Machine Learning for Software Engineering: A Tertiary Study

ZOE KOTTI, RAFAILA GALANOPOULOU, and DIOMICIS SPINELLIS, Athens University of Economics and Business, Greece

Machine learning (ML) techniques increase the effectiveness of software engineering (SE) lifecycle activities. We systematically collected, quality-assessed, summarized, and categorized 83 reviews in ML for SE published between 2009 and 2022, covering 6,117 primary studies. The SE areas most tackled with ML are software quality and testing, while human-centered areas appear more challenging for ML. We propose a number of ML for SE research challenges and actions, including conducting further empirical validation and industrial studies on ML, reconsidering deficient SE methods, documenting and automating data collection and pipeline processes, reexamining how industrial practitioners distribute their proprietary data, and implementing incremental ML approaches.

CCS Concepts: • Software and its engineering → Extra-functional properties; Automatic programming • General and reference → Surveys and overviews • Computing methodologies → Machine learning approaches; Machine learning algorithms;

Additional Key Words and Phrases: Tertiary study, machine learning, software engineering, systematic literature review

ACM Reference format:
Zoe Kotti, Rafaila Galanopoulou, and Diomidis Spinellis. 2023. Machine Learning for Software Engineering: A Tertiary Study. ACM Comput. Surv. 55, 12, Article 256 (March 2023), 39 pages.
https://doi.org/10.1145/3572905

1 INTRODUCTION

Machine learning (ML) is a thriving discipline with various practical applications and active research topics, many of which nowadays entangle the discipline of software engineering (SE) [113]. Through ML we can address SE problems that cannot be completely algorithmically modeled, or for which existing solutions do not provide satisfactory results yet (e.g., defect/fault detection [16, 165, 180]). In addition, ML finds application in SE tasks where data cannot be easily analyzed with other algorithms (e.g., software requirements, code comments, code reviews, issues [9, 91, 174]). Another important aspect of ML is that it can significantly reduce manual effort in common SE tasks (e.g., automatic program repair [157], code suggestion [61], defect

This work has received funding from the European Union’s Horizon 2020 research and innovation programme under Grant Agreement No. 825328 (FASTEN project).
Authors’ address: Z. Kotti, R. Galanopoulou, and D. Spinellis, Athens University of Economics and Business, Patission 76, Athens, Greece, 10434; emails: [zoekotti, rgalanopoulou, dds]@aueb.gr.
Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for components of this work owned by others than ACM must be honored. Abstracting with credit is permitted. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee. Request permissions from permissions@acm.org.
© 2023 Association for Computing Machinery.
0360-0300/2023/03-ART256 $15.00
https://doi.org/10.1145/3572905

ACM Computing Surveys, Vol. 55, No. 12, Article 256. Publication date: March 2023.
prediction [19], malware detection [147], feature location [40]) with great accuracy results [146, 164]. In fields such as health informatics ML and SE are considered complementary disciplines, since the growing scale and complexity of healthcare datasets have posed a challenge for clinical practice and medical research, requiring new engineering approaches from both fields [38].

In the early 1990s, Huff and Selfridge [68] recognized the need for creating software systems that partially take some responsibility for their own evolution, offering the ability to implement, measure, and assess changes easily. These changes should also contribute to the overall improvement of the corresponding systems [142]. Around the same time, Brooks [29] prompted software practitioners to investigate evolutionary advancements rather than waiting for revolutionary ones, since magic solutions are not around the corner. As a result, a wave of evolutionary approaches was developed to address certain inherent essential software challenges including complexity (“software entities are more complex for their size than perhaps any other human construct”), changeability (“software is constantly subject to pressures for change”), conformity (“software must conform to the human institutions and systems it comes to interface with”), and invisibility (“the reality of software is not inherently embedded in space”) [28].

Among the proposed solutions, ML methods were introduced as a viable alternative to existing SE approaches, yielding encouraging results. Shortly after 2000, Zhang and Tsai [179] classified existing applications of ML methods to SE tasks into seven activity types: prediction and estimation; property and model discovery; transformation; generation and synthesis; reuse library construction and maintenance; requirement acquisition or recovery; development knowledge management. Around sixty publications were identified as relevant and assigned to these categories, underpinning the increasing trend of employing ML in SE. However, as the authors emphasize, “ML is not a panacea for all the SE problems. To better use ML methods as tools to solve real-world SE problems, we need to have a clear understanding of both the problems, and the tools and methodologies utilized.” Specifically, it is vital to be aware of the available ML methods, their characteristics and theoretical foundations, and the circumstances under which they are most effectively applied.

Twenty years later, ML has considerably affected the entire SE lifecycle, allowing developers to design, develop, and deploy software in a better, faster, and cheaper manner [31]. In the requirements phase theorem provers are used to identify systems with mutually compatible requirements that can coexist together, while in the execution phase multi-objective genetic algorithms can simplify a system’s configuration. ML tools can contribute to a system’s monitoring and optimization by limiting the required cloud resources, while in testing—the most covered phase by ML according to a bibliometric analysis by Heradio et al. [66]—ML can automate the prioritization and execution of test suites. Furthermore, ML tools can support the automatic identification and repair of software bugs. By logging these activities, quality models can be trained to predict useful system features including software development and issue resolution time, bug locations, or software development anti-patterns.

ML for SE, which concerns the application of ML techniques to SE processes and tools, should not be confused with the similarly sounding “SE for ML” field. Although the second field’s title contains almost the same terms, its topic is completely different, namely, the application of the SE discipline in the development and operation of ML applications [109]. Consequently, SE for ML will not concern us further in this review.

To facilitate and assess the impact of ML in SE, along with the aforementioned study by Zhang and Tsai [179], various other secondary reviews have been performed. Due to the extended associated primary research that has been published—more than 2,000 related documents were retrieved from Elsevier Scopus (see Section 3.2.1), secondary reviews usually focus on a particular SE area, such as software testing (e.g., References [44, 48, 178]) or design (e.g., References [96, 176]). Still, one might wonder what is the overall impact and current state of the practice of ML in SE, taking
also into account that some of the ML methods currently employed in SE are rarely encountered in conventional ML [113]. To the best of our knowledge, there is no available tertiary review systematically summarizing and evaluating all the published secondary studies in the intersection of the two fields.

This study aims to fill this gap by methodically collecting, assessing, analyzing, and categorizing existing secondary research in *Machine Learning for Software Engineering (ML4SE)*. Through the research questions outlined in Section 3.1 we identify what SE tasks have been tackled with ML techniques, which SE knowledge areas could be better covered by ML techniques as well as the prominent ML techniques applied in SE. We also provide a classification scheme for categorizing ML techniques in SE along four axes. Our findings suggest that ML is mainly employed for automating and optimizing testing; for predicting software faults, changes, quality, maintainability, and defects; and for estimating cost and effort. Research opportunities lie in the areas of software construction, configuration management, models and methods. In addition, we identify a need for more empirical and industrial studies evaluating the application of ML techniques in SE. The majority of secondary reviews summarize supervised (i.e., the training data are labeled), offline (i.e., the system weights are constant), model-based (i.e., patterns are detected in the training data) learning techniques applied for classification, clustering, regression, pattern discovery, information retrieval, and generation tasks.

Our research is structured as follows. In Section 2 we present related work comprising all identified tertiary reviews in SE and ML4SE. Section 3 includes a detailed description of the research objectives, questions, and methods we adopted to perform this tertiary review. In Section 4 we describe the study findings with respect to the data extraction process and the research questions, with their discussion and implications unfolded in Section 5. The study limitations are acknowledged in Section 6, and our final remarks and recommendations for researchers and practitioners are outlined in Section 7. Following published recommendations [74], the code and data1 associated with this endeavor are openly available online, and can be used to perform further empirical studies.

2 RELATED WORK
Tertiary studies (also called tertiary reviews) are *systematic literature reviews (SLRs)* that aggregate the data and information from a number of existing systematic (secondary) studies (e.g., SLRs, systematic mapping studies, taxonomies) over a specific topic [83]. There has been a noteworthy increase in the number of tertiary studies for the SE field since 2007, when recommended guidelines for performing SLRs in SE were published by Kitchenham and Charters [83]—in Section 2.1 we present some key efforts. These help us identify the applicable methods, research questions, and possible findings. At the time of writing, there is only one published tertiary study in ML4SE (focusing on a specific SE area)—this is summarized in Section 2.2.

2.1 Tertiary Studies in SE
Through a tertiary study Kitchenham et al. [85] describe the status of SLRs in SE in terms of context and quality, covering the years 2004–2008, and extending a previous work [84]. The authors report both quantitative and qualitative information about the identified studies, such as the corresponding authors’ names and institutions, and the addressed SE topics. The latter are investigated in terms of the *knowledge areas (KAs)* introduced by the Guide to the *Software Engineering Body of Knowledge (SWEBOK)* [26], and their relation with the courses of the Curriculum Guidelines for Undergraduate Degree Programs in SE [117]. They conclude that there has been an

1https://doi.org/10.5281/zenodo.7082429.
increase in the proportion of evidence-based SE SLRs. Most studies tackle general SE topics, and are either industrial case studies or industrial surveys. With regard to authors, Jørgensen was the main contributor between 2004 and 2007, and since then 51 researchers have co-authored up to two reviews each. In terms of origin, research in Europe has increased, complementing the previous single presence of U.S. institutions. The authors argue that, although the number of published SLRs is increasing, the majority do not follow an established method. Nevertheless, the quality of the examined SLRs abiding by the recommended guidelines has improved.

A number of tertiary reviews examine the evolution of systematic studies either in the complete SE field or in a specific subfield. Salma et al. [73] highlight that the Journal of Information and Technology, the International Conference on Evaluation and Assessment in Software Engineering, and the Empirical Software Engineering Journal are the venues with the most significant contributions in SE. Regarding methodology, the most troublesome SLR stage appears to be the Search Strategy, followed by the Data Extraction, and the Inclusion/Exclusion Criteria. Da Silva et al. [43] report an increase in the number of SE systematic reviews (particularly of systematic mapping studies) published between 2004 and 2009 as well as in the number of covered SE topics. Still, the quality of reviews seems to remain inferior. Hanssen et al. [63] summarized systematic studies in the area of global software engineering (GSE) investigating agile practices. Twelve SLRs were identified in GSE between 1990 and 2009, with some of them describing agile practices as an evolving trend. Another study by Marimuthu and Chandrasekaran [106] presents 60 publications on the topic of software product lines between 2008 and 2016, summarizing their type, quality, authors, publication venue, research topic, and limitations.

In the area of requirements engineering (RE), Bano et al. [21] retrieved 53 systematic reviews published between 2006 and 2014, and classified them according to the RE subareas. Non-functional requirements were assessed as the most frequent subarea. The authors also evaluated the quality of the reviews using the York University, Centre for Reviews and Dissemination Database of Abstracts of Reviews of Effects (DARE-4) criteria, which we also used in our work—these are presented in Table 2. Acknowledged inefficiencies of the reviews concern unreported or few primary studies, and inadequately addressed RE subareas.

Distributed software development (DSD—also global software development) was another SE area summarized in the identified tertiary studies. Alinne et al. [47] introduced a systematic tertiary study on communication in DSD, aiming to identify and synthesize factors that influence its effectiveness, and discover its impact on project design. The authors suggest that more research should be conducted on the topic, particularly on processes for effectively assessing the maturity of communication in distributed teams. In another work, Marques et al. [107] collected 14 systematic studies between 2008 and 2011 discussing the challenges of DSD, and mapped them with the identified solutions and approaches that still need further investigation. Using the SWEBOK KAs, most studies were categorized in SE management and process, software design, and requirements. With respect to authors and institutions, it appears that there is considerable cooperation among researchers worldwide. Finally, Verner et al. [162] enumerated DSD systematic reviews between 2005 and 2011, and identified their topics, active researchers, publication venues, and study quality.

In the area of software testing, Garousi et al. [57] systematically summarized all state-of-the-art SLRs published between 1994 and 2015. The authors identified the investigated areas of software testing, the addressed RQs, and the citations of the secondary studies, along with characteristics of the associated primary studies (e.g., quality and types). The tertiary findings reveal a slow improvement in the quality of the secondary studies over the years. Regular surveys compose the most frequent type of review, and also receive significantly more citations than SLRs and

2https://web.archive.org/web/20070918200401/https://www.york.ac.uk/inst/crd/faq4.htm.
systematic mapping studies. The most popular testing method seems to be the model-based approach both in mobile and web services, while regression and unit testing were assessed as the most popular testing phases. There appears to be room for further secondary studies in various testing areas including test management, beta-testing, exploratory testing, test stopping criteria, and test-environment development.

2.2 Tertiary Study in ML4SE

In the area of software effort estimation, Sreekumar et al. [130] going through 14 SLRs highlight that, although most studies employ regression-based and ML techniques, it appears that expert judgment is still preferred by the industry due to its intuitiveness. The use of ML techniques for effort estimation has been growing since 2017, combined with analogy-based estimation models. Concerning accuracy metrics, there is an increasing use of Mean Magnitude of Relative Error (MMRE), Median Magnitude of Relative Error (MdMRE), and Prediction Pred (25%), with 78% of primary studies employing MMRE. According to the authors, there is a need for simple comprehensive global models, due to the distributed nature of software development, while further research should be conducted to further improve estimation results derived with ML approaches.

3 REVIEW METHODS

To conduct this tertiary review, we followed the guidelines outlined by Kitchenham and Charters [83]. A tertiary review employs the same methods with a typical SLR, differing in that primary studies of the latter are considered secondary studies in the former. Hence, the review was organized according to the three recommended main phases of an SLR: planning, conducting, and reporting. For the planning phase, a formal protocol (included in the provided dataset)3 was developed and reviewed by all authors, documenting the review procedures associated with the following processes: search and selection, quality assessment, data extraction, synthesis, and analysis. In all manual activities that required human judgment, the data extraction and data checking approach was adopted, as suggested by Brereton et al. [27], where the second author of this article was the extractor, and the first was the checker. The complete review method is presented through a UML information flow diagram in Figure 1, after recommended guidelines for systematic studies to visualize the adopted review process [163].

3File review-protocol.md.
3.1 Research Objectives and Questions

This study aims to: provide a quality-evaluated catalog of the identified systematic reviews to the research community; summarize and assess all published systematic reviews concerning ML approaches applied in SE activities; describe the current state of research in ML4SE; and highlight potential research opportunities in the intersection of the two fields. To achieve these objectives, ensuring that the study is comprehensive in its nature, while providing an in-depth analysis of the use of ML in SE activities, the following research questions were defined.

RQ1 What SE tasks have been tackled with ML techniques?
RQ2 What SE knowledge areas could be better covered by ML techniques?
RQ3 What ML techniques have been used in SE?

By answering these questions, we aim to identify how ML has contributed to SE activities, uncover SE areas underrepresented by ML, and identify what ML techniques have been used in the SE activities described in the collected systematic studies. Following the practice of other tertiary studies [21, 85] we present the quantitative information associated with the examined material in Section 4.1, rather than dealing with it through a separate research question. The methods employed to answer each research question as well as collect and present the related quantitative information are detailed in Section 3.6.

3.2 Search Strategy

The search strategy was completed in four stages: automated search in digital sources, manual search in digital sources, backward, and forward snowballing. In the first two stages (depicted at the beginning of Figure 1), we searched for studies published between January 2015 and June 2020, whereas in the last two (visualized at the end of Figure 1), earlier and subsequent studies were also examined.

3.2.1 Automated Search. We selected 2015 as the starting year of the automated search process for the following reason. We searched in Elsevier Scopus\(^4\) for documents whose title, abstract, or keywords contained the terms *machine learning* and *software engineering* up to 2020, resulting in 2316 results. We then extracted the yearly distribution of these documents in CSV format from Scopus’s *Analyze search results* page, and visualized them as seen in Figure 2. We observe a constant increase in the number of publications belonging to the intersection of the two fields after 2015. Therefore, we consider this year an inflection point for the joint evolution of the fields, which would conceivably also mark the appearance of corresponding review surveys. Studies published outside the selected time window were identified through repeated snowballing (see Section 3.2.3).

\(^4\)https://www.scopus.com.
The automated search was implemented in two steps. First, a search string was composed. Second, this search string was used to systematically query three online digital libraries: IEEE Xplore, ACM Digital Library, and Scopus. We aimed to identify secondary studies in ML4SE, namely, studies reviewing ML techniques that have been applied in SE activities. Table 1 presents all keywords used in the search string composition, sorted in three conceptual groups: keywords related to SE, ML, and secondary studies. For the SE field, keywords were derived from the 15 SWEBOK V3 KAs [26]. The areas of Computing Foundations, Mathematical Foundations, and Engineering Foundations were excluded, because they were considered outside the study’s scope [160]. Despite the V3 guide’s relatively old publication year (2014), all of its KAs remain relevant, as can be observed from the overview of the ongoing SWEBOK V4 [72]. V4 consists of the same KAs, and redistribute some material to three new KAs: Software Architecture, Software Operations, and Software Security [72].

To ensure that the identified studies would be secondary, we composed a group consisting of 35 keywords adapted from two sources: a set of 15 keywords introduced in the tertiary study on SLRs in SE by Kitchenham et al. [85]; and a set of 20 keywords manually extracted from the titles of the surveys published in the ACM Computing Surveys journal. Specifically, we queried the ACM Digital Library applying the filter ACM Computing Surveys and the ACM CCS 2012 [138] concept Surveys And Overviews (10002944.10011122.10002945). A set of 304 papers were retrieved and exported in BibTeX format. Next, titles were isolated and canonicalized by automatically removing all stop words and punctuation. The second author examined the canonicalized titles by hand to identify any additional terminology used for describing secondary studies that was not already part of the 15 aforementioned keywords. As a result, 20 additional keywords were included in the group of keywords for secondary studies.

