Systematic Literature Review on Machine Learning and its Impact on APIs Deployment

Jose Rojas Valdivia, Javier Gamboa-Cruzado,
Percy de la Cruz Vélez de Villa

Universidad Nacional Mayor de San Marcos,
Facultad de Ingeniería de Sistemas e Informática,
Peru

{josegerman.rojas, pdelacruzv}@unmsm.edu.pe,
jgamboa65@hotmail.com

Abstract. Machine Learning is being used worldwide in the deployment of API's (Application Programming Interface). The development of machine learning presents: techniques, algorithms, sequences, logic based on facts, and predictions of future errors in various processes of organizations such as the process of deployment of API's/functionalities/software. A systematic literature review (SLR) was conducted on machine learning for the process of API/functionality deployment/error detection. The search strategy identified 176378 papers in digital libraries such as: Scopus, ProQuest, ScienceDirect, IEEE Xplore, Taylor & Francis Online, Web of Science, Wiley Online Library and ACM Digital Library; which were filtered by exclusion and quality criteria obtaining as final result, for review and analysis, 85 papers. The results of the systematic review have focused on machine learning papers recently published in recent years regarding the deployment of API's, software, monitoring and control tools, error detection where machine learning offers alternatives to improve and be more efficient in those processes that fail regularly today. The RSL has allowed a broad view on the studies and findings presented in this study.

Keywords. Artificial intelligence, machine learning, deployment, APIs, finance, systematic literature review.

1 Introduction

The detection of errors in the deployment processes either at the level of API's development, software using machine learning significantly reduces the implementation costs of these new requirements because their deployment dates would be prolonged by not being able to detect these errors in time.

Machine learning is evolving over the years in the IT area, companies are successfully implementing its use in business processes that involve return on investment in the short term, it is currently used to detect errors in systems before they happen, its method of action is proactive and not reactive because it is based on concrete facts and depending on it makes an internal analysis and determines the best way forward, this guided not only by Artificial Intelligence but also by a analyst who validates the proper functioning of the implemented.

To use machine learning it is first necessary to define whether it will be supervised or unsupervised [10, 5], once the type of machine learning to be used has been identified, it can be validated if a framework can be used or the development can be created from scratch, also the best known machine learning algorithms can be used such as linear regression [79], logistic regression [46, 57], decision tree [22, 23] among others, in order to meet the needs of what is presented.

The main objective of this study is to identify the state of the art of machine learning and its impact on API/software deployment processes and early error detection.

The paper is organized as follows. Section II presents the Background and related works, Section III details the Review Method, Section IV presents the Results and Discussion.
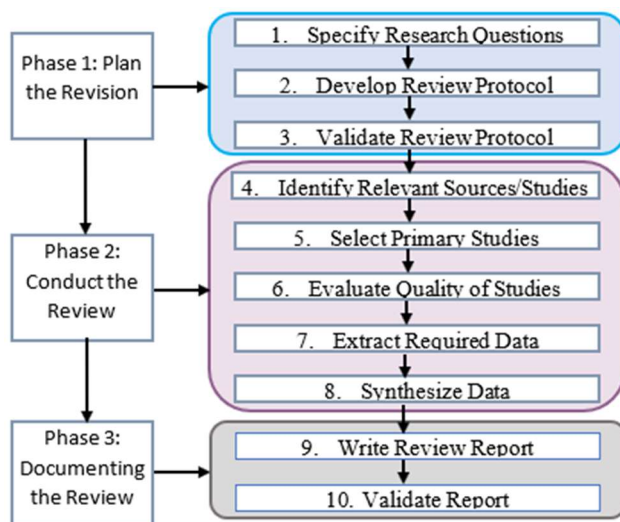
Fig. 1. RSL process proposed by Kitchenham

Table 1. Research Questions and Objectives

Research Question	Objetive
RQ1: What are the most widely used algorithms in Machine Learning research?	Determine the most commonly used algorithms in Machine Learning research.
RQ2: What are the Cooccurring Keywords in Machine Learning Research and their Impact on API Deployment?	Identify and select the keywords that present Cooccurrence in Machine Learning research and their impact on API Deployment.
RQ3: Which are the publications with the highest Objectivity in their Abstracts, by country, on Machine Learning and its impact on the Deployment of API's?	To know the publications that present a greater Objectivity in their Abstracts, by country, on Machine Learning and its impact on the Deployment of API's.
RQ4: Which types of Machine Learning are most commonly used in experimental research?	Identify which types of Machine Learning are most commonly used in experimental research.
RQ5: What are the named entities (NERs): people, organizations, places, time expressions and quantities that are most frequently presented in Machine Learning Research Abstracts and their impact on API Deployment?	Determine the named entities (NERs): people, organizations, places, time expressions, and quantities that occur most frequently in Machine Learning Research Abstracts and their impact on API Deployment.
RQ6: What are the most used and relevant Machine Learning keywords and their impact on API Deployment?	Identify the most used and relevant Machine Learning keywords and their impact on API Deployment.

