software engineering techniques at the service of DL models, i.e., SE4AI. For example, Guo et al. [5] utilized software testing techniques to locate bugs in the DL frameworks. They present a search-based approach, AUDEE, to identify three types of bugs: logical bugs, crashes, and Not-a-Number (NaN) errors. Specifically, they initialized diverse seeds by exploring hidden layers, inputs, parameters, and model structures and adopted three mutation strategies to generate test cases: Network-level mutation, Input-level mutation, and Weight-level mutation. They then leveraged a heuristic-based cross-checking approach to detect output inconsistencies among different DL frameworks. Finally, they located the corresponding layers in the network by using the causal-testing technique. To improve the ability to resist adversarial attacks, Du et al. [3] performed quantitative robustness analysis on RNN-based DL frameworks to estimate the capability of an RNN neural network in tolerating input perturbations. They built an abstract model to conduct light-weight robustness estimation for real-time Dl applications.

We also performed an analysis of the cumulative number of publications as shown in Fig. 5(b). We fit the cumulative number of publications as a Cubic function, showing the publication trend in the last five years. We can notice that the slope of the curve fitting the distribution increases substantially between 2015 and 2020, and the coefficient of determination (R^2) attains the peak value (0.99928), which indicates that the number of relevant studies using DL in SE intends to experience a strong rise in the future. Therefore, after analyzing Fig. 5, it can be foreseen that using DL techniques to address various SE tasks has become a prevalent trend since 2015, and huge numbers of studies will adopt DL to address further challenges of SE.

B.2 Distribution of publication venues

We reviewed 250 studies published in various publication venues, including 22 conference proceedings and symposiums as well as 10 journals, which covers most research areas in SE. Table 15 lists the number of relevant papers published in each publication venue. 79.6% of publications appeared in conferences and symposiums, while



(a) Number of publications per year.

(b) Cumulative number of publications per year.

Fig. 5. Publication trends of DL-based primary studies in SE.

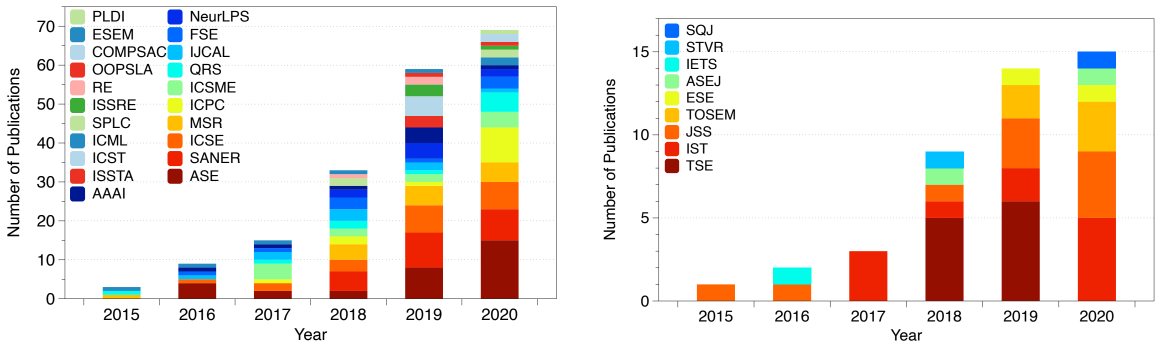
Table 15. Publication Venues with DL-based Studies in SE.

Conference venue				Journal venue	
Acronym	**# Studies**	**Acronym**	**# Studies**	**Acronym**	**# Studies**
ASE	31	AAAI	8	TSE	13
SANER	22	ISSTA	7	IST	11
ICSE	20	ICST	5	JSS	10
MSR	13	ICML	5	ESE	8
ICPC	12	SPLC	4	TOSEM	5
ICSME	12	ISSRE	4	ASEJ	1
ICLR	11	RE	3	IETS	1
QRS	10	OOPSLA	2	STVR	1
IJCAI	9	COMPSAC	2	SQJ	1
FSE	9	ESEM	1		
NeurIPS	8	PLDI	1		

only 20.4% of journal papers leveraged DL techniques for SE tasks. Among all conference papers, 8 different conferences include over 10 studies using DL in SE in the last five years, i.e., ASE, SANER, ICSE, MSR, ICPC, ICSME, ICLR, and QRS. Compared with other conference proceedings, ASE is the most popular one containing the highest number of primary study papers (31), followed by SANER (22). There are 20 and 13 relevant papers published in ICSE and MSR, respectively. Meanwhile, in all journals, TSE includes the highest number of relevant papers (13), followed by IST (11). 10 and 8 studies related to DL techniques were published in JSS and EMSE, respectively. And 5 were published in TOSEM.

We also checked the distribution of primary studies published in conferences and journals between 2015 and 2020, shown in Fig. 6. Fig 6(a) illustrates that the publication trend of various conference proceedings and symposiums has a noticeable increase from 2015 to 2020. 86.8% of conference papers were published between 2018 and 2020, while only a few different conferences or symposium venues included relevant papers between 2015 and 2017, which demonstrates a booming trend in the last few years.

Fig. 6(b) shows the number of primary study papers published in different journal venues. It can be seen that there is an increasing trend in the last five years, especially between 2018 and 2020. Furthermore, the relevant papers published in TSE, as one of the most popular journals, accounts for the largest proportion in 2018 and 2019; while another popular journals, IST and JSS, also make up a large percentage in 2019 and 2020.



(a) Number of primary studies published in various conference proceedings.

(b) Number of primary studies published in various journals.

Fig. 6. Distribution of papers in different publication venues.

Table 16. The definition of five main contributions in primary studies.

Main contribution	**Definition**
New technique or methodology	The study provided a solid solution or developed a novel framework to address specific SE issues.
Tool	The study implemented and published the source code of the DL model or a tool demo targeting SE issues.
Empirical study	The study collected primary data and performed a quantitative and qualitative analysis on the data to explore interesting findings.
Case study	The study analyzed certain SE issues based on one or more specific cases.
User study	The study conducted a survey to investigate the attitudes of different people (e.g., developers, practitioners, users, etc) towards SE issues.