Equivalently, the third group consists of 27 keywords manually extracted from the titles of the ML-related surveys of the ACM Computing Surveys journal. Again, we queried the ACM Digital Library applying the filter ACM Computing Surveys and the ACM CCS 2012 concept Machine Learning (10010147.10010257). In total, 148 papers were fetched and their titles were canonicalized. Similarly, the second author inspected the canonicalized titles by hand to identify the ML terminology used in secondary studies, resulting in the 27 keywords listed in Table 1.

All possible 3-tuples occurring from these three groups were used to compose search strings and query the fields of document title, abstract, and author keywords in the digital libraries. Since

---

The table below lists the search keywords used in the study:

| Keywords for SE: Software Configuration Management, Software Construction, Software Design, Software Engineering Economics, Software Engineering Management, Software Engineering Methods, Software Engineering Models, Software Engineering Process, Software Engineering Professional Practice, Software Maintenance, Software Quality, Software Requirements, Software Testing |
| Keywords for ML: Artificial Neural Networks, Bayesian Classifier, Classification, Clustering, Computational Intelligence, Computer Learning, Data Mining, Decision Tree Classification, Deep Learning, Deep Neural Network, Ensemble Learning, Generative Adversarial Networks, Genetic Programming, Grammars, Intelligent Computing, Learning Algorithms, Learning Based, Machine Learning-based Applications, Machine Learning, Meta-Learning, Natural Language Processing, Regression, Reinforcement Learning, Semi-supervised Learning, Supervised Learning, Support Vector Machines, Transfer Learning |
| Keywords for Secondary Studies: analysis of research, body of published research, centralized tutorial, common practices, comparative study, comprehensive overview, conceptual analysis, editorial, editorial overview, editor’s preview, evidence-based software engineering, functional overview, general overview, in-depth analysis, literature analysis, literature review, literature survey, lookup table, manifesto, meta-analysis, meta-survey, methodologies, overview of existing research, past studies, review of studies, strategic directions, structured review, study, subject matter expert, survey and classification, survey, systematic approach, systematic mapping study, systematic review, taxonomy |
each library has its own syntax, the procedure was adjusted accordingly. In the end, a set of 1,897 studies were collected, from which duplicates were removed based on the studies’ digital object identifiers keeping the latest occurrences, resulting in 1,566 unique studies.\textsuperscript{11}

3.2.2 Manual Search. To increase the coverage of the automated search process, we additionally performed a manual search in each digital library using one random search string of all possible 3-tuples. In this way, one more relevant paper was found (1,567 studies in total).

3.2.3 Backward and Forward Snowballing. After completing the quality assessment of the secondary reviews described below in Section 3.5, the backward snowballing procedure \textsuperscript{167} was applied on their referenced studies. Following the data extraction and data checking process, a set of 3,195 studies referenced by the quality-accepted reviews were evaluated using the inclusion and exclusion criteria (IC/EC) outlined in Section 3.3, after reading their title, keywords, and abstract.\textsuperscript{12} In this way, 16 additional secondary studies were included and quality-assessed, with the earliest study having been published in 2003.\textsuperscript{13} Of these 16 studies, seven passed the quality assessment and made it into the interim set of reviews (Figure 1). One more backward snowballing round was performed on these seven studies, which did not result in any further relevant reviews.

A single iteration of forward snowballing \textsuperscript{168} was performed on the quality-accepted studies that occurred from the initial search and the backward snowballing process.\textsuperscript{14} Although Wohlin et al. \textsuperscript{168} recommend Google Scholar as a search engine (compared to IEEE Xplore and ACM Digital Library), we opted for Scopus, which has a satisfactory citation coverage \textsuperscript{108}, provides automated search functionality, and supports citation information extraction in CSV format. In contrast, extracting citations from Google Scholar by hand would entail excessive manual effort, hinder reproducibility, and might involve missed records from the human raters \textsuperscript{127}. Consequently, we automatically retrieved from Scopus on June 29, 2022 a total of 2,461 studies referencing the quality-accepted reviews, removed duplicates, and evaluated them following the same process we used for backward snowballing.\textsuperscript{15} An additional set of 84 studies were included, from which 43 were quality-accepted. Two of these accepted studies extended accepted studies from the initial search, and we kept the extensions as they are more complete.\textsuperscript{16}

3.3 Selection Criteria

The following set of IC/EC were applied to all studies collected with the search strategy (Section 3.2) to ensure that only relevant secondary studies would be included in the tertiary review.

\textit{Inclusion Criteria.}

- Only secondary studies (i.e., SLRs, systematic mapping studies, meta-analyses) conducted with documented systematic methods (defined research questions, search process, data extraction and presentation) are included.
- Taxonomies with the following planning characteristics \textsuperscript{160} are included. (I) A particular SWEBOK KA is examined. (II) The objectives and scope of research are clearly defined. (III) The subject matter of classification (units of classification, classes, categories) is described. (IV) A specific classification structure type (hierarchy, tree, paradigm, facet-based)

\textsuperscript{10}File \texttt{dl_search_queries.txt}.
\textsuperscript{11}File \texttt{dl_search_results.csv}.
\textsuperscript{12}File \texttt{backward_snowballing_references.csv}.
\textsuperscript{13}File \texttt{backward_snowballing.csv}.
\textsuperscript{14}One iteration is sufficient according to the SLR guidelines by Wohlin et al. \textsuperscript{168}.
\textsuperscript{15}Files \texttt{forward_snowballing_reviewer_{1,2}.csv}.
\textsuperscript{16}The review by Gonçales et al. \textsuperscript{60} extends Reference \textsuperscript{59}, and the review by Idri et al. \textsuperscript{70} extends Reference \textsuperscript{71}.

ACM Computing Surveys, Vol. 55, No. 12, Article 256. Publication date: March 2023.
is selected. (V) A classification procedure type (qualitative, quantitative, or both) is defined. (VI) The data sources and collection methods are documented.

- Publications reporting results on the use of ML techniques in SE activities are included.

**Exclusion Criteria.**

- Non-secondary studies are excluded. These include: empirical studies; experimental evaluation studies; comparative studies with experimental results; reports and summaries of workshops (e.g., References [14, 35, 55, 95, 155]); non-implemented future research plans (e.g., Reference [175]).
- Publications mentioning the use of ML without describing the employed techniques are excluded.
- Inaccessible papers and reports (i.e., only the abstract is available) are excluded.
- Publications that are not written in English are excluded (e.g., References [116, 119]).
- Informal literature surveys (i.e., with undefined research questions, undocumented search, data extraction or analysis processes) are excluded.

### 3.4 Selection Process

After collecting the candidate secondary studies through the search strategy described in Section 3.2, we manually applied the IC/EC (Section 3.3) to exclude irrelevant instances. We also included three more studies [9, 91, 174] that, though not identified through the search strategy, were suggested during the paper’s review and satisfied the other selection criteria.

Aligning with the adopted guidelines [83], the selection process was based on the papers’ title, author keywords, and abstract, and was a two-step process (depicted in the middle of Figure 1). First, the data extractor and data checker reviewed a set of 15 randomly selected studies, and determined their inclusion or exclusion.\(^1\) Their level of agreement (inter-rater reliability) on this set was measured using Cohen’s Kappa statistic [124], and any discrepancies that occurred were resolved by consensus [83, 85, 109]. This step was repeated until a score of at least 0.8 was reached—in our case, only one iteration was needed, in which 14 studies were excluded and one was included by both authors. In this way, we ascertained that both researchers agreed on the IC/EC, allowing them to individually review the abundant remaining studies of the automated and manual search \((n = 1,552)—\text{Sections 3.2.1, 3.2.2}\) with high inter-rater reliability.

Consequently, in the second step, the remaining papers were split in two, and each of the first two authors individually reviewed a half \((n = 776)\), again based on the IC/EC.\(^2\) In case the authors could not determine a paper’s inclusion only by its title, keywords, or abstract, the full text was consulted. The inclusion of a limited number of studies, whose scope remained miscellaneous even after the full-text reading, was determined after discussion between the first two authors. The same method was adopted for the backward and forward snowballing processes (Section 3.2.3). Eventually, from all searches, a set of 140 distinct secondary studies were selected and quality-assessed, as detailed in the following Section 3.5.

### 3.5 Quality Assessment

We manually assessed the quality of the 140 selected secondary reviews to ensure concreteness of our study results. For this, we followed a recommended quality assessment process for tertiary studies [82, 84] using the DARE-4 criteria introduced in Section 2, and presented in Table 2. These are recommended criteria for assessing the quality of tertiary studies by Kitchenham et al. [85],

---

\(^1\) File cohen_kappa_agreement.csv.

\(^2\) Files study_selection_reviewer\_\{1,2\}\_csv.
and are also the most commonly used ones in SE tertiary studies [41]. Although there is a more recent version of the DARE criteria (i.e., DARE-5), we opted for DARE-4, which is mostly similar to DARE-5 apart from Criterion 3 (Were the included studies synthesized?), which is not clearly prescribed and we did not consider relevant to the goals of our study.

The DARE-4 criteria are based on four questions. Kitchenham et al. [85] refined them by attributing points to each criterion. In this way each criterion is scored either as Y (yes—1 point), P (partially—0.5 point), or N (no—0 points). The total score assigned to a study is the aggregate of the scores of all four questions. Thus, the highest possible score for a study is four, while the lowest is zero. Included studies should receive a score of at least two.

Again, we followed the data extraction and data checking approach, reaching an inter-rater agreement of 82%. The majority of disagreements occurred in the last question (QA4), which concerns the provided information about the reviewed primary studies—we attribute this to the higher entailed subjectivity of the particular question. Through this process, 57 of 140 (41%) studies were excluded, with a total score less than two. The total scores of accepted studies are presented in Tables 3 and 4. We observed that excluded secondary studies with inferior quality do not explicitly document their IC/EC (QA1) or search sources (QA2), or fail to assess the quality of the included primary studies (QA3).

### 3.6 Data Extraction

The information extracted from each quality-accepted secondary study was the following.

- Title and source (journal, workshop proceedings, conference proceedings, book chapter)
- Publication year—to outline the annual evolution and research interest in ML4SE.
- Publication venue—to highlight prominent publishers in the particular area.
- Author names, institutions, and countries—to discover leading research teams.
- Study type (e.g., SLR, systematic mapping study, taxonomy)
- Research method—to investigate guidelines highly adopted by secondary studies.
- Quality assessment score
- Number of primary studies—to approximate how many primary studies are implicitly covered by our tertiary study.

---

19. [https://www.crd.york.ac.uk/CRDWeb/AboutPage.asp](https://www.crd.york.ac.uk/CRDWeb/AboutPage.asp) (About DARE).
20. File `dare_assessment.csv`.
| Study         | Venue                  | Year | Publisher                      | QA Score | Primary | Covered Years          |
|--------------|------------------------|------|--------------------------------|----------|---------|-------------------------|
| [136]        | ESEM ’09               | 2009 | IEEE                            | 4.0      | 15      | 1994–2008               |
| [133]        | Int. J. Soft. Eng. Comput. | 2010 | International Science Press    | 2.5      | 23      | 2002–2010               |
| [62]         | IEEE Trans. Softw. Eng. | 2012 | IEEE                            | 4.0      | 36      | 2002–2010               |
| [166]        | Inf. Softw. Technol.   | 2012 | Elsevier                        | 4.0      | 84      | 1992–2010               |
| [25]         | Empir. Softw. Eng.     | 2014 | Springer                        | 3.0      | 79      | 1999–2011               |
| [20]         | J. Syst. Softw.        | 2015 | Elsevier                        | 3.0      | 13      | 2005–2014               |
| [45]         | Requir. Eng.           | 2015 | Springer                        | 4.0      | 29      | 1999–2013               |
| [69]         | SNPD ’15               | 2015 | IEEE                            | 3.5      | 35      | 2000–2013               |
| [99]         | Appl. Soft Comput.     | 2015 | Elsevier                        | 4.0      | 64      | 1995–2013               |
| [100]        | ICRITE ’15             | 2015 | IEEE                            | 2.0      | 21      | 1998–2014               |
| [36]         | Empir. Softw. Eng.     | 2016 | Springer                        | 2.0      | 167     | 1999–2014               |
| [102]        | Int. J. Softw. Eng. Knowl. Eng. | 2016 | World Scientific Publishing    | 4.0      | 96      | 1991–2015               |
| [70]         | J. Syst. Softw.        | 2016 | Elsevier                        | 3.0      | 24      | 2000–2016               |
| [171]        | ICSEME ’16             | 2016 | IEEE                            | 3.5      | 29      | 2000–2015               |
| [89]         | SEAA ’16               | 2016 | IEEE                            | 3.5      | 19      | 1997–2015               |
| [101]        | Int. J. Comput. Appl. Technol. | 2016 | Inderscience Publishers        | 2.0      | 21      | 1998–2011               |
| [150]        | SNPD ’16               | 2016 | IEEE                            | 2.0      | 38      | 2007–2015               |
| [178]        | J. Syst. Softw.        | 2016 | Elsevier                        | 3.0      | 79      | 2005–2015               |
| [5]          | IEEE Access            | 2017 | IEEE                            | 3.5      | 103     | 2005–2016               |
| [46]         | APSEC ’17              | 2017 | IEEE                            | 2.5      | 40      | 1998–2016               |
| [78]         | ACM Comput. Surv.      | 2017 | ACM                             | 2.5      | 47      | 2007–2015               |
| [104]        | Swarm Evol. Comput.    | 2017 | Elsevier                        | 4.0      | 78      | 1992–2015               |
| [96]         | SPLC ’17               | 2017 | ACM                             | 3.5      | 25      | 2005–2017               |
| [156]        | Softw. Qual. J.        | 2017 | Springer                        | 3.5      | 10      | 2012–2014               |
| [158]        | Artif. Intell. Rev.    | 2017 | Springer                        | 2.5      | 32      | 2003–2015               |
| [176]        | ICET ’17               | 2017 | IEEE                            | 2.0      | 22      | 1998–2016               |
| [10]         | CTCEEC ’17             | 2018 | IEEE                            | 2.5      | 17      | 2006–2014               |
| [120]        | J. Syst. Softw.        | 2018 | Elsevier                        | 4.0      | 52      | 2000–2016               |
| [9]          | ACM Comput. Surv.      | 2018 | ACM                             | 2.0      | 91      | 2007–2018               |
| [53]         | SPICE ’18              | 2018 | Springer                        | 2.5      | 25      | 1998–2017               |
| [118]        | CITC ’18               | 2018 | Springer                        | 2.0      | 20      | 2013–2016               |
| [135]        | IEEE Access            | 2018 | IEEE                            | 4.0      | 113     | 1993–2016               |
| [144]        | J. Syst. Softw.        | 2018 | Elsevier                        | 3.0      | 445     | 1996–2016               |
| [112]        | Comput. Electr. Eng.   | 2019 | Elsevier                        | 4.0      | 31      | 2002–2017               |
| [6]          | SEAA ’19               | 2019 | IEEE                            | 3.5      | 30      | 2007–2018               |
| [30]         | Int. J. Softw. Eng. Knowl. Eng. | 2019 | World Scientific Publishing    | 3.0      | 26      | 1999–2016               |
| [17]         | Inf. Softw. Technol.   | 2019 | Elsevier                        | 3.5      | 15      | 2000–2017               |
| [11]         | ICETCA ’19             | 2019 | IEEE                            | 3.0      | 15      | 2007–2017               |
| [48]         | IEEE Trans. Reliab.    | 2019 | IEEE                            | 3.0      | 48      | 1995–2018               |
| [67]         | IEEE Trans. Softw. Eng. | 2019 | IEEE                            | 4.0      | 30      | 2008–2015               |
| [148]        | Symmetry               | 2019 | MDPI                            | 3.0      | 98      | 1995–2018               |
| [51]         | e-Inform. Softw. Eng. J. | 2019 | Wroclaw University of Science and Technology | 3.5     | 82    | 2000–2018               |
| [53]         | e-Inform. Softw. Eng. J. | 2019 | Wroclaw University of Science and Technology | 3.0     | 38    | 2000–2019               |
| [5]          | J. Softw.: Evol. Process | 2019 | Wiley                           | 4.0      | 75      | 1991–2017               |
| [80]         | IEEE Access            | 2019 | IEEE                            | 3.0      | 58      | 2016–2019               |
| [114]        | ICSRE ’19              | 2019 | IEEE                            | 2.5      | 46      | 1995–2017               |
| [153]        | ICETC ’19              | 2019 | ACM                             | 2.0      | 31      | 2003–2019               |
| [13]         | ICPC ’20               | 2020 | ACM                             | 2.0      | 33      | 2012–2019               |
| [32]         | SEAA ’20               | 2020 | IEEE                            | 2.5      | 38      | 2009–2019               |
| [33]         | SEAA ’20               | 2020 | IEEE                            | 2.5      | 196     | 2012–2017               |
| [7]          | ICOSSST ’20            | 2020 | IEEE                            | 3.5      | 34      | 2007–2019               |
| [147]        | IEEE Access            | 2020 | IEEE                            | 3.0      | 32      | 2009–2019               |
| [143]        | IET Softw.             | 2020 | IET                             | 3.5      | 28      | 2014–2020               |
| [9]          | Secur. Commun. Netw.   | 2020 | Wiley                           | 2.5      | 12      | 2011–2019               |
| [91]         | ACM Comput. Surv.      | 2020 | ACM                             | 2.0      | 267     | 1992–2019               |
Table 4. Overview of Secondary Studies (2/2)