Finally, Section V presents the Conclusions and Future Research.

2 Background and Related Work

The advancement of new developments deployments, Internet of Things, big data and mobile computing with new technologies leads to the need for intelligent services that enable context awareness and adaptability to their changing contexts [97], offering products and services as in today's business world, providing reliable customer service is as important as offering better products to maintain a sustainable business model [87].

Data is the foundation of today's technologies and researchers, especially in machine learning and deep learning [92] require greater detail of the

data. Security in data processing must give confidence to users so that they can interact with the various applications coming out of the emerging technology market, as well as machine learning [94] can detect anomalous user activities by analyzing sequences of user session data [89]. In financial institutions the problem in detecting online credit card fraud in e-commerce systems.

It has always been a concern that poses a major challenge for financial institutions and online merchants regarding financial losses [88], before these problems arise various solutions including the power to implement machine learning in their processes that have more risk to mitigate and reduce these threats in a short time, having real time information helps to identify in less time the existing threat, this in turn leads to the customization of products, services, provided to customers, to meet their needs, this has become a strategy to increase the added value of companies.

This study identifies a process within an organization that is deficient and how machine learning can help improve that process.

In this systematic review, information was collected to show the implications of the implementation of machine learning in organizations, as an improvement, in turn prevents possible errors by detecting them in time, depending on the configuration you have.

Likewise this review aims to provide the first literature review on the deployment of API's/software, error detection using Machine Learning, therefore to address the gap in the literature were used RQ's (Research Questions) on NER (named entity recognition) as people, organizations, locations, expressions of time and quantities that are most frequently presented in the abstracts, discussions and conclusions of the research, likewise it is considered important to mention that there are papers whose abstracts, discussions and conclusions are characterized by their high objectivity and low polarity on Machine Learning in the deployment of API's, software, error detection.

The research has been supported by technological tools such as Mendeley bibliographic manager and the Artificial Intelligence (RAj) technological tool authored by Dr. Javier Gamboa Cruzado, which was used to process the collected data.

Table 2. Search Descriptors and their Synonyms

Descriptor	Description
Machine learning	Independent Variable
Artificial intelligence	
Deep learning	
API Development	Dependent Variable
Deployment	
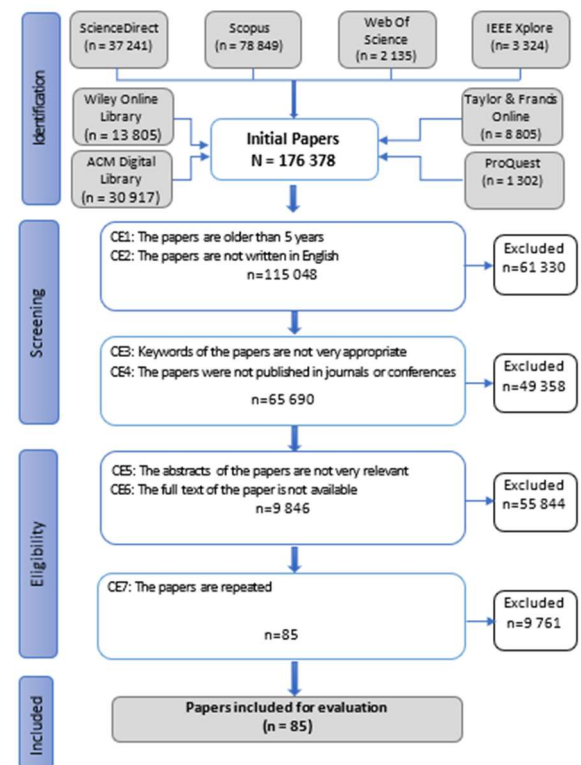
Fig. 3. PRISMA Flow Diagram

3 Review Method

The present research was conducted by adopting the systematic review approach defined by Kitchenham [86], where the literature is collected and analyzed.

According to the study guidelines, it consists of 3 main phases: planning, conducting and documenting the review. The phases are shown in Figure 1 below.

3.1 Research Problems and Objectives

In conducting a systematic literature review, the research questions assist in the search, extraction and analysis of data, as shown in Table 1 below.

3.2 Information Sources and Search Strategies

The libraries that were used to search for the required research papers are: Scopus, Web of Science, IEEE Xplore, ACM Digital Library, ProQuest, ScienceDirect, Taylor & Francis Online, and Wiley Online Library. The search strategy included searching for keywords relevant to the study (see Table 2).

The search procedure was carried out using search equations for the study, as shown in Table 3.

3.3 Identified Studies

At the end of the search for papers, the quantities shown in Figure 2 are obtained.

3.4 Exclusion Criteria

The Exclusion Criteria (EC) have been defined to accurately assess the quality of the literature. The papers that were formulated and used are:

EC1: The papers are older than 5 years.