B.3 Types of main contributions

We summarized the main contribution of each primary study and then categorized these studies according to their main contributions into five categories, i.e., New technique or methodology, Tool, Empirical study, Case study, and User study. We give the definition of each main contribution in Fig 7. The main contribution of 90.8% of the primary studies was to build a novel DNN as their proposed new technique or methodology for dealing with various problems in different SE activities. There are 101 studies whose source code of their DL tools or models is available, accounting for 40.4%. Sharing DL models proposed in studies is a valuable contribution for related researchers since it benefits to replicate and reproduce those models in their research. 27 relevant studies concentrated on performing assessment and empirical studies for exploring the benefits of DL towards different SE aspects, such as research on the differences between ML and DL to solve certain SE tasks, the performance of using DL to mine software repositories, applying DL in testing, etc. The main contribution of 5.6% was case studies, and 4 studies conducted user studies to evaluate the performance of DL models. 6 primary studies that both proposed a novel methodology and evaluated the novel methodology via a user study.

Summary

(1) DL has shown a booming trend in recent years.
(2) Most of primary study papers were published between 2018 and 2020.
(3) The number of conference papers employing DNNs for SE significantly exceeds that of journal papers.

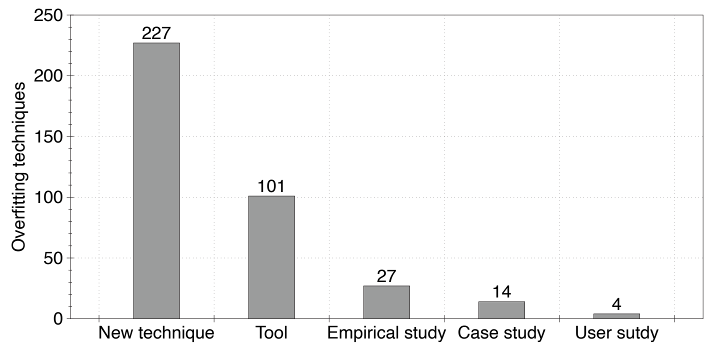


Fig. 7. Types of main contributions

(4) ASE is the conference venue publishing the most DL-based papers (31), while TSE includes the highest number of relevant papers among all journals (13).
(5) Most DL-based studies were only published in a few conference proceedings (e.g., ASE, SANER, ICSE, MSR, and ICPC) and journals (e.g., TSE, IST, JSS, EMSE, and TOSEM).
(6) The main contribution of 90.8% primary studies is to propose a novel methodology by applying various DL techniques, while only 4 primary studies performed a user study to better understand users' attitudes and experience toward various DNNs used for solving specific SE tasks.

C DL MODELS USED IN SE

Table 17 classifies the common DNNs used in primary studies based on their DL architectures and presents the distribution of DNNs in terms of publication time.

D DATA TYPES IN DATASETS

We classified the datasets used in all primary studies into six categories: code-, text-, metric-, graph-, software repository-based datasets, and combined datasets. Table 18 summarizes the specific data types in each category and also describes the usage distribution of those six categories according to the number of references.

E DL MODELS IN DIFFERENT SE ACTIVITIES

Table 19 to Table 24 illustrates the relationships of DNNs with respect to DL architectures, data types, task types, and problem types in six different SE activities, i.e., software requirement, software design, software development, software testing, software maintenance, and software management.

F EVALUATION METRICS FOR DL MODELS

Table 25 and Table 26 list common overfitting techniques and evaluation metrics for DNNs used in four different problem types, including regression, classification, recommendation, and generation SE tasks.

Table 17. The number of various DNNs applied in per year.

ArchitectureFamily		Model Name	2015	2016	2017	2018	2019	2020
Layered architecture	RNN-based model (72)	RNN	[IEEE83]	[IEEE15]	[ACM09, IEEE12, ACM22]	[ACM05, ACM06, IEEE20, IEEE52, ACM30, MITP02, IEEE114]	[IEEE04, IEEE06, SP04, ACM16, IEEE51, IEEE64,ACM29, EL05, EL21, IEEE126, IEEE107]	[ACM07, EL02, EL03, IEEE26]
		RtNN		[ACM02, IEEE15]		[IEEE80]		
		Bidirectional RNN (BRNN)						[ACM07, EL03]
		LSTM			[ACM09, ACM21, IEEE56, MK05, MK06, ICLR08]	[ACM05, ICLR09, IEEE49, IEEE42, IEEE53, MK04, MK09, ACM31, EL17, IEEE87, IEEE116, IEEE128, IEEE131]	[AAAI03, AAAI04, AAAI05, AAAI06, IEEE01, IEEE08, ICLR02, IEEE38, ACM17, IEEE63, EL14, IEEE74, IEEE77, IEEE134, IEEE110, IEEE104]	[AAAI07, ACM07, IEEE21, ICLR01, IEEE67, EL03, EL20, IEEE97, IEEE99, IEEE108, ACM32, IEEE135, IEEE141]
		Bi-LSTM			[IEEE54]		[ACM23, IEEE125, IEEE94]	[EL12, IEEE28, ACM18, EL03, IEEE35, IEEE92]
		GRU			[AAAI01, ICLR05]	[AAAI08]	[IEEE107, ACM37]	[ACM07, IEEE18, ACM10, EL16, EL03, EL11, IEEE136]
		Bidirectional GRU					[MK02]	[EL03]
		Recurrent Highway Network					[IEEE134]	
	CNN-based model	CNN		[AAAI02, AAAI05, IEEE13, IEEE16, ACM13, MK07]	[IEEE54, IEEE57, MK06, IEEE85]	[ACM03, ACM05, EL08, IEEE10, ICLR09, IEEE41, IEEE52, IEEE53, IEEE78, IEEE81, IEEE115, IEEE118, moran2018machine, IEEE130]	[EL07, ACM24, ACM19, IEEE50, IEEE62, IEEE65, IEEE69, EL05, IEEE73, IEEE76, IEEE125,MITP03, IEEE124, IEEE123, IEEE122, ACM34, IEEE111, IEEE109, IEEE106, IEEE103, IEEE95, IEEE94, MITP04]	[AAAI07, ACM08, IEEE18, IEEE22, IEEE23, IEEE02, IEEE30, SP08, IEEE46, IEEE47, IEEE24, IEEE67, ACM27, EL02, IEEE100, IEEE102, ACM36, IEEE135, IEEE139, IEEE140, IEEE142, IEEE132]
		Tree-based CNN (TBCNN)					[IEEE104]	[EL13]
		RCNN					[EL05]	[EL02]
		DPCNN						[MITP05]
		Deep Residual Network						[EL04]