| Study | Venue | Year | Publisher | QA Score | Primary | Covered Years |
|-------|-------|------|-----------|----------|----------|---------------|
| [44]  | SAC’20 | 2020 | ACM       | 2.0      | 320      | 2017–2019     |
| [105] | Soft Comput. | 2020 | Springer  | 3.5      | 36       | 1993–2019     |
| [125] | Inf. Softw. Technol. | 2020 | Elsevier  | 3.0      | 93       | 2004–2015     |
| [94]  | ACM Comput. Surv. | 2020 | ACM       | 2.0      | 109      | 1999–2019     |
| [4]   | Arab. J. Sci. Eng. | 2020 | Springer  | 4.0      | 17       | 2005–2018     |
| [52]  | J. Comput. Sci. Technol. | 2020 | Springer  | 3.5      | 77       | 2000–2018     |
| [125] | J. Syst. Softw. | 2021 | Elsevier  | 2.5      | 69       | 2005–2019     |
| [174] | ACM Comput. Surv. | 2021 | ACM       | 2.0      | 250      | 2006–2020     |
| [19]  | J. Comput. Sci. | 2021 | Science Publications | 3.0      | 40       | 2016–2020     |
| [111] | Intel. Autom. Soft Comput. | 2021 | Tech Science Press | 2.5      | 22       | 2016–2019     |
| [134] | Int. J. Adv. Comput. Sci. Appl. | 2021 | The Science and Information Organization | 2.5 | 48 | 2017–2020 |
| [139] | ACM Comput. Surv. | 2021 | ACM | 2.5 | 92 | 2010–2019 |
| [1]   | J. Softw.: Evol. Process | 2021 | Wiley | 3.5 | 145 | 1993–2018 |
| [8]   | J. Softw.: Evol. Process | 2021 | Wiley | 4.0 | 31 | 2011–2019 |
| [145] | Empir. Softw. Eng. | 2021 | Springer | 2.0 | 111 | 2009–2020 |
| [177] | REW’21 | 2021 | IEEE | 3.5 | 65 | 2010–2020 |
| [141] | SN Comput. Sci. | 2021 | Springer | 3.0 | 30 | 1995–2020 |
| [79]  | IEEE Access | 2021 | IEEE | 3.0 | 110 | 2004–2021 |
| [122] | Expert Syst. Appl. | 2021 | Elsevier | 4.0 | 154 | 1990–2019 |
| [18]  | Sci. Comput. Program. | 2021 | Elsevier | 4.0 | 75 | 1993–2019 |
| [60]  | Inf. Softw. Technol. | 2021 | Elsevier | 2.5 | 63 | 2010–2020 |
| [98]  | Softw.: Pract. Exp. | 2022 | Wiley | 4.0 | 35 | 1997–2020 |
| [164] | ACM Trans. Softw. Eng. Methodol. | 2022 | ACM | 3.0 | 128 | 2009–2019 |
| [173] | ACM Trans. Softw. Eng. Methodol. | 2022 | ACM | 3.0 | 421 | 2009–2020 |
| [23]  | Comput. Electr. Eng. | 2022 | Elsevier | 4.0 | 68 | 2010–2021 |
| [146] | IEEE Access | 2022 | IEEE | 2.0 | 62 | 2016–2021 |
| [121] | Eng. Appl. Artif. Intell. | 2022 | Elsevier | 2.0 | 146 | 2009–2020 |
| [93]  | Stud. Syst. Decis. Control | 2022 | Springer | 2.5 | 45 | 2005–2020 |

- Application domain in terms of SWEBOK KAs and subareas as well as SE tasks covered by each secondary study—to answer RQ1 and RQ2.
- Implications for further research and comments concerning the use of ML in SE—to answer RQ2.
- Employed ML techniques—to answer RQ3.

To extract the aforementioned information that was needed to answer the RQs introduced in Section 3.1, we employed the following methods.

**RQ1: What SE tasks have been tackled with ML techniques?** To answer this, we extracted from each secondary study its application domain in terms of related SWEBOK KA, subarea, and SE task(s).\(^{21}\) When a study was associated with multiple KAs/subareas, the most prominent one was kept (i.e., the most covered KA/subarea by the included primary studies, or the most analyzed one by the review authors). The process was implemented following the data extraction and data checking approach, and any conflicts that occurred were resolved by the last author. For the extraction of the SE tasks, we followed the open coding practice [39] by manually applying codes (i.e., SE tasks—e.g., test automation, software maintainability prediction, software defect prediction,

\(^{21}\)File knowledge_areas.csv.
bug prioritization) to the studies. The study list was split in two, and each of the first two authors individually applied codes (SE tasks) to a half (in a shared online spreadsheet). To maintain consistency between the two authors, the codes were mainly extracted from the study’s title, author keywords, abstract, or introduction. Next, the authors discussed and grouped together conceptually related codes by generalizing or specializing them, employing the Qualitative Content Analysis approach [97]. In the end, each secondary study was associated with at least one and up to three SE tasks. Consequently, a SE task may be associated with multiple KAs.

RQ2: What SE knowledge areas could be better covered by ML techniques? For this, we used the results of RQ1 to identify SWEBOK KAs that are insufficiently covered by ML techniques. Moreover, we extracted by hand any implications for further research as well as comments regarding the use of ML in SE that were mentioned in the associated reviews. To do this, we searched the sections of abstract, introduction, results, conclusion, and further research or future directions (where available) of all secondary studies to identify ML-related research opportunities in each KA. Last, we extracted from the same sections any identified issues or obstacles associated with the use of ML techniques in SE.

RQ3: What ML techniques have been used in SE? To address this, we classified each secondary study using a classification scheme, again following the data extraction and data checking approach. The classification scheme was constructed from two sources and consists of four axes: the role of AI in SE [65], the supervision type [77], the incrementality type [77], and the generalizability type [77]. The role of AI in SE includes the following three categories.

- Computational search and optimisation techniques (the field known as Search-based Software Engineering—SBSE): The goal of this area is to reconstruct SE problems as optimization problems, which can then be tackled with computational search-related AI techniques.
- Fuzzy and probabilistic methods for reasoning in the presence of uncertainty: AI techniques are used to address real-world problems, which are inherently fuzzy and probabilistic (e.g., the use of Bayesian probabilistic reasoning to model software reliability or analyze users).
- Classification, learning, and prediction: This area involves the application of ML techniques such as artificial neural networks, case-based reasoning, and rule induction to model and predict SE tasks (e.g., software project prediction, ontology learning, defect prediction).

Supervision expands to supervised, unsupervised, semi-supervised, and reinforcement learning. In supervised learning, the training dataset used by the ML-based system includes the desired solutions (i.e., labels), whereas in unsupervised learning, the training dataset is unlabeled. Semi-supervised learning involves many unlabeled data combined with a few labeled instances, while reinforcement learning is concerned with learning to control a system, to maximize a numerical performance measure that expresses a long-term objective [152]. Contrary to supervised, in reinforcement learning, only partial feedback is provided to the system about its predictions.

The third axis, incrementality, consists of online/incremental and batch/offline learning. In online learning, the ML algorithms are trained incrementally by feeding them data instances sequentially on the fly (as they arrive), either individually or in small groups (i.e., mini-batches). These algorithms constantly update the system weights; thus the error calculation uses different weights for each input sample. However, in offline learning, the ML algorithms are first trained with all available training data, and are then released into production without the ability to learn incrementally—they only apply what they have learned. These algorithms keep the system weights constant while computing the error associated with each input sample.

22 File further_research.csv.
23 File ml_techniques.csv.
The axis of generalizability expands to instance-based and model-based learning. In instance-based learning, the system stores the data and generalizes to new instances by employing a similarity measure, whereas in model-based learning, patterns are detected in the training data, and are used to build a predictive model. In all axes, studies were classified to the most prominent category (when more than one categories could be mapped). In addition, we extracted by hand the ML techniques employed in the primary studies, when reported in the corresponding secondary, to determine the most popular ones for SE tasks.

4 RESULTS

In this section, we present our research findings in regard to the data extraction process described in Section 3.6 and the research questions outlined in Section 3.1.

4.1 Data Extraction

The papers in our final set of 83 quality-accepted secondary studies were published between 2009 and 2022, and cover 6,117 non-unique primary studies (conference papers, journal papers, theses, and technical reports) published between 1990 and 2021. The majority of secondary reviews \( n = 63 \; (76\%) \) were published in journals as opposed to conference proceedings \( n = 20 \; (24\%) \). An overview of all reviews sorted by publication year is presented in Tables 3 and 4.

**Top authors.** In total, 274 researchers contributed to the 83 secondary studies. Between 2009 and 2022, the most active researcher in the field was Ruchika Malhotra, having co-authored six studies, followed by Alain Abran and Ali Idri.

**Top institutions.** The studies originate from 140 institutions. Delhi Technological University (Delhi, India) is on the top of the list with seven studies, followed by École de Technologie Supérieure (Montreal, Canada), Mohammed V University (Rabat, Morocco), and University of Adelaide (Adelaide, Australia).

**Distribution of studies.** Figure 3 depicts the number of publications by year and publisher. Most secondary studies were published between 2019 and 2021, while no studies were found from 2011 and 2013. Overall, we observe a notable increase in the number of studies after 2015, which aligns with the Scopus results visualized in Figure 2. Regarding publishers’ distribution, IEEE is first with 25 publications, followed by Elsevier with 17, Springer with 13, ACM with 12, and Wiley with 5 studies.

**Quality of studies.** As deduced from Figure 4, there seems to be a fixed average quality of secondary studies after 2014. The total average score remains above average (2) each year, implying an overall adequate (yet not perfect) quality of secondary studies. Although few studies were published in 2009 and 2012, these had the highest scores in all questions, suggesting that the DARE-4 criteria (Table 2) have been systematically adopted from early on.
Research types of studies. The majority of secondary studies \((n = 53; 64\%)\) are primarily SLRs, while \(19\% (n = 16)\) are systematic mapping studies, \(16\% (n = 13)\) are surveys, and a single study is a taxonomy. Seven studies include a second research type: SLR (together with systematic mapping study) \([51, 120]\), and meta-analysis (with SLR as primary) \([17, 52, 67, 112, 147]\).

Research methods of studies. The most commonly adopted guidelines for SLRs and surveys are those by Kitchenham et al. \([81, 83, 86]\), while most systematic mapping studies follow the guidelines by Petersen et al. \([126, 127]\), and Kitchenham et al. \([87]\). In addition, some studies employ the structure proposed by Hall et al. \([62]\) for conducting reviews and presenting results. The snowballing search method by Wohlin et al. \([167, 169, 170]\) is also used in some studies complementary to the aforementioned guidelines, based on published recommendations regarding the inclusion of manual target searches in systematic reviews \([76]\). To compose the research questions, some reviews adopt recommendations by Easterbrook et al. \([50]\) and Sabir et al. \([140]\). To assess the quality of primary studies, various criteria have been used, such as the ones by Zhou et al. \([181]\) and Dybå et al. \([49]\), and the Systematic Review Checklist by the Critical Appraisal Skills Programme (CASP) \([131]\). Moreover, a variety of methods are used for data synthesis, analysis, and visualization, including content analysis \([90]\), grounded theory \([34]\), and box plots \([42]\).

4.2 RQ1: What SE Tasks Have been Tackled with ML Techniques?

The classification of the 83 studies according to the SWEBOK KAs and subareas, as described in Section 3.6, revealed a coverage of the eleven KAs presented in Table 5. For each KA and subarea, the number, percentage, and references of the associated secondary studies are included as well as the number of primary studies reviewed by the secondary. The most addressed KA is Software Quality, being the focus of 25 (30\%) secondary studies. Subsequent KAs include Software Testing \((n = 17; 20\%), \) SE Process \((n = 14; 18\%), \) SE Management \((n = 12; 14\%), \) and Software Requirements \((n = 6; 6\%). A single study was found related to Engineering Foundations, covering the subarea of Statistical Analysis, despite this KA being less related to SE. In Figure 5, we also visualize the yearly distribution of KAs. KAs are sorted in the figure bottom-up according to their appearance frequency in Table 5. It appears that Software Quality, Software Testing, and SE Process are also the most trending ones in recent years. In the following sections, we present for each KA, the SE tasks that have been tackled with ML techniques. Codes resulting from the manual coding process for the extraction of SE tasks from the associated studies are set in **bold**.

4.2.1 Software Quality. In this area, ML techniques are frequently used for **software change** and **quality prediction**, replacing traditional statistical methods. ML-based software change prediction aims to identify change-prone components during the early phases of software development, leading to higher quality and maintainable software at lower cost \([100, 101]\). To evaluate
ML techniques’ effectiveness, Malhotra and Khanna [103] summarize different software change prediction models, experimental setups, data analysis algorithms, statistical validation tests, and associated threats. Feature selection is considered one of the most essential and complex activities in data pre-processing [11]. In software quality prediction we identify various applications of Bayesian networks, while the majority of the reviewed work employs expert knowledge [156].

Another common task in software quality is software maintainability prediction. By measuring quality attributes, developers can improve software design, optimize resource allocation, and develop cost-effective, high-quality, maintainable software systems [102, 105]. Managers can evaluate and compare productivity across projects, perform effective resource planning, and control maintenance costs [102]. An accuracy analysis of software maintainability prediction models reveals that the most accurate ones are fuzzy and neuro fuzzy systems, and artificial neural networks [51]. Moreover, the use of open-source datasets in the training process of maintainability prediction models has increased in recent years [102].

ML-based software defect prediction is widely covered in software quality. Uncovering defects at the early phases of software development improves the system’s cost-effectiveness and maintainability [120]. Some reviews recommend the use of supervised and deep learning techniques [19, 111]. Pachouly et al. [121] propose an architecture for synthesizing training datasets for multi-label classification of software defects. A popular topic is cross project defect prediction: training ML models with data gathered from various projects to predict defects in completely new

| SWEBOK KA | Subarea | Sec. | % | References | Prim. |
|-----------|---------|------|---|------------|-------|
| Software (SW) Quality | Practical Considerations | 22 | 27 | [1, 4, 11, 17, 19, 35, 51, 52, 67, 93, 148, 156] | 1,309 |
| | SW Quality Fundamentals | 2 | 2 | [30, 144] | 471 |
| | SW Quality Management Processes | 1 | 1 | [147] | 32 |
| SW Testing | Test Techniques | 15 | 18 | [5, 7, 23, 44, 62, 78, 79, 99, 112, 118, 122, 134, 135, 143, 178] | 1,255 |
| | Test Process | 2 | 2 | [48, 80] | 106 |
| SE Process | SW Life Cycles | 4 | 5 | [32, 146, 164, 173] | 649 |
| | SW Measurement | 4 | 5 | [13, 36, 53, 104] | 303 |
| | SW Process Assessment & Improvement | 3 | 4 | [46, 145, 150] | 189 |
| | SE Process Tools | 3 | 4 | [9, 91, 174] | 608 |
| SE Management | SW Project Planning | 12 | 14 | [5, 6, 18, 70, 89, 98, 114, 125, 133, 141, 166, 171] | 563 |
| SW Requirements | Requirements Analysis | 2 | 2 | [10, 177] | 82 |
| | Requirements Elicitation | 2 | 2 | [2, 20] | 25 |
| | Requirements Process | 2 | 2 | [8, 45] | 60 |
| SW Maintenance | Techniques for Maintenance | 1 | 1 | [94] | 109 |
| | Key Issues in SW Maintenance | 1 | 1 | [158] | 32 |
| | SW Maintenance Tools | 1 | 1 | [153] | 31 |
| SW Design | SW Structure & Architecture | 1 | 1 | [176] | 22 |
| | SW Design Tools | 1 | 1 | [96] | 25 |
| SW Configuration Management | SW Configuration Management Tools | 1 | 1 | [123] | 69 |
| SE Models & Methods | Analysis of Models | 1 | 1 | [25] | 79 |
| SE Professional Practice | Group Dynamics & Psychology | 1 | 1 | [60] | 63 |
| Engineering Foundations | Statistical Analysis | 1 | 1 | [69] | 35 |
(unseen) projects [67]. An ideal prediction model should highlight the severity of defects, uncover security-related defects and system vulnerabilities, and also identify defects on systems that it was not trained on [148].

Other popular quality tasks include malware, smell, and data exfiltration detection. In JavaScript ML models offer higher malware detection rates than non-ML ones [147]. In smell detection we distinguish the use of deep learning, J48, JRip, Decision Tree, and Random Forest algorithms [4, 17, 30, 93]. These involve training models on datasets of source code metrics and smells to classify new unseen software components [144]. Some efforts target smell detection at the design and code levels [1]. In the area of data exfiltration (also known as data theft and data leakage [159]) there are several ML-based countermeasures, which are classified according to four axes: type of approach (data- or behavior-driven); employed features (behavioral, content-based, statistical, syntactical, spatial, or temporal); evaluation dataset (simulated, synthesized, or real); and reported performance measures [139].

4.2.2 Software Testing. Here ML techniques are mainly used for test automation, specifically for test case generation, evaluation, and optimization. Genetic algorithms are frequently proposed [80, 118]. In the test oracle problem, which is concerned with a software’s output behavior based on a set of inputs, automation is achieved by training ML models to predict the outcome [48]. In exhaustive testing, where developers typically use auto-generated test data, ML algorithms are used to produce ample efficient test case routines [48]. In mobile application testing the Swift Hand automated technique [37] can be used to produce sequences of test inputs that enable visiting unexplored states of the application without restarting it [178]. In test evaluation, testers assess with ML models the extent to which test suites cover the observable program behavior, and predict the feasibility of test cases [48]. In test optimization historical information is analyzed with ML techniques to calculate multi-objective metrics [78]. These metrics are used to improve testing performance by reducing resource and time consumption, especially in regression testing where retesting is costly [79, 134]. ML-based test case prioritization is useful when the source code is not accessible, and for enhancing fault detection in applications [44]. Last, Black-box test specification can be refined with ML techniques [135].

Furthermore, ML is frequently used in software fault prediction. In large datasets deep learning models outperform data mining and ML ones [23]. In interaction testing ML techniques are used to create diverse test suites, covering as many constraints as possible [3]. ML-based classification algorithms effectively determine a module or class’s fault-proneness, usually more efficiently than statistical models [99, 122]. The results of ML methods are also more generalizable than statistical ones [122]. Still, ML techniques can perform worse than statistical models, because they require parameter fine-tuning, and may depend on unbalanced or uncleared data [62]. To perform parameter optimization and feature selection, bio-inspired algorithms are recommended, namely, genetic algorithms and particle swarm optimization [7].

Another testing area of ML interest is software vulnerability detection. Deep learning methods (convolutional and recurrent neural networks) are frequently employed for vulnerability analysis on source code [143]. The majority of training datasets consist of data from a single programming language, mainly C/C++ and JavaScript [143]. In penetration testing ML applications mainly involve attack planning through attack graph generation or attack tree modeling [112]. Two predominant methods for attack planning are the Markov Decision Process and genetic algorithms [112].

4.2.3 SE Process. Various tasks related to SE processes are approached with ML. Some software fault prediction models are developed based on topic modeling. Topic modeling is applied on source code to approximate software concerns as topics, analyze failed executions and the
defect-proneness of systems, or determine dependencies between source code elements and developers [150]. Apart from fault prediction, other applications of topic modeling are: architecting, bug handling, coding, documentation, maintenance, refactoring, requirements, and testing [145]. In software quality prediction ML techniques are employed to estimate four predominant quality attributes: effort, defect- and change-proneness, and maintainability [104]. Furthermore, ML models are preferred for traceability link recovery, concept location, bug triaging, clone identification, source code summarization, and refactoring [13, 36].

A number of reviews concern software process mining and automation. In agile software development, process mining is used to discover processes followed by agile teams based on task tracking applications [53]. The most prominent tool for this purpose is ProM [161]. In software effort estimation, process mining is used to improve the accuracy of models [46]. In general, ML is intensively used in the requirements phase for automation and improvement [146], and in the maintenance phase for prediction [173]. It is also widely used for the automation of decision-making tasks and for predictive analysis [146, 173]. Hybrid models combining ML with AI techniques improve the models’ performance, notably when training datasets consist of multi-dimensional and diverse instances [146]. Furthermore, deep learning techniques are increasingly employed in SE processes due to their automated feature engineering capabilities, superior efficiency, and ability to replace human expertise [164, 173].

Other emerging areas of SE process are source code analysis, program generation, and recommender systems. Source code is contrasted to natural language, since their common statistical properties can be used to build better SE tools [9]. Code-generating, code representational, and pattern-mining ML and deep learning models find applications in: recommender systems; coding convention inference; defect detection; code translation, copying, and cloning; code-to-text and text-to-code; documentation, traceability, and information retrieval; and program synthesis and analysis [9, 91, 174].

4.2.4 SE Management. In this area, we distinguish ML-based software development cost and effort estimation. Decision trees preponderate in software development cost estimation [114], and use case points stand out in software development effort prediction [18]. Ensemble effort estimation models, which are usually constructed from single (i.e., base) models joined with linear and non-linear combiner functions, perform better than single techniques [70, 98]. In general, the estimation accuracy of ML models is superior than that of regression models, although the application of the former in the industry is still limited [89, 125, 166]. Again, bio-inspired feature selection algorithms improve even further the accuracy of ML models [6]. Bayesian networks can also introduce expert knowledge in the models through strictly defined probability functions, especially when no empirical data from older projects are available [133].

A small number of reviews concern software enhancement (maintenance) effort estimation [141]. Regression problems of enhancement effort prediction are addressed with single prediction models, which outperform statistical ones [141]. In open source software, effort estimation and maintenance activity time prediction (e.g., bug fixing) models are trained on source code and people-related metrics [171].

4.2.5 Software Requirements. Here ML is used to support a range of tasks including: volatility prediction [10]; reuse of requirements and feature and variability extraction in the context of software product lines [20]; requirements elicitation, analysis, specification, prioritization, and negotiation [2, 8, 45]; and requirements ambiguity resolution [177].

4.2.6 Software Maintenance. Bug prioritization and software rename refactoring are frequently approached with ML techniques in this area. Especially natural language processing
models are used to mine, summarize, and prioritize bug reports [153, 158]. In software re-
name refactoring ML techniques outperform traditional approaches that are based on empirical
rules [94].

4.2.7 Software Design. Researchers here apply ML to software architecture recovery,
reverse engineering variability, and feature and variability extraction. In software archi-
tecture recovery, ML-based classification techniques are recommended for the estimation of the
positional probability of edges of a weighted graph using information gathered from real-world
object-oriented reference software systems [176]. Reverse engineering variability and feature and
variability extraction mainly concern the process of migrating individual software systems to
software product lines [96].

4.2.8 Software Configuration Management. In this area, we distinguish efforts in software per-
formance prediction and software configuration interpretability and optimization. The
large number of configuration options of modern software systems makes it impossible to ex-
plore the entire configuration space, to satisfy functional and non-functional needs [123]. As a
workaround, researchers frame the software configuration problem as a ML one by training mod-
els on samples of configuration measurements [123]. The software configuration problem is also
related to compiler autotuning and database management system tuning [123].

4.2.9 SE Models and Methods. ML techniques are proposed for systematically retrieving large-
scale information from software artifacts to support trace recovery [25]. Specifically, trace link
structures are extracted from software artifacts, and are used as input to ML voting systems to
assess the importance of each artifact [25].

4.2.10 SE Professional Practice. Here ML techniques are used to estimate the cognitive load
of software developers when performing SE tasks. To improve estimation results, these techniques
are usually combined with feature sets related to developers’ cognitive load [60].

4.2.11 Engineering Foundations. In this area, ML is used in the task of missing value imputa-
tion in SE datasets, to improve the accuracy of software development effort estimation results [69].

4.3 RQ2: What SE Knowledge Areas Could be Better Covered by ML Techniques?

From Table 5 we deduce that some SWEBOK KAs are either covered by few ML-related secondary
studies, or are not covered at all. Specifically, Software Construction and SE Economics are not ad-
dressed by any secondary study. Moreover, Software Configuration Management, SE Models and
Methods, and SE Professional Practice are only addressed by a single secondary study each, there-
fore, they appear less covered compared to the other KAs. Some KAs are also more comprehen-
sively covered than others as their associated studies span more subareas. This is the case for
Software Quality, SE Process, Software Requirements, and Software Maintenance, which span vari-
ous subareas, as opposed to SE Management, which contains an equivalent number of reviews
mapped to a single subarea. The sparse coverage of certain KAs is also recognized by the authors
of many secondary studies through their calls for further research on the application of ML tech-
niques to the associated SE tasks. In the subsequent sections we provide an extensive description
of how each KA and SE task could be better covered, as evidenced from the authors’ remarks
through the process described in Section 3.6, as well as any issues and obstacles related to the use
of ML techniques in SE. We also provide some general recommendations that apply to all KAs in
Section 4.3.1.

4.3.1 General Recommendations. Various recommendations apply to all KAs. These include:
conducting more comparative analyses between ML methods and traditional statistical techniques
$n = 13$ studies,\textsuperscript{24} performing more empirical analyses to increase the quality of ML techniques, and establish their cost-effectiveness ($n = 12$); publishing and using more open-source, diverse, large-scale, and high-quality datasets ($n = 16$); experimenting with new, hybrid, ensemble, and incremental techniques (e.g., transfer, few-shot, weakly, semi-supervised, and active learning, blockchain technology, search-based and multi-objective methods, automated feature engineering techniques, regression-based methods—$n = 21$); ensuring industrial relevance and scalability of ML models by applying them in real settings and commercial datasets, by conducting in-depth case studies with practitioners, and by developing concrete methods for building reliable models ($n = 18$); optimizing hyper-parameters of ML models (e.g., with the grid search algorithm—$n = 3$); and handling class imbalance in training datasets and model over-fitting ($n = 3$).

4.3.2 Software Quality. A number of research suggestions are observed in the associated SE tasks of this area. In software change and quality prediction researchers should explore cross-organization and cross-company validation, effective transfer learning, and temporal validation [103]. In software maintainability prediction we observe literature ambiguities concerning maintainability definitions and characteristics that affect ML models’ performance [52]. Researchers propose: measuring design metrics dynamically instead of statically (e.g., with Dynamic Lack of Cohesion, Dynamic Response For a Class) [102]; investigating maintainability for other types of applications (e.g., web, mobile, model-driven, and cloud computing) [51, 102]; analyzing the effect of diverse software development and process management factors on maintainability (e.g., risk analysis, project planning, requirement analysis) [51, 102]; and focusing on maintainability before delivery of the software product to detect issues and quality failures early [51]. In software defect prediction there are needed more empirical analyses on the validity of cross project defect prediction datasets [67, 121, 148]. Furthermore, in smell detection further research is needed on: smell types [93]; smell prioritization [1]; the mutual effect between smells to identify highly correlated ones [1, 17]; the false-positiveness of the proposed ML techniques, which could be high due to deficient smell definitions [1, 4, 94, 144]; and the effect of data transformations on the smell detection process [1].

4.3.3 Software Testing. Here, we summarize the following promising research directions. In ML-based mobile application testing most existing studies only target the Android platform, therefore there is a need for including other prevalent platforms as well (e.g., Apple iOS, Windows Phone) [178]. In mutation testing there is considerable room for expediting existing ML-based solutions for detecting possible equivalent mutants as well as automating more facets of the process, which are currently handled by humans [48]. In test suite optimization, there are only a few ML-based approaches [80]. In test case prioritization, including software requirement attributes in the training datasets could possibly improve models’ effectiveness [134]. In software fault prediction researchers could investigate less popular ML and evolutionary algorithms, such as Logit Boost, Ada Boost, Rule-based Learning, Bagging, Alternating Decision Tree, Radial Basis Function, Ant Colony Optimization, and Genetic Programming [3, 122]. More empirical analyses are desired on the performance of bio-inspired parameter optimization and feature selection algorithms with the traditional algorithms (e.g., grid search, random search, greedy search, best-first search) [7]. Moreover, in software vulnerability prediction assessment criteria should include more qualitative measures (e.g., consequence, impact) for determining the effectiveness of ML techniques [112]. Suggestions for ML models include: designing approaches to identify exploitable vulnerabilities in real-time [112]; studying the impact of multiple programming language datasets [143]; and

\textsuperscript{24}The complete list of associated studies for each general recommendation is available in file \textit{further\_research\_general.txt}.
performing finer-grained vulnerability detection by identifying the precise location of the vulnerabilities in the source code files or functions [143].

4.3.4 SE Process. Regarding SE processes, in the tasks of software fault and quality prediction, and traceability link recovery, we recognize the following recommendations. In fault and quality prediction researchers should further explore and assess the employed search-based techniques through multiple evaluation factors including cost-effectiveness, comprehensibility, generalizability, and execution time [104]. To ease the application of search-based approaches in prediction models, practitioners could develop and establish relevant tool suites [104]. To reduce bias in the evaluation process, different validation techniques such as inter-release, cross-project, and temporal validation could be combined [104]. Subsequent research should thoroughly document its associated threats to validity [104]. In traceability link recovery more emphasis should be placed on: recovering links between trace artifacts that are commonly used in modern software development (e.g., user stories, accepted test cases and source code); building traceability systems beyond text-based recovery (e.g., recovering traceability links between design images and requirements); advanced static program analysis, such as value flow analysis [149] and pointer aliasing analysis [92], to support more precise change impact analysis; and evaluating industrial datasets and survey practitioners to gain valuable feedback for further improvements [13].

In software process mining and automation the following remarks are observed. There is a need for: more approaches for extracting requirement-related information from community forums; replicable, standardized, baseline approaches for comparisons; experiments with transformers (e.g., BERT) in clone detection and program repair; exploring less popular pre-processing techniques (e.g., directed graphs, lookup tables, execution trace vectors); increasing the interpretability of deep learning solutions; developing guidelines and a supporting infrastructure for comparing metrics and evaluating ML approaches; standardizing the data pre-processing pipelines to reduce bias; and more user studies to gain insights into when and where automated techniques are useful to humans and more accurate than manual methods [146, 164, 173].

Numerous suggestions are made in the tasks of source code analysis, program generation, and recommender systems. Some promising areas for deep learning applications are: debugging, traceability, code completion and synthesis, education, and assistive tools (e.g., IDEs) [9]. Researchers propose: building web platforms associated with the ML models; developing modular neural network architectures to combat issues with compositionality, sparsity, and generalization; developing deep learning models that fit multiple programming languages; more concise and discrete representations of language and code to perform complex reasoning and predictions; constructing an evaluation metric that can incorporate both semantic meaning and grammatical and execution correctness; simplifying deep source code models by learning from human experience; employing generative models to address the representation learning issues in program generation; developing more practical and engineering-friendly frameworks for rapid new concept learning and code generation; and experimenting with code-in-code-out systems for generation and evaluation [9, 91, 146].

Various ideas inferred from the secondary reviews of SE process concern further experimentation with topic modeling. Fruitful application areas include: feature location; software regression testing; developer recommendation; software refactoring; software fault prediction; traceability link recovery; and software analytics [36, 98, 145, 150]. Suggested applications of topic modeling are: searching collections of software systems; measuring the evolutionary trends of repositories; establishing traceability links between emails and source code; and analyzing software systems by applying topic models on email archives and execution logs [36]. To improve the results of prior studies, replications could be conducted after fine-tuning the parameters of topic models,
and improving the data pre-processing by analyzing the value of query expansion and context consideration [36]. Future topic models could incorporate the structure of software development data [36].

4.3.5 SE Management. Here, we distinguish the following recommendations related to software effort and cost estimation. More empirical research is needed on: the application of rarely used ML techniques, to help researchers formulate better processes, and assist practitioners in decision making [89, 125, 166]; the performance evaluation of ensemble estimation techniques that are based on regression trees and case-based reasoning [70, 125]; and the accuracy assessment of bio-inspired feature selection algorithms [6]. In addition, more experiments should be conducted with: heterogeneous ensemble effort estimation models (i.e., models that combine at least two different base models); ML models that employ genetic programming and genetic algorithms; cascade correlation neural networks; developer-related metrics (e.g., individual contribution and performance) to predict bug fixing time; and size-related metrics to estimate open source software maintenance effort [5, 70, 171].

4.3.6 Software Requirements. The following research gaps are observed in this area. Further empirical research is needed on how to assess and select the most suitable ML techniques in requirements volatility prediction and ambiguity resolution [10, 177], and how to automate with ML the extraction of software requirements from natural language documents [8, 20]. Researchers should experiment with ML in more requirements activities, such as requirements specifications and management [8]. Some research ideas include sharing standard pre-labeled datasets, standardizing nonfunctional requirements, applying sentiment analysis on functional and nonfunctional requirements, and performing change impact analysis in ML-based software requirements [2, 177].

4.3.7 Software Maintenance. Here, we distinguish recommendations in bug prioritization and software rename refactoring. In bug prioritization researchers suggest further exploring ML and bug tossing (i.e., reassignment) graphs [75] for automating developer assignment in bug reports [158] as well as exploiting ML to automate the process of bug report summarization [153]. In software rename refactoring there is a need for more models that automatically execute and detect renamings of software entities [94]. Suggestions include investigating the usefulness of advanced identifier splitting approaches, the preservation of name bindings based on language features, and the performance of different renaming representation techniques [94]. Although the primary purpose of renaming is to improve program comprehension, researchers should also consider its reverse application: using ML-based renaming techniques for identifier obfuscation [94].

4.3.8 Software Design. There is fertile ground in software architecture recovery. Future studies should go beyond recovering components and connectors of software architectures, to identifying the employed design patterns and architectural styles, as well as the associated system concerns in existing software systems [176]. More analyses are suggested on recovered architectures with respect to their conceivable similarity with the legacy systems’ architecture [176]. A prospective direction could be identifying faults in recovered architectures, that could possibly lead to system failures either during or after the maintenance of the legacy systems [176].

4.3.9 Software Configuration Management. In software performance prediction, configuration interpretability, and optimization, although the ML models’ results are quite accurate, there is still room for reducing learning errors, and generalizing predictions to multiple computing environments [123].
4.3.10 SE Models and Methods. To improve trace recovery, Borg et al. [25] suggest combining probabilistic retrieval methods with ML techniques, and conducting more research on the scalability of ML models in large projects.

4.3.11 SE Professional Practice. In cognitive load estimation the following remarks are noted. SE research currently lacks effective tools and methods for measuring and evaluating practitioners’ cognitive load [60]. For this, more replication studies are needed that document in detail any experiences and lessons learned from the application of ML-based methods for cognitive load estimation [60]. Two promising research directions concern evaluating the effectiveness of psychophysiological metrics in cognitive load estimation, and predicting the unproductive periods of developers, e.g., identifying when their cognitive load levels are error- and bug-prone. [60].