Architecture	Family	Model Name	2015	2016	2017	2018	2019	2020
Layered architecture	FNN-based model	FNN		[IEEE14, IET01, EL18]	[IEEE55]	[ACM04, EL09, IEEE10, SP01, EL17, IEEE86, IEEE96, IEEE121, IEEE120, W01]	[IEEE07, IEEE09, EL15, IEEE88]	[IEEE60, EL01, IEEE71, IEEE82, IEEE119, IEEE91, IEEE93, IEEE25, IEEE117, IEEE58]
		RBFNN	[EL19, ACM20]					
		Deep Sparse FNN					[ACM14]	
		MLP					[SP04]	
	GNN-based model	GGNN			[ICLR10]		[IEEE01, IEEE06, MITP03, IEEE104]	[MITP05, IEEE28, IEEE138]
		Graph Matching Network (GMN)					[IEEE64]	[ICLR01, ACM39]
		GNN						[ACM38]
		ConvGNN						[IEEE136]
	Tailored model	Deep Beliefe Network (DBN)	[IEEE84]	[IEEE43]		[IEEE127]		
		HAN					[EL05]	[IEEE45]
		Deep Forest					[EL06]	[IEEE90]
		GAN				[MITP01]		
		Deep fusion learning model						[ACM28]
		Mata-learning						[SP06, IEEE48, ACM39]
	Transformer	Transformer						[IEEE34, IEEE36, ACM10, ACM26]
		Bert						[ACM07] [IEEE191, IEEE29]
Encoder-Decoder	RNN-based model	RNN		[IEEE15]		[MK08, IEEE79, IEEE113]	[gao2019automating, SP03, ACM15, IEEE75, ACM35, IEEE112]	[IEEE59]
		LSTM			[IEEE11]	[IEEE31, IEEE41]	[ICLR07, IEEE61, MITP06, MITP07]	[IEEE37, ACM11, IEEE47, MITP08, IEEE101, SP10]
		Bi-LSTM						[IEEE32, IEEE66]
		LSTM-CRF						[IEEE58]
		GRU			[ICLR11]			
	CNN-based model	CNN			[ACM12]		[IEEE05]	[IEEE44, ACM33]
	FNN-based model	FNN				[EL10]	[MK03]	[IEEE17, ACM26]

Architecture	Family	Model Name	2015	2016	2017	2018	2019	2020
AutoEncoder	RNN-based model	Bi-GRU						[IEEE137]
		GRU						[SP07]
		RNN					[AAAI05]	
		LSTM				[ICLR03]		
		Bi-LSTM						[IEEE33]
	CNN-based model	CNN						[ACM33]
	FNN-based model	FNN			[IEEE40]	[EL10, IEEE39]	[SP04, ICLR04, IEEE68, IEEE105]	[IEEE72]
Siamese Network	RNN-based model	GRU						[IEEE27]
		LSTM						[ACM25]
		Bi-LSTM						[IEEE48]

Table 18. Data types of datasets involved in primary studies.

Family	Data types	References
Code-based datasets	Source code	[AAAI01, AAAI02, AAAI03, AAAI04, AAAI05, AAAI06, ACM01, ACM02, ACM04, ACM06, ACM09, EL01, IEEE109, IEEE01, IEEE32, IEEE34, IEEE35, IEEE37, SP09, ACM10, ICLR06, ICLR07, ICLR10, ACM18, ACM20, ACM23, ACM17, IEEE67, MK08, MK09, EL16, EL20, IEEE82, IEEE83, MITP02, MITP06, MITP07, ACM38, IEEE25, IEEE112, IEEE121, IEEE141, IEEE17, IEEE66, IEEE63, IEEE64, IEEE65, IEEE68, ACM27, EL06, EL17, IEEE74, IEEE102, IEEE103, IEEE105, IEEE114, IEEE116, IEEE124, IEEE128, IEEE131, IEEE06, IEEE09, IEEE10, IEEE15, IEEE27, SP07, SP04, ICLR01, ICLR02, ICLR03, ICLR04, ICLR05, ACM11, ACM12, ACM13, IEEE38, ACM15, ACM16, IEEE42, IEEE43, IEEE47, IEEE51, IEEE55, MK03, MK04, MK05, MK06, MK07, ACM28, EL08, IEEE77, IEEE80, MITP01, MITP03, MITP04, MITP05, MITP08, ACM37, IEEE84, IEEE85, IEEE86, IEEE87, IEEE91, IEEE92, IEEE101, IEEE28, IEEE104, IEEE110, IEEE113, IEEE115, IEEE115, W01, IEEE122, IEEE126, IEEE138, IEEE81, ACM39, IEEE132, IEEE98]
	Source code in DSL (Domain-Special Language)	[IET01, ICLR08, ICLR11, IEEE72]
	Test case	[ACM26, ACM31, EL03, ACM30]
	Defects	[ACM29, EL10, ACM35]
	Patch	[IEEE29, IEEE123]
	Execution trace	[IEEE08]
	Code change	[IEEE127]
	Game bug	[IEEE07]
Text-based datasets	Bug report	[IEEE40, IEEE54, EL07, EL12, EL13, IEEE39, IEEE60, IEEE71, IEEE137, IEEE139, IEEE142]
	Requirement documentation	[IEEE58, EL09, IEEE94, IEEE95, IEEE96, IEEE118, IEEE119, IEEE58, IEEE12]
	Issue report	[IEEE191, IEEE134, SP02, IEEE130]
	Log information	[IEEE21, IEEE45, IEEE88]
	Code comment	[IEEE108, IEEE36, ACM34, IEEE98]
	Incident report	[ACM08, IEEE05, IEEE22]
	Dialog	[ACM05] [IEEE48, SP10, IEEE03]
	configuration documentation	[ACM14, ACM21]
	API	[SP05, SP03]
	User behavior	[ACM22, SP06]
	Protocol message	[IEEE61]
	Vulnerability descriptions in CVE Details websit	[IEEE57]
	Defect report	[IEEE62]
	Use case	[EL02]
	Method names	[IEEE59]
	Design documentation	[IEEE97]
	Certification	[IEEE52]
	SATD	[IEEE100]
	Web request	[IEEE30]
	Text information (PDF)	[IEEE12]
Metric-based datasets	Software metric	[EL19, ACM32, IEEE46, IEEE56, EL18, IEEE50, IEEE93]
	Code metric	[IEEE117]