4.3.12 Engineering Foundations. In the task of missing value imputation researchers could experiment with ML techniques that have not been employed yet in the SE field, including novel ideas and methods from related disciplines [69].

4.4 RQ3: What ML Techniques Have Been Used in SE?

The classification of the 83 studies according to the four axes described in Section 3.6 is presented in Table 6. With regard to the role of AI in SE, the majority of studies (n = 54; 65%) were classified in the Classification, learning, and prediction category, followed by Fuzzy and probabilistic methods for reasoning in the presence of uncertainty (n = 17; 20%) and Computational search and optimisation techniques (n = 12; 14%). In the supervision axis, most studies (n = 65; 78%) adopt supervised learning, followed by unsupervised (n = 11; 13%), semi-supervised (n = 5; 6%), and reinforcement learning (n = 2; 2%). According to the incrementality axis, almost all studies perform batch/offline learning, and only one study appears to adopt online/incremental learning. Finally, in the generalizability axis, the majority of studies (n = 72; 87%) perform model-based learning, while the remaining (n = 11; 13%) employ instance-based learning.

| Axis                                      | Technique                                                                 | Total | %   | Studies                                                                 |
|-------------------------------------------|--------------------------------------------------------------------------|-------|-----|-------------------------------------------------------------------------|
| Role of AI in SE                         | Computational search and optimisation techniques                          | 12    | 14  | [1, 3, 5, 6, 7, 30, 53, 78, 80, 104, 112, 118, 134]                      |
|                                           | Fuzzy and probabilistic methods for reasoning in the presence of uncertainty | 17    | 20  | [2, 9, 10, 13, 20, 25, 36, 70, 89, 91, 96, 123, 135, 145, 150, 156, 166]|
|                                           | Classification, learning, and prediction                                 | 54    | 65  | [4, 5, 8, 11, 17–19, 23, 32, 33, 44–46, 48, 51, 52, 60, 62, 67, 69, 79, 93, 94, 98–103, 105, 111, 114, 120–122, 125, 135, 136, 139, 141, 143, 144, 146–148, 153, 158, 164, 171, 173, 174, 176–178] |
| Supervision                              | Supervised learning                                                      | 65    | 78  | [1, 3–11, 17, 19, 23, 30, 32, 33, 44–46, 48, 51–53, 60, 62, 67, 69, 78, 79, 89, 91, 93, 94, 98, 100–105, 111, 114, 118, 120, 121–123, 125, 133, 134, 136, 139, 143, 144, 146–148, 158, 164, 166, 171, 173, 174, 177, 178] |
|                                           | Unsupervised learning                                                    | 11    | 13  | [2, 13, 20, 25, 36, 96, 135, 145, 150, 153, 176]                        |
|                                           | Semi-supervised learning                                                 | 5     | 6   | [18, 70, 99, 141, 156]                                                |
|                                           | Reinforcement learning                                                   | 2     | 2   | [80, 112]                                                              |
| Incrementality                           | Batch/offline learning                                                   | 82    | 99  | [1–11, 13, 17–20, 23, 25, 30, 32, 33, 44–46, 48, 51–53, 60, 62, 67, 69, 70, 78–80, 89, 91, 93, 94, 96, 98–105, 111, 112, 114, 118, 120, 121–123, 125, 133–136, 139, 141, 143, 144–148, 150, 153, 156, 158, 164, 166, 167, 171, 173, 174, 176, 177] |
|                                           | Online/incremental learning                                              | 1     | 1   | [178]                                                                  |
| Generalizability                         | Model-based learning                                                     | 72    | 87  | [1, 3–11, 17–19, 23, 30, 32, 33, 44–46, 48, 51–53, 60, 62, 67, 70, 78–80, 89, 91, 93, 94, 99–105, 111, 112, 114, 118, 120–123, 125, 133–136, 139, 141, 143, 144, 146–148, 153, 156, 158, 164, 166, 171, 173, 174, 176, 177] |
|                                           | Instance-based learning                                                  | 11    | 13  | [2, 13, 20, 25, 36, 69, 98, 145, 150, 178]                             |
In Figure 6, we visualize the percentage distribution of the studies across their assigned SWEBOK KAs (Table 5) and ML techniques (Table 6). The four axes are separated by vertical lines, and for each KA, the techniques of each axis sum up to one. For instance, 10% of studies assigned to SE Management employ computational search and optimisation techniques, 30% employ fuzzy and probabilistic methods, and 60% employ classification, learning, and prediction techniques. As expected from Table 6, in all KAs researchers mainly employ classification, learning, and prediction techniques, and apply supervised, batch/offline, model-based learning. Interestingly, in the areas of SE Process, Software Design, and Software Requirements, a considerable number of studies involve fuzzy and probabilistic methods of unsupervised, instance-based learning. In SE Testing, we also observe a lot of reviews on computational search and optimisation techniques (the field known as Search-based Software Engineering—SBSE).

Classifying the manually extracted ML techniques (Section 3.6) according to the SE tasks outlined in Section 4.2 results in no insight—the same algorithms appear to be used in all SE tasks. What differentiates their use is the ML application task. In ML4SE, we recognize the following ML tasks: classification, clustering, regression; pattern discovery; dimensionality reduction; information retrieval; stochastic search; generation. We classified the identified ML techniques according to these ML tasks, and also included two additional categories: hybrid and miscellaneous. Hybrid techniques concern combinations of the aforementioned ML tasks (e.g., stochastic search and clustering), while miscellaneous include techniques that do not fall into a particular category. In Table 7 we list the techniques used in each ML task.

5 DISCUSSION AND IMPLICATIONS

In the past 20 years, diverse studies identified, summarized, and assessed the contribution of ML in SE. Despite the considerable number of ML-based approaches that have been proposed in the associated academic literature for a large number of SE tasks, their practical adoption and application by the industrial community appears limited. From the analysis of RQ2 (Section 4.3), we conclude that some reasons for this could be the lack of: empirical work evaluating the quality and cost-effectiveness of these approaches, comparative analyses contrasting their performance
Table 7. ML Techniques Grouped by Application Task

| Classification, Clustering, Regression | Artificial Neural Network (Back Propagation, Multi-Layer Perceptron, Cascade Feed Forward, General Regression, Radial Basis Function, Convolutional—CNN, Probabilistic, Graph, Recurrent—RNN, Long, Short-term Memory—LSTM, Gated Recurrent Unit—GRU, Fuzzy, Siamese, Deep Belief, Restricted Boltzmann Machine, Generative Adversarial, Autoencoder, Encoder-Decoder), Bayesian Network (Meta-learner, Converging Star, Causal, Dynamic, Transfer, Weighted, Augmented, Boosting), Binary Classifier; Case-based Reasoning; Clustering variations (Hierarchical Agglomerative, Hierarchical Conceptual with COBWEB, Incremental Diffusive, Self Organizing Map, LIMBO-based Fuzzy Hierarchy), Decision Tree (C4.5, C5.0, M5, Partial, J48, Alternating, Naive Bayes, Classification and Regression, Reduced Error Pruning Tree, Tree Discretiser, Chi-square Automatic Interaction Detection, Plausible Justification Tree); Ensemble Learner (Bagging, Logit Boost, AdaBoost, XGBoost, Analog-based); Expectation-Maximization algorithm, Feature-gathering Dependency-based Software Clustering (SARF), Fisher’s Linear Discriminant, Fuzzification/Defuzzification, Gaussian Mixture Model, Grid Search, Instance-based Learner (k-Nearest Neighbors, K-star, k-Nearest, K-Star, k-Means, Fuzzy K-Means, Fuzzy C-Means, X-Means, K-Medoids, SKP-Means, Affinity Propagation, Learning Finite Automata (e.g., hw-Inference), Most Common Attribute, Naive Bayes Classifier (Binarized, Bernoulli, Multinomial, Tree Augmented, Gaussian), Q-Learning; Random Forest (Adaptive Deep Forest, Rotation Forest, Isolation Forest, Global Abnormal Forest); Regression Analysis (Univariate Linear, Multivariate, Multivariate Adaptive Regression Splines); Regression variations (Linear, Meta-learner Linear, Ensemble Linear, Multiple Linear with Backward Elimination/Stepwise Selection, Logistic, Additive, Ordinary Least Square, Symbolic, Polynomial, Multiplicative Adaptive Spline, Projection Pursuit); Support Vector Machine (SVM), Relevance Vector Machine, One-class SVM; Systematic Method for Software Architecture Recovery (SysMar) |
| Pattern Discovery | Association Rule Learning (e.g., Apriori, FP-Growth, ECLAT), Non-Nested Generalisation (NNGE), Reduced Incremental Pruning to Produce Error Reduction (Ripper), Zero Rule, One Rule, Fuzzy Rule |
| Dimensionality Reduction | Correlation Feature-based Selection, Isomap, Principal Component Analysis, Self-organizing Map, Generative Topographic Map, Singular Value Decomposition |
| Information Retrieval | Artificial Immune System, Artificial Immune Recognition System, Best Match 25, Binary Independence Model, Contrastive Analysis, Language Model, Latent Dirichlet Allocation (LDA—Delta, Dynamic, Labeled, jLDA, Maximum-likelihood Representation, with Gibbs Sampling, Temporal), Latent Semantic Analysis, Latent Semantic Indexing (LSI), Probabilistic LSI, Probabilistic Inference Network, Topic Model (Correlated, Relational, Biterm, Multi-feature, Citation Influence, Collaborative), Vector Space Model (VSM), Generative VSM |
| Stochastic Search | Ant Colony Optimization, Ant Colony-based Data Miner (Ant-Miner), Algorithm, Cuckoo Search, Firefly Algorithm, Gene Expression Programming, Genetic Algorithm, Genetic Programming, Group Search Optimization, Hill Climbing, Particle Swarm Optimization, Sequential Minimal Optimization, Simulated Annealing, Tabu Search |
| Generation | Domain-specific Language Guided Model, Memory-augmented Neural Network (Memory Network, End-to-End Memory Network, Recurrent Entity Network), n-gram Language Model, Non-recurrent Neural Network (CNN, Dynamic CNN, Convolutional Sequence to Sequence Learning, BERT, Transformer, WaveNet), Pre-trained Word Embeddings (Word2Vec, FastText, Global Vectors for Word Representation—GloVe, Contextualized Word Vectors—CoVe, Character to Word—C2W), Probabilistic Grammar (Abstract Syntax Tree, Suffix Tree, Context-Free Grammar, Probabilistic Context-Free Grammar, Tree Substitution Grammar, Tree Adjoining Grammar), Recurrent Neural Network (Vanilla RNN, LSTM, GRU, Fast-Slow RNN, Recurrent Highway Network) |
| Hybrid | Artificial Neural Network-Evolutionary Programming, Evolutionary Decision Tree (LEGAL Tree), Genetic Algorithm-Artificial Neural Network, Genetic Algorithm-Support Vector Machine with a linear/radial basis kernel function; Genetic Programming-Decision Tree, Hyper-heuristic Evolutionary Decision Tree (HEDD Tree); Particle Swarm Optimization-Artificial Neural Network; Simulated Annealing-Probabilistic Neural Network |
| Miscellaneous | CODEP (Combined DEfect Predictor) algorithm for cross project defect prediction [17]; ML model for system-level test case prioritization using black-box metadata and natural language test case descriptions [44]; SwiftHand tool for automated Android GUI testing [176] |

and execution time to that of conventional statistical techniques, and industrial trials assessing their relevance, efficiency, and scalability in the context of large projects. A starting point to address the latter and improve the quality of future ML4SE studies could be thorough industrial case studies aiming to unveil any obstacles in the adoption of ML approaches, as suggested by Wen et al. [166].

**IMPLICATION 1. Further empirical validation studies, comparative analyses, and industrial trials assessing and contrasting the quality of the proposed ML techniques for SE tasks to that of conventional statistical approaches are required to amplify the salience of the former, and boost their practical adoption and application. These are mostly needed in the areas of software quality, testing, and engineering management.**

Apart from the lack of empirical and comparative analyses assessing the quality of existing ML models, another obstacle in their adoption and advancement could be the lack of up-to-date methods for developing reliable and selecting suitable models. This deficiency was mainly observed in the tasks of smell detection, software fault and maintainability prediction, and requirements volatility prediction. Particularly in smell detection, the inconsistency observed by Sharma and Spinellis [144] between smell definitions and detection methods seems to be a result of the absence of smell literature establishing standards for smell definitions, their implementations, and commonly used metrics. Similar remarks are noted in software maintainability prediction concerning maintainability definitions and characteristics [52]. ML models are typically founded on
clearly defined principles and rules extracted from the training data (otherwise learning would simply correspond to memorization) [115]. Therefore, it seems that the growth of ML models is indirectly impacted by inadequately established SE concepts and general literature shortcomings.

**Implication 2.** The academic research community could consider taking a step back to address its fundamental SE literature shortcomings and inconsistencies including outdated and deficient methods, which appear to impact the development and selection of robust and reliable ML models for SE tasks. Such deficiencies are mainly observed in the tasks of smell detection, software fault and maintainability prediction, and requirements volatility prediction.

Looking at Table 5 it appears that SE tasks falling into more technical SWEBOK KAs such as software quality and testing are more frequently addressed with ML approaches, compared to KAs targeting the human factor, such as SE professional practice or software requirements. This could be a result of the inadequate performance of existing ML models of the latter KAs, as observed in the results of RQ2 (Section 4.3), discouraging developers from performing further studies in these KAs, and prompting them to more fertile grounds (i.e., technical KAs)—a tendency known as the streetlight effect [22, 24]. It could be the case that human-centered SE tasks entailing a high rate of subjectivity are more difficult to be approximated with ML, either due to inherent limitations imposed by subjectivity on the evaluation of the respective ML models, or the lack of ground-truth datasets. Interestingly, a similar distribution of the KAs is also observed in the reverse field of SE for AI, according to a recent survey by Martínez-Fernández et al. [109].

Regarding data availability, in a recent study about Mining Software Repositories data papers [88] the identified datasets about developers’ attributes were considerably fewer than those about software attributes, such as version control system data, or software faults, failures, and smells. Gathering and labeling data about developers’ mental, behavioral, or sentimental characteristics has long been a challenge for the research community, remaining an open issue [88]. Similarly, automatically extracting software requirements from natural language documents with ML, as suggested by Bakar et al. [20], has been difficult, because the usually unstructured nature of the documents impedes their systematic processing. On the contrary, gathering data from a program’s execution, testing, and debugging phases can be automatically achieved with various tools. The preponderance of datasets with software faults, failures, and smells in our aforementioned study [88] confirms this. Review authors suggest the incorporation of developers’ real-time emotion-sensing biometric data (e.g., heart rate, eye blinking, and electroencephalogram) in human-centered datasets to potentially improve a ML-based system’s performance (e.g., for emotion detection) [59]. However, disclosing and employing such private information might raise privacy concerns [137].

**Implication 3.** SE tasks associated with human-centered SWEBOK KAs such as SE professional practice or software requirements appear less tackled with ML techniques compared to more technical ones including software quality and testing. Addressing the weak spots requires investment into the difficult tasks of collecting and labeling training data about developers’ attributes, and evaluating the typically subjective accuracy of the ML-based systems.

Complementary to the aforementioned difficulties of collecting and labeling data for human-centered SE tasks, further concerns related to the datasets’ quality were remarked in the secondary studies. Data quality is often dubious due to the inadequate documentation of the data collection, cleaning, and pre-processing methods (i.e., the data pipeline) [62]. These shortcomings are not only
encountered in ML4SE; they further expand to SE for AI [109], suggesting major field-agnostic data issues that need to be resolved. Along with better documentation, the automation of the data pipeline activities through ML frameworks such as Auto-WEKA [154] or Auto-sklearn [54] could further improve data quality, and consequently, the performance of the trained ML models [132].

**Implication 4.** To increase the quality trustworthiness of training datasets, researchers should document their data collection and pipeline processes, and investigate the cost-benefit of automating them through ML frameworks.

Additional dataset issues arise from their industrial relevance and scalability. Some practitioners seem reluctant to utilize ML models from academia that are only trained on open data, considering them less realistic and representative of industrial contexts [67], and less scalable to large projects [25]. In addition, they may also fear that ML models trained solely on publicly available data will not produce novel results, or be unwilling to work with ML models developed by a different organization—also called the *not invented here syndrome* [129]. These last two cases were also observed by us [88] with regard to the use of data papers, recommending to methodology researchers, conference program committees, and journal editorial boards the embracement of a procedure similar to that of pre-registered studies [64] (i.e., publishing a data paper and then employing it for empirical SE research). To strengthen the industrial application of ML models to SE tasks, the same paradigm could also be employed in the ML and SE intersection by promoting the advance publication of datasets used in the development of ML-based systems. Furthermore, industrial partners should consider sharing more of their proprietary data to help academia build more robust and realistic ML models, which will likely benefit the industry as well.

**Implication 5.** To improve the industrial relevance, scalability, and performance of ML models, practitioners might want to consider sharing more of their proprietary data with academia. Moreover, methodology researchers, conference program committees, and journal editorial boards could investigate the value of adopting a research paradigm where training datasets are published before the ML models that use them.