	Driver properties	[IEEE14]
	resource utilization traces	[EL11]
Graph-based datasets	GUI images	[ACM33, moran2018machine, IEEE41, IEEE23, IEEE69, ACM25, IEEE44]
	program screenshot	[SP08, ACM24, IEEE140, ACM36]
	Vedio screenshot	[IEEE78]
	behaviour trajectory of the model class	[EL04]
Software repository -based datasets	Q&A pair (Knowledge unit) in forums	[ACM03, IEEE13, IEEE16, IEEE125, IEEE70, IEEE76, IEEE79]
	Pull-requests	[IEEE04, IEEE99]
	Issues and commits	[ACM07, EL14]
	Tags in forum	[SP01, EL05]
	Discuss	[IEEE111]
	Commits	[IEEE90]
Combined datasets	source code and comment	[AAAI07, AAAI08, IEEE33, IEEE20, IEEE24, IEEE26, IEEE136, IEEE31, IEEE49, EL21, IEEE53]
	Source code and bug report	[MK01, IEEE89, IEEE135]
	Source code and commit message	[ACM19]
	Code change and commit message	[IEEE73, IEEE75]
	Source code and Q&A pair in SO	[IEEE02]
	Source code, diff files, and commit message	[MK02]
	Diff file and commit message	[IEEE11]
	Code review and code clone pair	[IEEE106]
	Test case and log file	[IEEE18]

Table 19. The relationships of DNNs with respect to DL architecture, task types, problem types, as well as data types in software requirement.

Task type	**Problem type**	**DNN**	**DL architecture**	**Data type**	**Reference**
Requirement extraction	classification	LSTM-CRF	Encoder-decoder	text-based data	[IEEE58]
		LSTM, CNN		text-based data	[IEEE94]
		Bi-LSTM, deep siamese network		text-based data	[IEEE48]
		LSTM, Bert	Transformer	text-based data	[IEEE19]
		CNN		text-based data	[IEEE118]
		FNN		text-based data	[EL09]
	recommendation	FNN		text-based data	[IEEE581]
		FNN		text-based data	[IEEE120]
Requirement validation	classification	CNN		text-based data	[IEEE95]
Requirement traceability	recommendation	FNN		text-based data	[IEEE96]

Table 20. The relationships of DNNs with respect to DL architecture, task types, problem types, as well as data types in software design.

Task type	Problem type	DNN	DL architecture	Data type	Reference
Software design pattern detection	classification	CNN		text-based data	[IEEE109]
		CNN	Autoencoder	image-based data	[ACM33]
GUI modeling	Generation	CNN		image-based data	[IEEE129]
		CNN, RNN	Encoder-decoder	image-based data	[IEEE41]

Table 21. The relationships of DNNs with respect to DL architecture, task types, problem types, as well as data types in software development.

Task type	Problem type	DNN	DL architecture	Data type	Reference
Code representation	Generation	RNN		code-based data	[IEEE83]
		RNN		code-based data	[MITP02]
		LSTM		code-based data	[ACM09]
		LSTM		code-based data	[EL20]
		LSTM	Encoder-decoder	code-based data	[ICLR07]
		Bi-LSTM		code-based data	[ACM18]
		GRU		code-based data	[EL16]
		CNN		code-based data	[AAAI02]
		FNN	Encoder-decoder	code-based data	[ACM20]
		Bi-RNN		code-based data	[ACM23]
		FNN		code-based data	[IEEE82]
		GGNN		code-based data	[ICLR10]
		GNN		code-based data	[ACM38]
Code generation	Generation	RNN	Encoder-decoder	code-based data	[IEEE32]
		RNN	Encoder-decoder	code-based data	[IEEE37]
		LSTM		code-based data	[SP09]
		LSTM		code-based data	[ICLR08]
		LSTM		code-based data	[MITP07]
		LSTM	Encoder-decoder	code- and text-based data	[MITP08]
		LSTM	Encoder-decoder	code-based data	[ICLR03]
		LSTM, CNN		code- and text-based data	[ICLR09]
		Bi-LSTM	Encoder-decoder	code-based data	[IEEE66]
		Bi-LSTM		code-based data	[MITP06]
		GRU	Encoder-decoder	code-based data	[ICLR11]
		Transformer	Transformer	code-based data	[ACM10]
Code comment generation	Generation	GRU		code- and text-based data	[AAAI08]
		RNN		code- and text-based data	[EL21]
		LSTM		code- and text-based data	[IEEE49]
		LSTM	encoder-decoder	code-based data	[IEEE101]
		LSTM		code- and text-based data	[IEEE108]
		Bi-LSTM	encoder-decoder	code- and text-based data	[IEEE33]
		Bi-LSTM		code- and text-based data	[IEEE35]
		multiple DNN models		code- and text-based data	[IEEE36]

		GRU	autoencoder	code-based data	[SP07]
Code search	Recommendation	RNN	Encoder-decoder	code-based data	[ACM02]
		RNN		code- and text-based data	[IEEE26]
		CNN		code- and text-based data	[IEEE02]
		CNN		code- and text-based data	[IEEE24]
		FNN		code-based data	[IEEE25]
		CODEnn		code- and text-based data	[IEEE20]
		GGNN		code-based data	[IEEE01]
		DPCNN, GNN		code-based data	[MITP05]
		multiple		code-based data	[ACM01]
Code localization	Classification	CNN		image-based data	[SP08]
		CNN		image-based data	[IEEE140]
		CNN		image-based data	[ACM24]
		CNN		image-based data	[ACM36]
		CNN		image-based data	[IEEE78]
Code completion	Generation	Bert	Transformer	code-based data	[IEEE3]
		LSTM		code-based data	[MK09]
		LSTM		code-based data	[IEEE141]
		FNN		code-based data	[IEEE121]
Code summarization	Generation	RNN	Encoder-decoder	text-based data	[IEEE31]
		RNN	Encoder-decoder	code-based data	[MK08]
		RNN		code-based data	[ACM16]
		CNN		code-based data	[ACM13]
		ConvGNNs, GRU		code- and text-based data	[IEEE136]
Method name generation	Generation	RNN	Encoder-decoder	code- and text-based data	[IEEE112]
		seq2seq	encoder-decoder	code- and text-based data	[IEEE59]

Table 22. The relationships of DNNs with respect to DL architecture, task types, problem types, as well as data types in software testing.