In respect to the incrementality of employed ML techniques in SE (Section 4.4), there seems to be a vast preference for batch/offline learning, despite the benefits of online learning. Online learning is more computationally effective for dealing with new data, and also works well for systems that receive data as a continuous flow and need to adapt to change rapidly or autonomously [77]. Motivated by this, there has been an emergence of promising incremental data retrieval methods and tools recently (e.g., the works by Mastorakis et al. [110], Fu et al. [56], Aydin et al. [15]). At the same time, other science and engineering disciplines, such as healthcare [128] and transportation engineering [115], have already started experimenting with online/incremental ML techniques. For instance, in the earthquake engineering domain, there is an active research area concerned with developing ML-based structural control schemes for earthquake mitigation [172]. In this context, Suresh et al. [151] accomplished real-time online adaptation of an artificial neural network-based controller through the use of an extended minimal resource allocation network. The authors argue that online ML-based structural controllers appear more effective in mitigating the adverse effects of earthquake hazards on buildings than traditional approaches.

The SE community could be inspired by cross-domain online ML applications like the aforementioned, and adapt them to the SE field, e.g., for real-time monitoring of applications. Promising data sources include build and execution logs, crash reports, security incidents, integrated development environment and user interactions, telemetry, and the internal usage of code abstractions.
(e.g., software functions, API endpoints). An instance of online ML application in a middleware could involve the real-time verification of the availability of the associated endpoint servers as well as the real-time analysis of potentially defective software components to determine potential self-healing actions.

**Implication 6.** *Online and incremental ML-based applications in SE provide a fertile ground for further research, due to their computational effectiveness, rapid changeability and adaptability, and thanks to recent advances in incremental data retrieval methods and tools.*

The general idea of experimenting with ML approaches applied in different domains and contexts is also supported by the authors of some secondary studies (Section 4.3). Recommendations pertain to combining probabilistic or search-based techniques with ML approaches [3, 25, 67, 70, 104], and transferring novel methods from relevant fields [69, 166]. The lower percentage of studies classified in the categories of *Computational search and optimization techniques* (14%) and *Fuzzy and probabilistic methods for reasoning in the presence of uncertainty* (20%) as well as the limited number of employed hybrid ML techniques, compared to the ones under the category of *Classification, Clustering, Regression* (see Section 4.4), aligns with the above recommendations, suggesting room for improvement. Furthermore, the encouraging achieved results in effort estimation and defect prediction with hybrid models, as concluded by Malhotra et al. [104], is a positive indicator for performing more experiments with them.

**Implication 7.** *Hybrid ML techniques encompassing probabilistic or search-based approaches, and cross-disciplinary novel ML methods have yielded positive results in certain SE tasks, hence they might be worth of further investigation.*

6 *THREATS TO VALIDITY*

We use the classification scheme proposed by Ampatzoglou et al. [12] to classify the limitations of this study. This is inspired by the *planning* phase of reviews (i.e., search process, study selection, data extraction, and data analysis) [83], and is extended with an additional category that concerns threats from the entire lifecycle of the review [12].

**Study Selection Validity.** The adopted study search and selection strategies are associated with the risk of missing relevant studies. Some research may have been missed as a result of the selected year range in the automated search (i.e., 2015–2020), the preferred digital libraries, and the constructed search strings (Section 3.2), or the applied selection criteria (Section 3.3). The year 2015 was considered the inflection point for the joint evolution of the two fields, as elaborated in Section 3.2.1, allowing us to center our analysis on the interdisciplinary growth. To reduce the threat of missing relevant reviews, we searched the digital libraries that are most likely to include the majority of studies in ML4SE. However, we cannot eliminate the chance that we may have missed some germane studies while conducting the automated search in these databases. To cope with the interdisciplinarity of the subject area, the keywords for our search strings (Table 1) were derived from established sources.

The quality assessment process (Section 3.5) is also associated with a few threats. A number of pertinent studies were deliberately excluded to ensure high quality of our study results, as recommended in the adopted guidelines [83]. Furthermore, the DARE-4 framework employed in the quality evaluation of the reviews does not cover all quality facets [41]. This is a common threat of all existing quality assessment frameworks, and it is a recommended practice for tertiary reviews to select the framework that best satisfies the research goals [41]. For this reason, we
selected DARE-4, which was deemed the most appropriate framework for our evaluation, and is also the most commonly used one in SE tertiary studies [41].

**Data Validity.** One potential limitation stems from the data extraction process (Section 3.6). Some secondary studies did not provide all the information needed, and we had to infer it. For instance, some studies did not include a summary list of the associated primary research (e.g., Reference [94]). To extract the number of primary studies and their publication years in these cases (Tables 3 and 4), we looked up the bibliography section, omitting irrelevant research referenced, e.g., in introduction or related work. In addition, some secondary reviews did not cite the employed research method (e.g., References [144, 153]), despite their detailed descriptions. For these, we considered the method description and the complete review structure to infer the adopted guidelines. For example, SLRs following Kitchenham and Charter’s guidelines [83] typically report their research questions, search process, study selection method, quality assessment, and data extraction process.

Another data validity threat arises from one of the composing axes of the ML classification scheme (Table 6). Specifically, the *role of AI in SE* applies to a broader field than ML (i.e., AI). Consequently, it could be considered less appropriate for the categorization of studies targeting the application of ML in SE. We decided to use this axis, because we considered that it would complement the results with additional useful information. (To the best of our knowledge, there is no available study characterizing and categorizing the role of ML in SE.) To this end, all studies were successfully assigned to a category, while the data extractor and data checker maintained high inter-rater reliability, suggesting that the categories of this axis are suitable for the categorization of ML4SE research. Follow-up studies could validate the extent of congruence between the role of AI in SE and that of ML in SE.

**Research Validity.** The study’s research validity is partially concerned with the extent to which the results of our tertiary review can be generalized to the subject population. Therefore, one potential issue stems from assessing whether the secondary studies are representative of all the relevant studies in the subject area. To minimize this threat, we performed a comprehensive multi-phase search procedure (automated, manual, backward, and forward snowballing search) in more than one digital libraries (Section 3.2), during which we tried to be as inclusive as possible with respect to the selection criteria (Section 3.3), following established guidelines [83].

Other major threats to the research validity stem from the steps during which we followed manual processes involving subjective judgment. These include the manual and backward snowballing search processes (Section 3.2), the study selection (Section 3.4) and quality assessment (Section 3.5), the data extraction process, the classification of the studies using the SWEBOK KAs and the multi-axis ML scheme, the extraction of the tackled SE tasks by ML using the open coding practice, the identification of implications for further research in ML4SE, and the detection of the employed ML techniques in SE (Section 3.6). The reliability of these processes was improved by engaging multiple raters, and by basing them on standard research methods. However, we recognize that validity threats stemming from manual processes entailing subjective judgment cannot be nullified [127].

7  **CONCLUSION AND RECOMMENDATIONS**

In our tertiary review, we systematically retrieved 140 secondary studies in ML4SE and analyzed 83 of them that satisfied a set of recommended quality criteria. These 83 reviews span the years 2009–2022, were authored by 274 researchers affiliated with 140 institutions, and entail 6,117 primary works published between 1990 and 2021. To analyze the reviews, we followed established guidelines and designed a protocol that was internally agreed by all authors. The analysis was performed by hand and consisted of the classification of the reviews using the SWEBOK KAs and subareas, the extraction of SE tasks tackled with ML from the reviews, the extraction of SE topics
for further research using ML from the reviews, the categorization of the reviews using a four-axis ML classification scheme that was synthesized from two sources, and the extraction of the ML techniques employed in the reviews. Through these manual processes, the following key findings were obtained.

- The majority of secondary reviews in ML4SE target the SWEBOK KAs of software quality and testing, and SE process. Human-centered KAs such as SE professional practice and software requirements appear less tackled with ML techniques, due to the subjectivity entailed in the evaluation of the models, and the difficulty of collecting and labeling training data about developers’ characteristics.
- With regard to the role of AI in SE, most studies pertain to Classification, learning, and prediction tasks, and apply supervised learning. In terms of generalizability, model-based learning is vastly preferred. Despite the demonstrated benefits of online/incremental learning and the emergence of relevant tools, batch/offline learning is overwhelmingly used.
- Some major obstacles to the advancement of ML techniques result from the training datasets and SE literature discrepancies. Validity issues often arise from undocumented data collection and non-automated data pipeline processes, while the absence of proprietary data burdens the industrial relevance, scalability, and performance of ML models. Outdated and deficient methods obstruct researchers from developing robust and selecting appropriate ML models for SE tasks.

**Recommendations for Researchers.** From Section 4.3.1, we summarize the following suggestions. Researchers should further assess the proposed ML techniques, compare them to conventional statistical approaches, and evaluate their scalability, performance, and cost-effectiveness in industrial settings as well as through further empirical analyses. To this end, more in-depth case studies with practitioners should be conducted. A starting point to improve the quality of ML models is by optimizing their hyper-parameters, addressing class imbalance in training datasets, and developing concrete methods for building reliable systems. Hybrid, ensemble, and incremental ML techniques, and cross-domain methods comprise promising areas for additional experimentation.

**Recommendations for Practitioners.** Practitioners can benefit from existing ML4SE research through the various published ML-based open source tools for SE tasks. To select the most applicable ones, they can consult the associated meta-analyses summarized in this study [17, 52, 67, 112, 147]. ML-based tools can either be applied directly to their corporate projects, or be used as baselines to compare the performance of their own tools. In both cases care should be taken regarding the false-positiveness, fine-tuning, and training of the adopted systems. Furthermore, practitioners can take advantage of the diverse ML4SE research implications to improve their existing ML systems, or produce new ones to satisfy further needs.

To help researchers build more accurate ML models, the industry needs to release more open-source, large-scale datasets and collaborate with academia in industrial trials and case studies. Collaborations can happen through funded research projects, internships, regular workshops and seminars, conference participation, technology transfer test labs (for piloting research ideas), and the involvement of industry partners in research education [58]. Through practitioners’ feedback and support researchers will be able to apply their models in large projects, understand the industry’s needs, and improve their methods. Closing this loop should provide practitioners with better ML-based SE tools.

This is the first systematic tertiary study providing a comprehensive overview of the current state of the practice in ML4SE. With these final considerations, we hope to increase awareness on certain issues identified in the intersection of the two fields and steer researchers’ attention toward under-explored areas and topics requiring further investigation.
REFERENCES

[1] Amjad AbuHassan, Mohammad Alshayeb, and Lahouari Ghatti. 2021. Software smell detection techniques: A systematic literature review. J. Softw.: Evol. Process 33, 3 (2021), e2320. DOI: https://doi.org/10.1002/smr.2320

[2] Arshad Ahmad, Chong Feng, Muzammil Khan, Asif Khan, Ayaz Ullah, Shah Nazir, Adnan Tahir, and Iqtaedar Hussain. 2020. A systematic literature review on using machine learning algorithms for software requirements identification on stack overflow. Secur. Commun. Netw. 2020 (Jan. 2020), 19. DOI: https://doi.org/10.1155/2020/8830683

[3] Bestoun S. Ahmed, Kamal Z. Zamlı, Wasif Afzal, and Miroslav Bures. 2017. Constrained interaction testing: A systematic literature study. IEEE Access 5 (2017), 25706–25730. DOI: https://doi.org/10.1109/ACCESS.2017.2771562

[4] Ahmed Al-Shaaby, Hamoud Aljamaan, and Mohammad Alshayeb. 2020. Bad smell detection using machine learning techniques: A systematic literature review. Arab. J. Sci. Eng. 45, 4 (Jan. 2020), 2341–2369. DOI: https://doi.org/10.1007/s13369-019-04311-w

[5] Asad Ali and Carmine Gravino. 2019. A systematic literature review of software effort prediction using machine learning methods. J. Softw.: Evol. Process 31, 10 (2019), e2211. DOI: https://doi.org/10.1002/smr.2211

[6] Asad Ali and Carmine Gravino. 2019. Using bio-inspired features selection algorithms in software effort estimation: A systematic literature review. In Proceedings of the 45th Euromicro Conference on Software Engineering and Advanced Applications (SEAA’19). IEEE. DOI: https://doi.org/10.1109/seaa.2019.00043

[7] Asad Ali and Carmine Gravino. 2020. Bio-inspired algorithms in software fault prediction: A systematic literature review. In Proceedings of the 14th International Conference on Open Source Systems and Technologies (ICOSST’20). IEEE. DOI: https://doi.org/10.1109/icosst51357.2020.9332995

[8] Nazakat Ali, Jang-Eui Hong, and Lawrence Chung. 2021. Social network sites and requirements engineering: A systematic literature review. J. Softw.: Evol. Process 33, 4 (2021), e2332. DOI: https://doi.org/10.1002/smr.2332

[9] Miltiadis Allamanis, Earl T. Barr, Premkumar Devanbu, and Charles Sutton. 2018. A survey of machine learning for big code and naturalness. Comput. Surveys 51, 4, Article 81 (July 2018), 37 pages. DOI: https://doi.org/10.1145/3212695

[10] Ahmed M. Alsaleemi and Eng-Thiam Yeoh. 2018. A systematic literature review of requirements volatility prediction. In Proceedings of the International Conference on Current Trends in Computer, Electrical, Electronics and Communication (CTCEEC’17). IEEE, 55–64. DOI: https://doi.org/10.1109/CTCEEC.2017.8455174

[11] Hadeel Alsolai and Marc Roper. 2019. A systematic review of feature selection techniques in software quality prediction. Proceedings of the International Conference on Electrical and Computing Technologies and Applications. DOI: https://doi.org/10.1109/ICECTA48151.2019.8959566

[12] Apostolos Ampatzoglou, Stamatia Bibi, Paris Avgeriou, Marjin Verbeek, and Alexander Chatzigeorgiou. 2019. Identifying, categorizing and mitigating threats to validity in software engineering secondary studies. Info. Softw. Technol. 106 (Feb. 2019), 201–230. DOI: https://doi.org/10.1016/j.infsof.2018.10.006

[13] Thazhin Win Win Aung, Huan Huo, and Yulei Sui. 2020. A literature review of automatic traceability links recovery for software change impact analysis. In Proceedings of the 28th International Conference on Program Comprehension. ACM, New York, NY, 14–24. https://doi.org/10.1145/3387904.3389251

[14] Paris Avgeriou, Neil A. Ernst, Robert L. Nord, and Philippe Kruchten. 2016. Technical debt: Broadening perspectives report on the seventh workshop on managing technical debt. SIGSOFT Softw. Eng. Notes 41, 2 (May 2016), 38–41. DOI: https://doi.org/10.1145/2894784.2894800

[15] Ahmet Aydin and Ken Anderson. 2017. Batch to real-time: Incremental data collection & analytics platform. In Proceedings of the 50th Hawaii International Conference on System Sciences. Hawaii International Conference on System Sciences. DOI: https://doi.org/10.24251/hicss.2017.712

[16] Nathaniel Ayewah, William Pugh, J. David Morgenthaler, John Penix, and YuQian Zhou. 2007. Evaluating static defect detection on production software. In Proceedings of the 7th ACM SIGPLAN-SIGSOFT Workshop on Program Analysis for Software Tools and Engineering. ACM, 1–8. DOI: https://doi.org/10.1145/1251535.1251536

[17] Muhammad Ilyas Azeem, Fabio Palomba, Lin Shi, and Qing Wang. 2019. Machine learning techniques for code smell detection: A systematic literature review and meta-analysis. Info. Softw. Technol. 108 (Apr. 2019), 115–138. DOI: https://doi.org/10.1016/j.infsof.2018.12.009

[18] Mohammad Azzeh, Ali Bou Nassif, and Imtinan Basem Attili. 2021. Predicting software effort from use case points: A systematic review. Sci. Comput. Program. 204 (Apr. 2021), 102596. DOI: https://doi.org/10.1016/j.scico.2020.102596

[19] Ahmed Bahaa, Enas Mohamed Fathy, Ahmed Sharaf Eldin, Laila A. Abd-Elmegid, Ahmed Bahaa, and Ahmed Sharaf Eldin. 2021. A systematic literature review of software defect prediction using deep learning. J. Comput. Sci. 17, 5 (May 2021), 490–510. DOI: https://doi.org/10.3844/jcssp.2021.490.510

[20] Noor H. Bakar, Zarina K. Kasirun, and Norsaremah Salleh. 2015. Feature extraction approaches from natural language requirements for reuse in software product lines: A systematic literature review. J. Syst. Softw. 106, C (Aug. 2015), 132–149. DOI: https://doi.org/10.1016/j.jss.2015.05.006

[21] Muneeva Bano, Didar Zowghi, and Naveed Ikram. 2014. Systematic reviews in requirements engineering: A tertiary study. In Proceedings of the IEEE 4th International Workshop on Empirical Requirements Engineering (EmpiRE’14). IEEE. DOI: https://doi.org/10.1109/empire.2014.6890110

ACM Computing Surveys, Vol. 55, No. 12, Article 256. Publication date: March 2023.
[66] Ruben Heradio, David Fernandez-Amoros, Cristina Cerrada, and Manuel Cobo. 2021. Machine learning for software engineering: A bibliometric analysis from 2015 to 2019. DOI: https://doi.org/10.24251/HICSS.2021.235

[67] Seyeddrevar Hosseini, Burak Turhan, and Dimuthu Gunaratna. 2019. A systematic literature review and meta-analysis on cross project defect prediction. IEEE Trans. Softw. Eng. 45, 2 (Feb. 2019), 111–147. DOI: https://doi.org/10.1109/TSE.2017.2770124

[68] K. E. Huff and O. G Selfridge. 1990. Evolution in future intelligent information systems. In Proceedings of the International Workshop on the Development of Intelligent Information Systems.