Task type	**Problem type**	**DNN**	**DL architecture**	**Data type**	**Reference**
bug-related detection	Classification	CNN		image-based data	[IEEE23]
		LSTM		metric-based data	[ACM32]
		Bi-LSTM		text-based data	[IEEE54]
		Bi-LSTM		text-based data	[EL12]
		GRU		code-based data	[ACM37]
		LSTM, FNN		code-based data	[EL17]
		LSTM, GNN		code-based data	[ICLR01]
		CNN		image-based data	[IEEE69]
		CNN		metric-based data	[IEEE102]
		CNN		code- and text-based data	[ACM19]
		CNN		code-based data	[IEEE50]
		FNN		text-based data	[IEEE88]
		FNN	Autoencoder	metric-based data	[IEEE68]
Bug localization	Classification	FNN	Autoencoder	text-based data	[IEEE40]
		CNN, RNN		code-based data	[MITP04]

	recommendation	CNN, LSTM, Deep walk		code- and text-based data	[AAAI07]
		CNN, LSTM	Encoder-decoder	code- and text-based data	[MK01]
		CNN, LSTM		code- and text-based data	[IEEE135]
		LSTM		code-based data	[IEEE116]
		CNN		code-based data	[MK07]
		CNN		text-based data	[EL07]
		CNN		code-based data	[IEEE103]
		CNN, LSTM		code-based data	[MK06]
	Recommendation	FNN		code- and text-based data	[IEEE89]
		RNN		code-based data	[ACM29]
		CNN		code- and text-based data	[IEEE124]
Vulnerability detection	Classification	LSTM		code-based data	[IEEE131]
		CNN		text-based data	[IEEE57]
		GRU, CNN		code-based data	[MITP03]
		RNN, LSTM, GRU, BRNN		code-based data	[EL03]
		FNN	Encoder-decoder	code-based data	[ICLR04]
		FNN	Encoder-decoder	text-based data	[MK03]
Testing techniques	Generation	RNN		text-based data	[IEEE12]
		LSTM		text-based data	[ACM31]
	Regression	LSTM	Siamese Network	metric-based data	[ACM25]
		CNN		metric-based data	[IEEE65]
		FNN		metric-based data	[IEEE14]
	Classification	FNN		code-based data	[IEEE07]
Test case generation	Generation	RNN		code-based data	[AAAI06]
		RNN		text-based data	[ACM22]
		RNN	Encoder-decoder	code-based data	[ACM26]
		FNN		image-based data	[IEEE93]
		FNN	Encoder-decoder	code-based data	[IEEE17]
		LSTM		code-based data	[IEEE63]
		FNN, LSTM		metric-based data	[IEEE61]
		RNN		text-based code	[ACM30]
Program analysis	Classification	LSTM		code-based data	[IEEE14]
		CNN		text-based data	[IEEE65]
		CNN, GRU		text-based data	[IEEE07]
		CNN, RNN, LSTM		text-based data	[ACM05]
	Recommendation	RNN		code-based data	[IEEE12]
		LSTM		code-based data	[ACM17]
		GGNN		code-based data	[ACM39]
Bug classification	Classification	TBCNN		code- and text-based data	[EL13]
	recommendation	FNN		text-based data	[IEEE60]
	CNN	Encoder	metric- and text-based data	[IEEE05]	
Certification validation	Recommendation	CNN, RNN		text-based data	[IEEE52]
Stateful service virtualization	Generation	LSTM	Encoder-deocder	text-based data	[SP10]

Table 23. The relationships of DNNs with respect to DL architecture, task types, problem types, as well as data types in software maintenance.

Task type	Problem type	DNN	DL architecture	Data type	Reference
defect prediction	classification	CNN, FNN		metric-based data	[IEEE10]
		RNN		metric-based data	[IEEE114]
		RNN		code- and text-based data	[IEEE135]
		LSTM		code-based data	[IEEE74]
		LSTM		metric-based data	[IEEE87]
		LSTM		code-based data	[IEEE128]
		Bi-LSTM, Tree-LSTM		code-based data	[IEEE92]
		CNN		text-based data	[IEEE30]
		CNN		code-based data	[IEEE46]
		CNN		code- and text-based data	[IEEE73]
		FNN	Autoencoder	metric-based data	[EL10]
		FNN		code-based data	[IEEE86]
		FNN		metric-based data	[IEEE117]
		FNN		metric-based data	[EL15]
		FNN	Autoencoder	code-based data	[IEEE72]
		DBN		metric-based data	[IEEE127]
		DBN		code-based data	[IEEE43]
		DBN		code-based data	[IEEE84]
		Deep forest		metric-based data	[EL06]
		Deep forest		metric-based data	[IEEE90]
		RBM		code-based data	[SP04]
		CNN		code-based data	[IEEE85]
Program repair	generation	RNN	Encoder-decoder	code-based data	[ACM35]
		LSTM		code-based data	[AAAI03]
		LSTM	Encoder-decoder	code-based data	[IEEE46]
		LSTM		code-based data	[IEEE42]
		GRU		code-based data	[ICLR05]
		GRU	Encoder-deocder	code-based data	[AAAI01]
		CNN		code-based data	[ACM27]
		CNN		code- and text-based data	[IEEE132]
		GGNN, Bi-GRU		code-based data	[IEEE138]
		GAN		code-based data	[MITP01]
		Bert	Transformer	code- and text-based data	[IEEE29]
	classifcation	LSTM		code-based data	[ICLR02]
	recommendation	LSTM	Encoder-decoder	code-based data	[ACM11]
		FNN	Autoencoder	code-based data	[IEEE105]
Code clone detection	classification	RNN		code-based data	[IEEE51]
		RtNN, RvNN		code-based data	[IEEE15]
		LSTM		code-based data	[AAAI04]
		LSTM		code-based data	[IEEE38]
		LSTM		code-based data	[MK04]
		LSTM		code-based data	[MK05]
		LSTM		code-based data	[IEEE77]
		LSTM		code-based data	[IEEE110]
		GRU	SiameseNetwork	code-based data	[IEEE27]