[69] Ali Idri, Bitisam Abnane, and Alain Abran. 2015. Systematic mapping study of missing values techniques in software engineering data. In Proceedings of the 16th IEEE/ACIS International Conference on Software Engineering, Artificial Intelligence, Networking and Parallel/Distributed Computing (SNPD’15). IEEE, 1–8. DOI: https://doi.org/10.1109/SNPD.2015.7176280

[70] Ali Idri, Mohamed Hosni, and Alain Abran. 2016. Systematic literature review of ensemble effort estimation. J. Syst. Softw. 118, C (Aug. 2016), 151–175. DOI: https://doi.org/10.1016/j.syssoftw.2016.05.016

[71] Ali Idri, Mohamed Hosni, and Alain Abran. 2016. Systematic mapping study of ensemble effort estimation. In Proceedings of the 11th International Conference on Evaluation of Novel Software Approaches to Software Engineering (ENASE’16). 132–139. DOI: https://doi.org/10.5220/0005822701320139

[72] IEEE-CS Professional & Educational Activities Board (PEAB) SWEBOK Evolution Team. 2022. IEEE-CS SWEBOK V4 Public Review. Retrieved from https://www.computer.org/volunteering/boards-and-committees/professional-educational-activities/software-engineering-committee/swebok-evolution. Accessed November 2022.

[73] Salma Imtiaz, Muneeera Bano, Naveed Ikram, and Mahmood Niazi. 2013. A tertiary study: Experiences of conducting systematic literature reviews in software engineering. In Proceedings of the 17th International Conference on Evaluation and Assessment in Software Engineering (EASE’13). ACM, New York, NY, 177–182. DOI: https://doi.org/10.1145/2460999.2461025

[74] Darrel C. Ince, Leslie Hatton, and John Graham-Cumming. 2012. The case for open computer programs. Nature 482, 7386 (2012), 485–488.

[75] Gaeul Jeong, Sunghun Kim, and Thomas Zimmermann. 2009. Improving bug triage with bug tossing graphs. In Proceedings of the 7th Joint Meeting of the European Software Engineering Conference and the ACM SIGSOFT Symposium on The Foundations of Software Engineering (FSE’09). ACM, New York, NY, 111–120. DOI: https://doi.org/10.1145/1595696.1595715

[76] Magne Jørgensen and Martin Shepperd. 2007. A systematic review of software development cost estimation studies. IEEE Trans. Softw. Eng. 33 (Feb. 2007), 33–53. DOI: https://doi.org/10.1109/TOSE.2007.256943

[77] Arvinder Kaur and Shubhra Goyal Jindal. 2018. Severity prediction of bug reports using text mining: A systematic review. In Proceedings of the International Conference on Advances in Computing, Communication Control and Networking (ICACCCN’18). IEEE. DOI: https://doi.org/10.1109/icacccn.2018.8748582

[78] Rafaqut Kazmi, Dayang N. A. Jawawi, Radziah Mohamed, and Imran Ghani. 2017. Effective regression test case selection: A systematic literature review. Comput. J. 52, 2 (June 2017), 32. DOI: https://doi.org/10.1145/3057269

[79] Muhammad Khatibsyarbini, Mohd Adham Isa, Dayang N. A. Jawawi, Muhammad Luqman Mohd Shafie, Wan Mohd Nasir Wan-Kadir, Haza Nuzly Abdul Hamed, and Muhammad Dhauardin Mohamed Suffian. 2021. Trend application of machine learning in test case prioritization: A review on techniques. IEEE Access 9 (2021), 166262–166282. DOI: https://doi.org/10.1109/access.2021.3155508

[80] Ayesha Kiran, Wasi H. Butt, Muhammad W. Anwar, Farooqaz Azam, and Bilal Maqbool. 2019. A comprehensive investigation of modern test suite optimization trends, tools and techniques. IEEE Access 7 (2019), 89093–89117. DOI: https://doi.org/10.1109/ACCESS.2019.2926384

[81] Barbara Kitchenham. 2004. Procedures for performing systematic reviews. Keele University Technical Report TR/SE-0401, Keele, UK.

[82] Barbara Kitchenham and Pearl Brereton. 2013. A systematic review of systematic review process research in software engineering. Info. Softw. Technol. 55, 12 (Dec. 2013), 2049–2075. DOI: https://doi.org/10.1016/j.infsof.2013.07.010

[83] Barbara Kitchenham and Stuart Charters. 2007. Guidelines for performing systematic literature reviews in software engineering. EBSE Technical Report EBSE-2007-01.

[84] Barbara Kitchenham, O. Pearl Brereton, David Budgen, Mark Turner, John Bailey, and Stephen Linkman. 2009. Systematic literature reviews in software engineering—A systematic literature review. Info. Softw. Technol. 51, 1 (Jan. 2009), 7–15. DOI: https://doi.org/10.1016/j.infsof.2008.09.009

[85] Barbara Kitchenham, Riallette Pretorius, David Budgen, O. Pearl Brereton, Mark Turner, Mahmood Niazi, and Stephen Linkman. 2010. Systematic literature reviews in software engineering—A tertiary study. Info. Softw. Technol. 52, 8 (Aug. 2010), 792–805. DOI: https://doi.org/10.1016/j.infsof.2010.03.006

[86] Barbara Ann Kitchenham, David Budgen, and Pearl Brereton. 2015. Evidence-based Software Engineering and Systematic Reviews. Chapman & Hall/CRC.
[87] Barbara A. Kitchenham, David Budgen, and O. Pearl Brereton. 2011. Using mapping studies as the basis for further research—A participant-observer case study. *Info. Softw. Technol.* 53, 6 (June 2011), 638–651. DOI: https://doi.org/10.1016/j.infsof.2010.12.011

[88] Zoe Kotti, Konstantinos Kravvaritis, Konstantina Dritsa, and Diomidis Spinellis. 2020. Standing on shoulders or feet? An extended study on the usage of the MSR data papers. *Empir. Softw. Eng.* 25 (July 2020), 3288–3322. DOI: https://doi.org/10.1007/s10664-020-09834-7

[89] Salma E. Koutbi, Ali Idri, and Alain Abran. 2016. Systematic mapping study of dealing with error in software development effort estimation. In *Proceedings of the 42th Euromicro Conference on Software Engineering and Advanced Applications (SEAA’16)*. IEEE, 140–147. DOI: https://doi.org/10.1109/SEAA.2016.39

[90] Klaus Krippendorff. 2018. *Content Analysis: An Introduction to Its Methodology* (4th ed.). SAGE Publications.

[91] Triet H. M. Le, Hao Chen, and Muhammad Ali Babar. 2020. Deep learning for source code modeling and generation: Models, applications, and challenges. *Comput. Surveys* 53, 3, Article 62 (June 2020), 38 pages. DOI: https://doi.org/10.1145/3383458

[92] Yuxiang Lei and Yulei Sui. 2019. Fast and precise handling of positive weight cycles for field-sensitive pointer analysis. In *Proceedings of the 26th International Symposium on Static Analysis*. Springer-Verlag, Berlin, 27–47. DOI: https://doi.org/10.1007/978-3-030-32304-2_3

[93] Tomasz Lewowski and Lech Madeyski. 2022. *Code Smells Detection Using Artificial Intelligence Techniques: A Business-Driven Systematic Review*. Springer International Publishing, Cham, 285–319. DOI: https://doi.org/10.1007/978-3-030-77996-0_12

[94] Guangjie Li, Hui Liu, and Ally S. Nyamawe. 2020. A survey on renamings of software entities. *Comput. Surveys* 53 (April 2020). DOI: https://doi.org/10.1145/3379443

[95] Ming Li, Hongyu Zhang, David Lo, and Lucia. 2015. Improving software quality and productivity leveraging mining techniques: [Summary of the second workshop on software mining at ASE 2013]. *SIGSOFT Softw. Eng. Notes* 40, 1 (Feb. 2015), 1–2. DOI: https://doi.org/10.1145/2693208.2693219

[96] Yang Li, Sandro Schulze, and Gunter Saake. 2017. Reverse engineering variability from natural language documents: A systematic literature review. In *Proceedings of the 21st International Systems and Software Product Line Conference—Volume A* (*SPLC’17*). ACM, 133–142. DOI: https://doi.org/10.1145/3106195.3106207

[97] Johan Linäker, Sardar Muhammad Sulaman, Rafael Maiani de Mello, and Martin Höst. 2015. *Guidelines for Conducting Surveys in Software Engineering*. Department of Computer Science, Lund University.

[98] Yasir Mahmood, Nazri Kama, Azri Azmi, Ahmad Salman Khan, and Mazlan Ali. 2022. Software effort estimation accuracy prediction of machine learning techniques: A systematic performance evaluation. *Softw.: Pract. Exper.* 52, 1 (2022), 39–65. DOI: https://doi.org/10.1002/spe.3009

[99] Ruchika Malhotra. 2015. A systematic review of machine learning techniques for software fault prediction. *Appl. Softw. Comput.* 27 (Feb. 2015), 504–518. DOI: https://doi.org/10.1016/j.ascom.2014.11.023

[100] Ruchika Malhotra and Ankita Bansal. 2015. Predicting change using software metrics: A review. In *Proceedings of the 4th International Conference on Reliability, Infocom Technologies and Optimization (iCRITO’15)*. IEEE, 1–6. DOI: https://doi.org/10.1109/iCRITo.2015.7359253

[101] Ruchika Malhotra and Ankita J. Bansal. 2016. Software change prediction: A literature review. *Int. J. Comput. Appl. Technol.* 54 (Jan. 2016), 240–256. DOI: https://doi.org/10.1504/IJCAT.2016.080487

[102] Ruchika Malhotra and Anuradha Chug. 2016. Software maintainability: Systematic literature review and current trends. *Int. J. Softw. Eng. Knowl.* 26, 08 (Oct. 2016), 1221–1253. DOI: https://doi.org/10.1007/s0218194016500431

[103] Ruchika Malhotra and Megha Khanna. 2019. Software change prediction: A systematic review and future guidelines. *e-Informat. Softw. Eng.* 13, 1 (2019), 227–259. DOI: https://doi.org/10.5277/E-INF190107

[104] Ruchika Malhotra, Megha Khanna, and Rajeev R. Raje. 2017. On the application of search-based techniques for software engineering predictive modeling: A systematic review and future directions. *Swarm Evolution. Comput.* 32 (Feb. 2017), 85–109. DOI: https://doi.org/10.1016/j.jswevo.2016.10.002

[105] Ruchika Malhotra and Kusum Lata. 2020. A systematic literature review on empirical studies towards prediction of software maintainability. *Soft Comput.* 24, 21 (May 2020), 16655–16677. DOI: https://doi.org/10.1007/s00500-020-05050-4

[106] C. Marimuthu and K. Chandrasekaran. 2017. Systematic studies in software product lines: A tertiary study. In *Proceedings of the 21st International Systems and Software Product Line Conference—Volume A* (*SPLC’17*). ACM, New York, NY, 143–152. DOI: https://doi.org/10.1145/3106195.3106212

[107] Anna Beatriz Marques, Rosiane Rodrigues, and Tayana Conte. 2012. Systematic literature reviews in distributed software development: A tertiary study. In *Proceedings of the IEEE Seventh International Conference on Global Software Engineering*. 134–143. DOI: https://doi.org/10.1109/ICGSE.2012.29

[108] Alberto Martin-Martín, Enrique Orduna-Malea, Mike Thelwall, and Emilio Delgado López-Cózar. 2018. Google scholar, web of science, and scopus: A systematic comparison of citations in 252 subject categories. *J. Informetr.* 12, 4 (Nov. 2018), 1160–1177. DOI: https://doi.org/10.1016/j.joi.2018.09.002
[109] Silverio Martinez-Fernández, Justus Bogner, Xavier Franch, Marc Oriol, Julien Siebert, Adam Trendowicz, Anna Maria Vollmer, and Stefan Wagner. 2022. Software engineering for AI-based systems: A survey. ACM Trans. Softw. Eng. Methodol. 31, 2, Article 37e (April 2022), 59 pages. DOI: https://doi.org/10.1145/3487043

[110] Spyridon Mastorakis, Peter Gusev, Alexander Afanasyev, and Lixia Zhang. 2018. Real-time data retrieval in named data networking. In Proceedings of the 1st IEEE International Conference on Hot Information-Centric Networking (HOTICN’18). IEEE. DOI: https://doi.org/10.1109/hoticn.2018.8605992

[111] Faseeha Matloob, Shabib Aftab, Munir Ahmad, Muhammad Adnan Khan, Areej Fatima, Muhammad Iqbal, Wesam Mohsen Alruwaili, and Nooh Sabri Elmoutawli. 2021. Software defect prediction using supervised machine learning techniques: A systematic literature review. Intell. Autom. Softw. Comput. 29, 2 (2021), 403–421. DOI: https://doi.org/10.32604/iasc.2021.017562

[112] Dean Richard McKinnel, Tooska Dargahi, Ali Dehghantanha, and Kim-Wang Raymond Choo. 2019. A systematic literature review and meta-analysis on artificial intelligence in penetration testing and vulnerability assessment. Comput. Electr. Eng. 75, C (May 2019), 175–188. DOI: https://doi.org/10.1016/j.compeleceng.2019.02.022

[113] Karl Meinke and Amel Bennaceur. 2018. Machine learning for software engineering: Models, methods, and applications. In Proceedings of the 40th International Conference on Software Engineering: Companion Proceedings (ICSE’18). ACM, New York, NY, DOI: https://doi.org/10.1145/3183440.3183461

[114] Assia Najm, Abdelali Zakrani, and Abdelaziz Marzak. 2019. Decision trees-based software development effort estimation: A systematic mapping study. Proceedings of the 2nd International Conference of Computer Science and Renewable Energies. DOI: https://doi.org/10.1109/ICCSRE.2018.8807544

[115] Diniti Pallapenerima, Rashmika Nawaratne, Tharindu Bandaragoda, Achihi Adikari, Su Nguyen, Thimal Kempiyita, Daswin De Silva, Damminda Alahakoon, and Dakshan Pothuhera. 2019. Online incremental machine learning platform for big data-driven smart traffic management. IEEE Trans. Intell. Transport. Syst. 20, 12 (Dec. 2019), 4679–4690. DOI: https://doi.org/10.1109/TITS.2019.2924883

[116] Marcus Norberto, Lukas Gaedcke, Maicon Bernardino, Guilherme Legramante, Fabio Paulo Basso, and Elder Macedo Rodrigues. 2019. Performance testing in mobile application: A systematic literature map. In Proceedings of the 28th Brazilian Symposium on Software Quality (SBQS’19). ACM, New York, NY, 99–108. DOI: https://doi.org/10.1145/3364641.3364653

[117] The Joint Task Force on Computing Curricula. 2004. Curriculum Guidelines for Undergraduate Degree Programs in Software Engineering. Technical Report. New York, NY, USA. DOI: https://doi.org/10.1145/2594168

[118] Pablo F. Ordoñez Ordoñez, Milton Quizhpe, Oscar M. Cumbicus-Pineda, Valeria Herrera Salazar, and Robert Figueroa-Diaz. 2018. Application of genetic algorithms in software engineering: A systematic literature review. In Proceedings of the 4th International Conference on Technology Trends (CITT’18). Springer International Publishing, 659–670. DOI: https://doi.org/10.1007/978-3-030-05532-5_50

[119] R. Özakinc and A. Tarhan. 2016. Yazılımlık geliştirmeye erken asamalarında toplanan verinin hata tahmin performansına etkisi. In Proceedings of the 10th Turkish National Software Engineering Symposium (UYMS’16). CEUR-WS, 532–543.

[120] Rana Özakunci and Ayça Tarhan. 2018. Early software defect prediction: A systematic map and review. J. Syst. Softw. 144 (Oct. 2018), 216–239. DOI: https://doi.org/10.1016/j.jss.2018.06.025

[121] Jalaj Pachouly, Swati Ahirrao, Ketan Kotechand, Ganesh Shree Selvachandran, and Ajith Abraham. 2022. A systematic literature review on software defect prediction using artificial intelligence: Datasets, data validation methods, approaches, and tools. Eng. Appl. Artific. Intell. 111 (May 2022), 104773. DOI: https://doi.org/10.1016/j.engappai.2022.104773

[122] Sushant Kumar Pandey, Ravi Bhushan Mishra, and Anil Kumar Tripathi. 2021. Machine learning based methods for software fault prediction: A survey. Expert Syst. Appl. 172 (June 2021), 114595. DOI: https://doi.org/10.1016/j.eswa.2021.114595

[123] Juliana Alves Pereira, Mathieu Acher, Hugo Martin, Jean-Marc Jézéquel, Goetz Botterweck, and Anthony Ventresque. 2021. Learning software configuration spaces: A systematic literature review. J. Syst. Softw. 182, C (Dec. 2021), 29. DOI: https://doi.org/10.1016/j.jss.2021.111044

[124] Jorge Pérez, Jessica Diaz, Javier García-Martín, and Bernardino Tabuenca. 2020. Systematic literature reviews in software engineering-enhancement of the study selection process using cohen’s kappa statistic. J. Syst. Softw. (2020), 110657.