		GGNN, GMN		code-based data	[IEEE98]
	regression	RTNN		code-based data	[IEEE80]
bug report related	classification	CNN		text-based data	[IEEE142]
		CNN		text-based data	[IEEE139]
		FNN		text-based data	[IEEE7]
	generation	Bi-GRU	autoencoder	text-based data	[IEEE137]
		FNN	autoencoder	text-based data	[IEEE39]
	recommendation	LSTM		text-based data	[SP02]
		BERT, CNN, RNN-LSTM, RNN-GRU, Bi-RNN		text-based data	[ACM07]
software reliability	regression	FNN		code-based data	[W01]
software maintainability		FNN		metric-based data	[EL18]
software readability	classification	CNN		code-based data	[EL08]
software trustworthiness		deep residual network		image-based data	[EL04]
software traceability	recommendation	LSTM		text-based data	[ACM21]
compiled-related	generation	RNN	Encoder-decoder	code-based data	[IEEE113]
		RNN, GGNN		code-based data	[IEEE06]
	recommendation	LSTM, CNN		code-based data	[IEEE67]
		FNN		code-based data	[IEEE91]
SATD detection	classification	Bi-LSTM	autoencoder	text-based data	[IEEE28]
		CNN		text-based data	[IEEE100]
		CNN		text-based data	[ACM34]
code smell detection	classification	CNN		code-based data	[IEEE115]
		CNN		code-based data	[IEEE122]
	.	CNN, LSTM		code-based data	[ACM12]
Code review	classification	CNN		code-based data	[IEEE106]
		CNN, LSTM	autoencoder	code-based data	[AAAI05]
	recommendation	LSTM		text-based data	[IEEE99]
software/code classification	classification	CNN, LSTM		code-based data	[IEEE53]
		GNN		code-based data	[IEEE64]
		TBCNN, LSTM, GGNN		code- and text-based data	[IEEE104]
code change	generation	RNN	Encoder-decoder	code-based data	[ACM15]
		HAN		text-based data	[IEEE45]
incident detection	recommendation	CNN		text-based data	[IEEE22]
	classification	CNN		text-based data	[ACM08]

Table 24. The relationships of DNNs with respect to DL architecture, task types, problem types, as well as data types in software management.

Task type	Problem type	DNN	DL architecture	Data type	Reference
effort cost prediction	regression	LSTM, recurrent highway network		text-based data	[IEEE134]
		CNN, RNN, CRNN		text-based data	[EL02]
		FNN		metric-based data	[IET01]
		FNN		metric-based data	[EL01]
		RBFNN		metric-based data	[EL19]
mining GitHub	generation	Bi-GRU		code- and text-based data	[MK02]
		RNN	Encoder-decoder	text-based data	[IEEE11]
		RNN	Encoder-decoder	code- and text-based data	[IEEE75]
		LSTM		code- and text-based data	[EL14]
		RNN		text-based data	[IEEE04]
	classification	RNN, GRU		code- and text-based data	[IEEE107]
mining Stack-Overflow	classification	RNN	Encoder-decoder	text-based data	[IEEE79]
		CNN		text-based data	[IEEE76]
		CNN		text-based data	[IEEE81]
	recommendation	CNN		text-based data	[IEEE16]
app mining	classification	CNN		text-based data	[IEEE111]
	generation	RNN	Encoder-decoder	text-based data	[IEEE03]
		RNN	Encoder-decoder	text-based data	[SP03]
tag mining	recommendation	FNN		metric-based data	[SP01]
		TagCNN, TagRNN, TagHAN and TagRCNN		text-based data	[EL05]
	generation	LSTM	Encoder-decoder	text-based data	[SP05]
		CNN	Encoder-decoder	image-based data	[IEEE44]
developer-based mining	classification	CNN		text-based data	[IEEE13]
		CNN		text-based data	[IEEE130]
	recommendation	meta learning		text-based data	[SP06]

Table 26. Evaluation metrics for different problem types.

problem type	Metric	# Studies	Reference
regression	MAE	3	[EL01, EL18, IEEE134]
	Standardized Accuracy (SA)	3	[EL01, EL02, IEEE134]
	MMRE	3	[IET01, EL18, IEEE134]
	MdAE	2	[EL02, IEEE134]

classification	precision	76	[AAAI04, ACM03, ACM04, ACM05, ACM07, ACM08, IEEE08, IEEE09, IEEE10, IEEE13, IEEE15, IEEE18, IEEE19, IEEE21, IEEE22, IEEE23, IEEE27, IEEE28, IEEE30, IEEE32, SP08, ICLR04, IEEE38, ACM17, ACM19, IEEE43, IEEE46, IEEE48, IEEE50, IEEE53, IEEE54, IEEE55, IEEE57, ACM24, MK03, MK04, IEEE67, MK05, ACM28, ACM30, EL03, EL06, EL12, IEEE73, IEEE76, IEEE77, IEEE79, IEEE81, ACM37, IEEE84, IEEE85, IEEE86, IEEE87, IEEE88, IEEE94, IEEE28, IEEE100, IEEE102, IEEE106, IEEE107, IEEE109, IEEE111, IEEE115, IEEE117, ACM34, IEEE122, IEEE123, IEEE125, IEEE127, IEEE128, IEEE130, IEEE131, IEEE139, IEEE140, IEEE14]
	recall	73	[AAAI04, ACM03, ACM04, ACM05, ACM07, ACM08, IEEE08, IEEE09, IEEE10, IEEE13, IEEE18, IEEE19, IEEE21, IEEE22, IEEE23, IEEE27, IEEE28, IEEE30, IEEE32, SP08, ICLR04, IEEE38, ACM17, ACM19, IEEE43, IEEE46, IEEE48, IEEE50, IEEE53, IEEE54, IEEE55, IEEE57, ACM24, MK04, IEEE67, MK05, ACM28, ACM30, EL03, EL06, EL12, IEEE73, IEEE76, IEEE77, IEEE79, IEEE81, ACM37, IEEE84, IEEE85, IEEE86, IEEE87, IEEE88, IEEE94, IEEE28, IEEE100, IEEE102, IEEE106, IEEE107, IEEE109, IEEE111, IEEE117, ACM34, IEEE122, IEEE123, IEEE125, IEEE130, IEEE131, IEEE127, IEEE139, IEEE140, IEEE142]
	F1-score	62	[AAAI04, AAAI05, ACM04, ACM05, ACM07, ACM08, IEEE09, IEEE10, IEEE13, IEEE18, IEEE19, IEEE21, IEEE23, IEEE27, IEEE28, IEEE32, ICLR04, IEEE38, ACM17, ACM19, IEEE43, IEEE46, IEEE48, IEEE50, IEEE53, IEEE57, ACM24, MK03, MK04, IEEE67, MK05, ACM28, ACM30, EL03, EL08, EL12, EL13, IEEE73, IEEE76, IEEE77, MITP03, IEEE84, IEEE85, IEEE87, IEEE88, IEEE94, IEEE95, IEEE28, IEEE100, IEEE102, IEEE106, IEEE107, IEEE109, IEEE111, ACM34, IEEE123, IEEE125, IEEE130, IEEE127, IEEE139, IEEE142]
	Accuracy	27	[ICLR02, ICLR04, ACM19, IEEE54, IEEE57, IEEE67, EL03, EL04, EL06, EL08, MITP03, IEEE86, IEEE88, IEEE95, IEEE104, IEEE109, IEEE122, IEEE123, IEEE130, IEEE139, IEEE140]
	AUC	22	[AAAI05, IEEE22, SP04, ICLR04, EL06, EL10, IEEE73, IEEE76, IEEE79, IEEE87, IEEE90, IEEE92, IEEE97, IEEE100, IEEE19, IEEE110, IEEE114, IEEE117, ACM32, IEEE123, IEEE135, IEEE139]
	MCC	8	[EL10, IEEE86, IEEE90, IEEE92, IEEE100, IEEE102, IEEE109, IEEE115]
	ROC	6	[ACM05, IEEE79, IEEE92, IEEE110, IEEE115, IEEE117]
	True positve rate	3	[MK03, ICLR02, IEEE86]
	False positive rate	2	[MK03, EL03]
	False negative rate	2	[MK03, EL03]
Recommendation	MRR	17	[AAAI07, IEEE02, IEEE16, IEEE20, IEEE24, IEEE25, IEEE26, SP06, EL07, IEEE89, IEEE99, IEEE116, ACM33, IEEE124, ACM36, IEEE126, IEEE135]
	MAP/MAP@k	11	[AAAI07, IEEE16, IEEE24, ACM21, MK06, EL07, IEEE89, IEEE124, ACM36, IEEE126, IEEE135]
	precision@k	7	[IEEE16, IEEE20, IEEE25, SP01, EL05, ACM33, ACM36]
	recall@k	6	[SP01, SP02, IEEE60, EL05, MITP05, IEEE99]
	F1-score@k	4	[SP01, EL05, IEEE96, ACM36]
	Recall	22	[IEEE04, IEEE06, IEEE29, IEEE32, SP05, IEEE35, SP07, ACM10, ICLR07, IEEE39, ACM20, IEEE45, ACM23, IEEE58, IEEE59, MK02, MK08, EL14, EL21, ACM38, IEEE101, IEEE137, IEEE119]
Generation	precision	21	[IEEE04, IEEE11, IEEE29, IEEE32, SP05, SP07, ICLR07, IEEE39, ACM20, IEEE45, ACM23, IEEE58, IEEE59, MK08, EL14, EL21, ACM38, IEEE101, IEEE58, IEEE129, IEEE137, IEEE119]
	BLEU	19	[IEEE03, IEEE11, IEEE31, IEEE33, SP03, IEEE36, SP07, SP09, ACM16, IEEE41, IEEE44, MK02, IEEE75, EL21, MITP06, MITP07, IEEE112, IEEE121, IEEE136]