[125] Mirko Perkusich, Lenardo Chaves e Silva, Alexandre Costa, Felipe Ramos, Renata Saraiva, Arthur Freire, Ednaldo Dilorenzo, Emanuel Dantas, Danilo Santos, Kyller Gorgônio, Kyller Almeida, and Angelo Perkusich. 2020. Intelligent software engineering in the context of agile software development: A systematic literature review. Info. Softw. Technol. 119 (Mar. 2020). DOI: https://doi.org/10.1016/j.infsof.2019.106241

[126] Kai Petersen, Robert Feldt, Shahid Mujtaba, and Michael Mattsson. 2008. Systematic mapping studies in software engineering. In Proceedings of the 12th International Conference on Evaluation and Assessment in Software Engineering (EASE’08). BCS Learning & Development, Swindon, GBR, 68–77.
[127] Kai Petersen, Sairam Vakkalanka, and Ludwik Kuzniarz. 2015. Guidelines for conducting systematic mapping studies in software engineering: An update. Info. Softw. Technol. 64 (2015), 1–18. DOI: https://doi.org/10.1016/j.infsof.2015.03.007

[128] Vasileios C. Pezoulas, Konstantina D. Kourou, Fanis Kalatzis, Themis P. Exarchos, Evi Zampeli, Saviana Gandolfi, Andreas Goules, Chiara Baldini, Fotini Skopouli, Salvatore De Vita, Athanasios G. Tzioufas, and Dimitrios I. Fotiadis. 2020. Overcoming the barriers that obscure the interlinking and analysis of clinical data through harmonization and incremental learning. IEEE Open J. Eng. Med. Biol. 1 (2020), 83–90. DOI: https://doi.org/10.1109/OJEMB.2020.2981258

[129] Henning Piezunka and Linus Dahlander. 2015. Distant search, narrow attention: How crowding alters organizations’ filtering of suggestions in crowdsourcing. Acad. Manage. J. 58, 3 (2015), 856–880. DOI: https://doi.org/10.5465/amj.2012.0458

[130] Sriekumar P. Pillai, S. D. Madhukumar, and T. Radharamanan. 2017. Consolidating evidence based studies in software cost/effort estimation—A tertiary study. In Proceedings of the TENCN IEEE Region 10 Conference. 833–838. DOI: https://doi.org/10.1109/TENCON.2017.8227974

[131] Critical Appraisal Skills Programme. 2022. CASP Systematic Review Checklist. Retrieved from https://casp-uk.net/casp-tools-checklists/. Accessed July 2022.

[132] Alexandre Quemy. 2019. Data pipeline selection and optimization. In Proceedings of the 21st International Workshop on Design, Optimization, Languages and Analytical Processing of Big Data (DOLAP’19), Vol. 2324. CEUR-WS.org.

[133] Łukasz Radlinski. 2010. A Survey of Bayesian Net Models for Software Development Effort Prediction. Int. J. Softw. Eng. Comput. 2, 2 (July 2010), 95–109.

[134] Ani Rahmani, Sabrina Ahmad, Intan Ermahani A. Jalil, and Adhitta Putra Herawan. 2021. A systematic literature review on regression test case prioritization. Int. J. Adv. Comput. Sci. Appl. 12, 9 (2021). DOI: https://doi.org/10.14569/ijacs.2021.0120929

[135] Saif U. Rehman Khan, Sai P. Lee, Nadeem Javaid, and Waddod Abdul. 2018. A systematic review on test suite reduction: Approaches, experiment’s quality evaluation, and guidelines. IEEE Access 6 (Feb. 2018), 11816–11841. DOI: https://doi.org/10.1109/ACCESS.2018.2809600

[136] Mehwish Riaz, Emilia Mendes, and Ewan Tempero. 2009. A systematic review of software maintainability prediction and metrics. In Proceedings of the 3rd International Symposium on Empirical Software Engineering and Measurement (ESEM’09). IEEE, 367–377. DOI: https://doi.org/10.1109/ESEM.2009.5314233

[137] Gregorio Robles, Laura Arjona Reina, Alexander Serebrenik, Bogdan Vasilesuc, and Jesús M. González-Barahona. 2014. FLOSS 2013: A survey dataset about free software contributors: Challenges for curating, sharing, and combining. In Proceedings of the 11th Working Conference on Mining Software Repositories (MSR’14). ACM, New York, NY, 396–399. DOI: https://doi.org/10.1145/2597073.2597129

[138] Bernard Rous. 2012. Major update to ACM’s computing classification system. Commun. ACM 55, 11 (Nov. 2012), 12. DOI: https://doi.org/10.1145/2366316.2366320

[139] Bushra Sabir, Faheem Ullah, M. Ali Babar, and Raj Gaire. 2021. Machine learning for detecting data exfiltration: A review. Comput. Surveys 54, 3, Article 50 (May 2021), 47 pages. DOI: https://doi.org/10.1145/3442181

[140] Fatima Sabir, Francis Palma, Ghulam Rasool, Yann-Gaël Guéhéneuc, and Naouel Moha. 2019. A systematic literature review on the detection of smells and their evolution in object-oriented and service-oriented systems. Softw: Pract. Exper. 49, 1 (2019), 3–39. DOI: https://doi.org/10.1002/spe.2639

[141] Zaineb Sakhrwai, Asma Sellami, and Nadia Bouassida. 2021. Software enhancement effort prediction using machine-learning techniques: A systematic mapping study. SN Comput. Sci. 2, 6 (Sept. 2021). DOI: https://doi.org/10.1007/s42979-021-00872-6

[142] Oliver G. Selfridge. 1993. The gardens of learning: A vision for AI. AI Mag. 14, 2 (Mar. 1993). DOI: https://doi.org/10.1609/aimag.v14i2.1041

[143] Abubakar Omari Abdallah Semasaba, Wei Zheng, Xiaoxue Wu, and Samuel Akwasi Ayemang. 2020. Literature survey of deep learning-based vulnerability analysis on source code. IET Softw. 14, 6 (Dec. 2020), 654–664. DOI: https://doi.org/10.1049/iet-sen.2020.00084

[144] Tushar Sharma and Diomidis Spinellis. 2018. A survey on software smells. J. Syst. Softw. 138 (2018), 158–173. DOI: https://doi.org/10.1016/j.jss.2017.12.034

[145] Camila Costa Silva, Matthias Galster, and Fabian Gilson. 2021. Topic modeling in software engineering research. Empir. Softw. Eng. 26, 6 (Nov. 2021), 62. DOI: https://doi.org/10.1007/s10664-021-10026-0

[146] Hazrina Sofian, Nur Arzilawati Md Yunus, and Rodina Ahmad. 2022. Systematic mapping: Artificial intelligence techniques in software engineering. IEEE Access 10 (2022), 51021–51040. DOI: https://doi.org/10.1109/access.2022.3174115

[147] Md. Fahimuzzaman Sohan and Anas Basalamah. 2020. A systematic literature review and quality analysis of javascript malware detection. IEEE Access 8 (2020), 190539–190552. DOI: https://doi.org/10.1109/access.2020.3031690
[148] Le Son, Nakul Pritam, Manju Khari, Raghvendra Kumar, Pham Phuong, and Pham Thong. 2019. Empirical study of software defect prediction: A systematic mapping. *Symmetry* 11, 2 (Feb. 2019), 212. DOI: https://doi.org/10.3390/sym11020212

[149] Yulei Sui and Jingling Xue. 2016. SVF: Interprocedural static value-flow analysis in LLVM. In *Proceedings of the 25th International Conference on Compiler Construction*. ACM, New York, NY, 265–266. DOI: https://doi.org/10.1145/2892208.2892235

[150] Xiaobing Sun, Xiangyue Liu, Bin Li, Yucong Duan, Hui Yang, and Jiajun Hu. 2016. Exploring topic models in software engineering data analysis: A survey. *Proceedings of the 17th IEEE/ACIS International Conference on Software Engineering, Artificial Intelligence, Networking and Parallel/Distributed Computing*. 357–362. DOI: https://doi.org/10.1109/SNPD.2016.7515925

[151] Sundaram Suresh, Sriram Narasimhan, Satish Nagarajaiah, and Narasimhan Sundararajan. 2010. Fault-tolerant adaptive control of nonlinear base-isolated buildings using EMRAN. *Eng. Struct.* 32, 8 (Aug. 2010), 2477–2487. DOI: https://doi.org/10.1016/j.enstruct.2010.04.024

[152] Csaba Szepesvári. 2010. *Algorithms for Reinforcement Learning*. Morgan & Claypool Publishers. DOI: https://doi.org/10.2200/S00268ED1V01Y201005ALM009

[153] M. Irtaza N. Tarar, Mubashir Ali, and Wasi H. Butt. 2019. Bug report summarization: A systematic literature review. In *Proceedings of the 11th International Conference on Education Technology and Computers (ICETC’19)*. ACM, New York, NY, 257–261. DOI: https://doi.org/10.1145/3369255.3369289

[154] Chris Thornton, Frank Hutter, Holger H. Hoos, and Kevin Leyton-Brown. 2013. Auto-WEKA: Combined selection and hyperparameter optimization of classification algorithms. In *Proceedings of the 19th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (KDD’13)*. ACM, New York, NY, 847–855. DOI: https://doi.org/10.1145/2487755.2487629

[155] Kashyap Todi, Jean Vanderdonckt, Xiaojuan Ma, Jeffrey Nichols, and Nikola Banovic. 2020. AI4UI: Workshop on AI methods for adaptive user interfaces. In *Proceedings of the 25th International Conference on Intelligent User Interfaces Companion (IUI’20)*. ACM, New York, NY, 17–18. DOI: https://doi.org/10.1145/3379336.3379359

[156] Ayse Tosun, Ayse B. Bener, and Shirin Akbarinasaji. 2017. A systematic literature review on the applications of bayesian networks to predict software quality. *Softw. Qual. J.* 25 (Mar. 2017), 273–305. DOI: https://doi.org/10.1007/s11219-015-9297-z

[157] Michele Tufano, Cody Watson, Gabriele Bavota, Massimiliano Di Penta, Martin White, and Denys Poshvyanych. 2018. An empirical investigation into learning bug-fixing patches in the wild via neural machine translation. In *Proceedings of the 33rd ACM/IEEE International Conference on Automated Software Engineering (ASE’18)*. ACM, 832–837. DOI: https://doi.org/10.1145/3238147.3240732

[158] Jamal Uddin, Rozaida Ghazali, Mustafa M. Deris, Rashid Naseem, and Habib Shah. 2017. A survey on bug prioritization. *Artif. Intell. Rev.* 47, 2 (Feb. 2017), 145–180. DOI: https://doi.org/10.1007/s10462-016-9478-6

[159] Faheem Ullah, Matthew Edwards, Rajiv Ramdhany, Ruzanna Chitchyan, M. Ali Babar, and Awaiz Rashid. 2018. Data exfiltration: A review of external attack vectors and countermeasures. *J. Netw. Comput. Appl.* 101 (Jan. 2018), 18–54. DOI: https://doi.org/10.1016/j.jnca.2017.10.016

[160] Muhammad Usman, Ricardo Britto, Jürgen Börstler, and Emilia Mendes. 2017. Taxonomies in software engineering: A systematic mapping study and a revised taxonomy development method. *Info. Softw. Technol.* 85 (2017), 43–59. DOI: https://doi.org/10.1016/j.infsof.2017.01.006

[161] B. F. van Dongen, A. K. A. de Medeiros, H. M. W. Verbeek, A. J. M. M. Weijters, and W. M. P. van der Aalst. 2005. The ProM framework: A new era in process mining tool support. In *Proceedings of the International Conference on Application and Theory of Petri Nets (ICATPN’05)*, Gianfranco Ciardo and Philippe Daronneau (Eds.), Springer, Berlin, 444–454. DOI: https://doi.org/10.1007/11494744

[162] June M. Verber, O. Pearl Breteron, Barbara A. Kitchenham, Mark Turner, and Mahmood Niazi. 2012. Systematic literature reviews in global software development: A tertiary study. In *Proceedings of the 16th International Conference on Evaluation Assessment in Software Engineering (EASE’12)*, 2–11. DOI: https://doi.org/10.1049/ic.2012.0001

[163] Hai Vu-Ngoc, Sameh Samir Elawady, Ghaleb Muhammad Mehyar, Amr Hesham Abdelhamid, Omar Mohamed Mattar, Oday Halhouli, Nguyen Lam Vuong, Citra Dewi Mohd Ali, Ummu Helma Hassan, Nguyen Dang Kien, Kenji Hirayama, and Nguyen Tien Huy. 2018. Quality of flow diagram in systematic review and/or meta-analysis. *PloS One* 13, 6 (June 2018), 1–16. DOI: https://doi.org/10.1371/journal.pone.0195955

[164] Cody Watson, Nathan Cooper, David Nader Palacio, Kevin Moran, and Denys Poshvyanych. 2022. A systematic literature review on the use of deep learning in software engineering research. *ACM Trans. Softw. Eng. Methodol.* 31, 2, Article 32 (March 2022), 58 pages. DOI: https://doi.org/10.1145/3485275

[165] Fadi Wedyan, Dalal Almruny, and James M. Bieman. 2009. The effectiveness of automated static analysis tools for fault detection and refactoring prediction. In *Proceedings of the International Conference on Software Testing Verification and Validation*. 141–150. DOI: https://doi.org/10.1109/ICST.2009.21
[166] Jianfeng Wen, Shixian Li, Zhiyong Lin, Yong Hu, and Changqin Huang. 2012. Systematic literature review of machine learning based software development effort estimation models. Info. Softw. Technol. 54 (Jan. 2012), 41–59. DOI: https://doi.org/10.1016/j.infsof.2011.09.002

[167] Claes Wohlin. 2014. Guidelines for snowballing in systematic literature studies and a replication in software engineering. In Proceedings of the 18th International Conference on Evaluation and Assessment in Software Engineering (EASE’14). ACM, New York, NY, Article 38, 10 pages. DOI: https://doi.org/10.1145/2601248.2601268

[168] Claes Wohlin, Emilia Mendes, Katia Romero Felizardo, and Marcos Kalinowski. 2020. Guidelines for the search strategy to update systematic literature reviews in software engineering. Info. Softw. Technol. 127 (Nov. 2020), 106366. DOI: https://doi.org/10.1016/j.infsof.2020.106366

[169] C. Wohlin and Rafael Prikladnicki. 2013. Systematic literature reviews in software engineering. Info. Softw. Technol. 55 (2013), 919–920.

[170] Claes Wohlin, Per Runeson, Martin Hst, Magnus C. Ohlsson, Bjrn Regnell, and Anders Wessln. 2012. Experimentation in Software Engineering. Springer.

[171] Hong Wu, Lin Shi, Celia Chen, Qing Wang, and Barry Boehm. 2016. Maintenance effort estimation for open source software: A systematic literature review. In Proceedings of the IEEE International Conference on Software Maintenance and Evolution (ICSME’16). IEEE. DOI: https://doi.org/10.1109/icsme.2016.87

[172] Yazhou Xie, Majid Ebad Sichani, Jamie E. Padgett, and Reginald DesRoches. 2020. The promise of implementing machine learning in earthquake engineering: A state-of-the-art review. Earthquake Spectra 36, 4 (June 2020), 1769–1801. DOI: https://doi.org/10.1177/8755293020919419

[173] Yanming Yang, Xin Xia, David Lo, Tingting Bi, John Grundy, and Xiaohu Yang. 2022. Predictive models in software engineering: Challenges and opportunities. ACM Trans. Softw. Eng. Methodol. 31, 3, Article 56 (Apr. 2022), 72 pages. DOI: https://doi.org/10.1145/3503509

[174] Yanming Yang, Xin Xia, David Lo, and John Grundy. 2021. A survey on deep learning for software engineering. Comput. Surveys (Dec. 2021). DOI: https://doi.org/10.1145/3505243

[175] Huishi Yin. 2015. A study plan: Open innovation based on internet data mining in software engineering. In Proceedings of the International Conference on Software and System Process. ACM. DOI: https://doi.org/10.1145/2785592.2795366

[176] Maryam Zahid, Zahid Mehmod, and Irum Inayat. 2017. Evolution in software architecture recovery techniques—A survey. In Proceedings of the 13th International Conference on Emerging Technologies (ICET’17). IEEE, 1–6. DOI: https://doi.org/10.1109/ICET.2017.8281704

[177] Kareshna Zamani, Didar Zowghi, and Chetan Arora. 2021. Machine learning in requirements engineering: A mapping study. In Proceedings of the 29th International Requirements Engineering Conference Workshops (REW’21). IEEE. DOI: https://doi.org/10.1109/rew53955.2021.00023

[178] Samer Zein, Norsaremah Salleh, and John Grundy. 2016. A systematic mapping study of mobile application testing techniques. J. Syst. Softw. 117, C (July 2016), 334–356. DOI: https://doi.org/10.1016/j.jss.2016.03.065

[179] Du Zhang and Jeffrey J. P. Tsai. 2003. Machine learning and software engineering. Softw. Qual. J. 11 (June 2003), 87–119. DOI: https://doi.org/10.1023/A:1023760326768

[180] J. Zheng, L. Williams, N. Nagappan, W. Snipes, J. P. Hudepohl, and M. A. Vouk. 2006. On the value of static analysis for fault detection in software. IEEE Trans. Softw. Eng. 32, 4 (2006), 240–253. DOI: https://doi.org/10.1109/TSE.2006.38

[181] You Zhou, He Zhang, Xin Huang, Song Yang, Muhammad Ali Babar, and Hao Tang. 2015. Quality assessment of systematic reviews in software engineering: A tertiary study. In Proceedings of the 19th International Conference on Evaluation and Assessment in Software Engineering (EASE’15). ACM, New York, NY, Article 14, 14 pages. DOI: https://doi.org/10.1145/2745802.2745815

Received 22 November 2021; revised 10 November 2022; accepted 22 November 2022