ROUGE	11	[AAAI08, IEEE04, IEEE31, SP09, IEEE39, IEEE44, IEEE75, MITP07, IEEE101, IEEE136, IEEE137]
F1-score	10	[IEEE04, IEEE32, SP05, SP09, ICLR07, ICLR10, ACM23, IEEE59, EL21, IEEE101]
Exact match	7	[ICLR03, ICLR09, IEEE41, MITP06, MITP08, IEEE112, IEEE138]
Running time	6	[IEEE41, ACM22, IEEE63, ACM31, IEEE113, IEEE121]
METEOR	5	[IEEE31, SP07, MK02, EL21, MITP07]
perplexity (PP)	2	[IEEE66, IEEE83]

G LIST OF PRIMARY STUDIES IN THE SLR

In this section, we classified all primary studies according to their publishers and listed them as follows: (**EL**: Elsevier; **MITP**: MIT Press; **MK**: Morgan Kaufmann; **SP**: Spring; **W**: Wiley)

AAAI01: Rahul Gupta, Soham Pal, Aditya Kanade, and Shirish Shevade. 2017. Deepfix: Fixing common c language errors by deep learning. In Thirty-First AAAI Conference on Artificial Intelligence.

AAAI02: Lili Mou, Ge Li, Lu Zhang, Tao Wang, and Zhi Jin. 2016. Convolutional neural networks over tree structures for programming language processing. In Thirtieth AAAI Conference on Artificial Intelligence.

AAAI03: Rahul Gupta, Aditya Kanade, and Shirish Shevade. 2019. Deep reinforcement learning for syntactic error repair in student programs. In Proceedings of the AAAI Conference on Artificial Intelligence, Vol. 33. 930–937.

AAAI04: Yan-Ya Zhang and Ming Li. 2019. Find Me if You Can: Deep Software Clone Detection by Exploiting the Contest between the Plagiarist and the Detector. In Proceedings of the AAAI Conference on Artificial Intelligence, Vol. 33. 5813–5820.

AAAI05: Shu-Ting Shi, Ming Li, David Lo, Ferdian Thung, and Xuan Huo. 2019. Automatic code review by learning the revision of source code. In Proceedings of the AAAI Conference on Artificial Intelligence, Vol. 33. 4910–4917.

AAAI06: Xiao Liu, Xiaoting Li, Rupesh Prajapati, and Dinghao Wu. 2019. Deepfuzz: Automatic generation of syntax valid c programs for fuzz testing. In Proceedings of the AAAI Conference on Artificial Intelligence, Vol. 33. 1044–1051.

AAAI07: Xuan Huo, Ming Li, and Zhi-Hua Zhou. 2020. Control flow graph embedding based on multi-instance decomposition for bug localization. In Proceedings of the AAAI Conference on Artificial Intelligence, Vol. 34. 4223–4230.

AAAI08: Yuding Liang and Kenny Zhu. 2018. Automatic generation of text descriptive comments for code blocks. In Proceedings of the AAAI Conference on Artificial Intelligence, Vol. 32.

ACM01: Jose Cambronero, Hongyu Li, Seohyun Kim, Koushik Sen, and Satish Chandra. 2019. When deep learning met code search. In FSE. 964–974.

ACM02: Xiaodong Gu, Hongyu Zhang, Dongmei Zhang, and Sunghun Kim. 2016. Deep API learning. In FSE. 631–642.

ACM03: Bowen Xu, Amirreza Shirani, David Lo, and Mohammad Amin Alipour. 2018. Prediction of relatedness in stack overflow: deep learning vs. SVM: a reproducibility study. In ESEM. 1–10.

ACM04: Gang Zhao and Jeff Huang. 2018. Deepsim: deep learning code functional similarity. In FSE. 141–151.

ACM05: Jinman Zhao, Aws Albarghouthi, Vaibhav Rastogi, Somesh Jha, and Damien Octeau. 2018. Neural-augmented static analysis of Android communication. In FSE. 342–353.

ACM06: Vincent J Hellendoorn, Christian Bird, Earl T Barr, and Miltiadis Allamanis. 2018. Deep learning type inference. In FSE. 152–162.

ACM07: Yutong Zhao, Lu Xiao, Pouria Babvey, Lei Sun, Sunny Wong, Angel A Martinez, and Xiao Wang. 2020. Automatically identifying performance issue reports with heuristic linguistic patterns. In Proceedings of the

Table 25. The distribution of various overfitting techniques used in primary studies.

Optimization	#Studies	References
Dropout	47	[AAAI01, AAAI06,AAAI07, ACM06, IEEE02, IEEE21, IEEE24, IEEE26, IEEE28, IEEE33, SP02, IEEE34, IEEE35, SP09, ACM10,ICLR07, ACM11, ACM13, ICLR10, IEEE39, ACM16, ACM18, ACM20, IEEE45, IEEE48, IEEE53, EL10, EL13,EL16, IEEE75, IEEE79, EL21, IEEE87, IEEE108, IEEE125, IEEE134, IEEE135, IEEE138, IEEE62, MK02,IEEE66, IEEE67, MK06, MK07, EL02]
Pooling	26	[ACM01, ACM04, ACM19, ACM23, ACM34, ACM33, IEEE05, IEEE06, IEEE15, IEEE20, IEEE38, IEEE41, IEEE54, IEEE62, EL02, EL05, EL20, IEEE78, IEEE94, IEEE96, IEEE106, IEEE113, IEEE123, IEEE124, IEEE125, IEEE126]
Regularization	24	[ACM14, ACM17, ACM21, ACM29, IEEE83, IEEE86 IEEE50, IEEE57, IEEE128, IEEE100, IEEE106, IEEE133, IEEE13, IEEE16, IEEE25, IEEE128, SP02, ICLR04, ICLR06, ICLR09, EL09, EL11, MITP03, IET01]
Data augmentation	9	[IEEE46, IEEE78, IEEE83, IEEE97, IEEE116, IEEE129, ACM25, ACM36, EL21]
Data balancing	5	[ICLR08, IEEE46, IEEE60, ACM35, ACM34]
Early stoping	4	[IEEE48, EL10, IEEE73, IEEE134]

28th ACM Joint Meeting on European Software Engineering Conference and Symposium on the Foundations of Software Engineering. 964–975.

ACM08: Yujun Chen, Xian Yang, Hang Dong, Xiaoting He, Hongyu Zhang, Qingwei Lin, Junjie Chen, Pu Zhao, Yu Kang, Feng Gao, et al. 2020. Identifying linked incidents in large-scale online service systems. In Proceedings of the 28th ACM Joint Meeting on European Software Engineering Conference and Symposium on the Foundations of Software Engineering. 304–314.

ACM09: Vincent J Hellendoorn and Premkumar Devanbu. 2017. Are deep neural networks the best choice for modeling source code?. In FSE. 763–773.

ACM10: Alexey Svyatkovskiy, Shao Kun Deng, Shengyu Fu, and Neel Sundaresan. 2020. Intellicode compose: Code generation using transformer. In Proceedings of the 28th ACM Joint Meeting on European Software Engineering Conference and Symposium on the Foundations of Software Engineering. 1433–1443.

ACM11: Michihiro Yasunaga and Percy Liang. 2020. Graph-based, self-supervised program repair from diagnostic feedback. In International Conference on Machine Learning. PMLR, 10799–10808.

ACM12: Dor Levy and Lior Wolf. 2017. Learning to align the source code to the compiled object code. In International Conference on Machine Learning. PMLR, 2043–2051.

ACM13: Miltiadis Allamanis, Hao Peng, and Charles Sutton. 2016. A convolutional attention network for extreme summarization of source code. In International conference on machine learning. PMLR, 2091–2100.

ACM14: Huong Ha and Hongyu Zhang. 2019. Deepperf: performance prediction for configurable software with deep sparse neural network. In ICSE. IEEE, 1095–1106.

ACM15: Michele Tufano, Jevgenija Pantiuchina, Cody Watson, Gabriele Bavota, and Denys Poshyvanyk. 2019. On learning meaningful code changes via neural machine translation. In ICSE. IEEE, 25–36.

ACM16: Alexander LeClair, Siyuan Jiang, and Collin McMillan. 2019. A neural model for generating natural language summaries of program subroutines. In ICSE. IEEE, 795–806.

ACM17: Rabee Sohail Malik, Jibesh Patra, and Michael Pradel. 2019. Nl2type: inferring javascript function types from natural language information. In ICSE. IEEE, 304–315.

ACM18: Aditya Kanade, Petros Maniatis, Gogul Balakrishnan, and Kensen Shi. 2020. Learning and evaluating contextual embedding of source code. In International Conference on Machine Learning. PMLR, 5110–5121.

ACM19: Kui Liu, Dongsun Kim, Tegawendé F Bissyandé, Taeyoung Kim, Kisub Kim, Anil Koyuncu, Suntae Kim, and Yves Le Traon. 2019. Learning to spot and refactor inconsistent method names. In ICSE. IEEE, 1–12.

ACM20: Chris Piech, Jonathan Huang, Andy Nguyen, Mike Phulsuksombati, Mehran Sahami, and Leonidas Guibas. 2015. Learning program embeddings to propagate feedback on student code. In International conference on machine Learning. PMLR, 1093–1102.

ACM21: Jin Guo, Jinghui Cheng, and Jane Cleland-Huang. 2017. Semantically enhanced software traceability using deep learning techniques. In ICSE. IEEE, 3–14.

ACM22: Peng Liu, Xiangyu Zhang, Marco Pistoia, Yunhui Zheng, Manoel Marques, and Lingfei Zeng. 2017. Automatic text input generation for mobile testing. In ICSE. IEEE, 643–653.

ACM23: Jian Zhang, Xu Wang, Hongyu Zhang, Hailong Sun, Kaixuan Wang, and Xudong Liu. 2019. A novel neural source code representation based on abstract syntax tree. In ICSE. IEEE, 783–794.

ACM24: Dehai Zhao, Zhenchang Xing, Chunyang Chen, Xin Xia, and Guoqiang Li. 2019. ActionNet: vision-based workflow action recognition from programming screencasts. In ICSE. IEEE, 350–361.

ACM25: Minxue Pan, An Huang, Guoxin Wang, Tian Zhang, and Xuandong Li. 2020. Reinforcement learning based curiosity-driven testing of Android applications. In ISSTA. 153–164.

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