EC2: The papers are not written in English.

EC3: The keywords of the papers are not very appropriate.

EC4: The papers were not published in journals or congresses.

EC5: The abstract of the papers is not very relevant.

EC6: The full text of the paper is not available.

EC7: The papers are repeated.

3.5 Study Selection

Originally 176378 papers were obtained based on the search performed using the keywords relevant to the study.
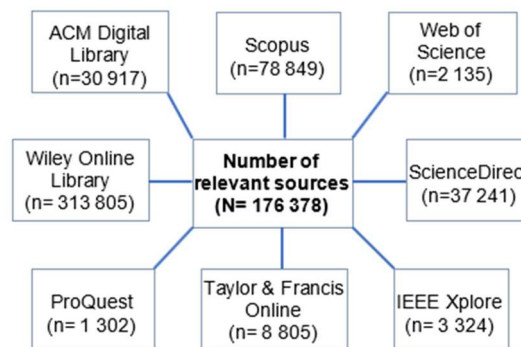

Fig. 2. Number of Papers in Relevant Sources

Table 3. Information sources and search equation

| Source	Search equation
Scopus	(ALL (("machine learning" OR "artificial intelligence" OR "deep learning")) AND ALL (("Api development" OR deployment)))
Web of Science	("machine learning" OR "artificial intelligence" OR "deep learning") (All Fields) AND ("Api development" OR deployment) (All Fields)
IEEE Xplore	("All Metadata":"machine learning" OR "All Metadata":"artificial intelligence" OR "All Metadata":"deep learning") AND ("All Metadata":"Api development" OR "All Metadata":deployment)
ACM Digital Library	[[All: "machine learning"] OR [All: "artificial intelligence"] OR [All: "deep learning"]] AND [[All: "api development"] OR [All: deployment]]
ProQuest	("machine learning" OR "artificial intelligence" OR "deep learning") AND ("Api development" OR deployment)
ScienceDirect	("machine learning" OR "artificial intelligence") AND ("Api development" OR deployment)
Taylor & Francis Online	[[All: "machine learning"] OR [All: "artificial intelligence"] OR [All: "deep learning"]] AND [[All: "api development"] OR [All: deployment]]
Wiley Online Library	"("machine learning" OR "artificial intelligence" OR "deep learning")" anywhere and "("Api development" OR deployment)" anywhere
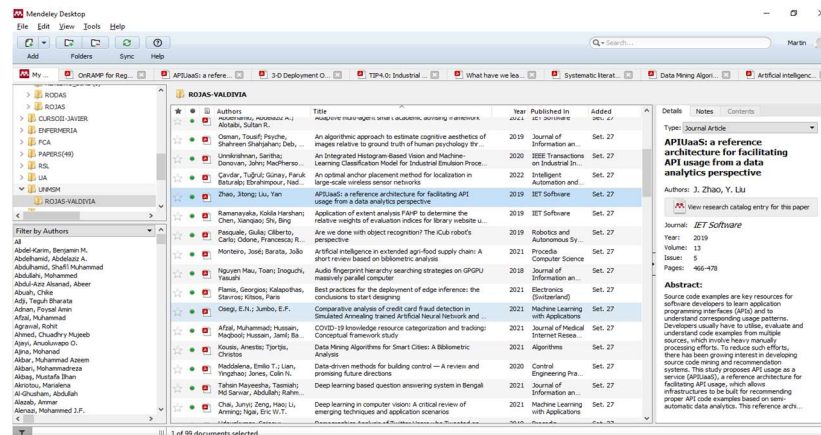
Fig. 4. Managing papers with Mendeley
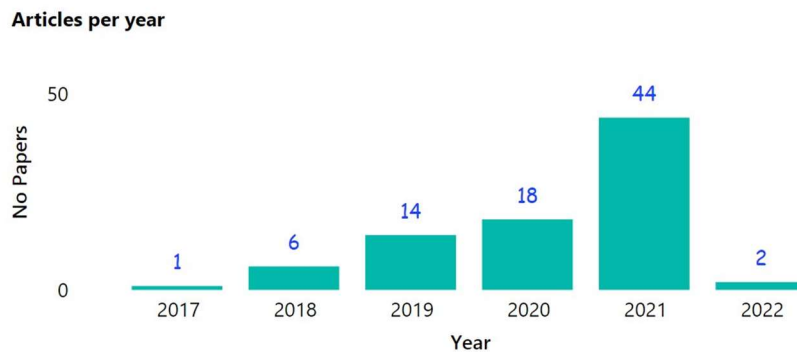
Fig. 5. Distribution of published papers by Year

The selection and filtering steps used were as follows:

Step 1: Apply exclusion criteria to obtain only the most relevant ones.

Step 2: Apply quality assessment to include papers that give the best answers to the research questions posed.

The final result of applying the steps described above is 85 papers, as shown in Figure 3.

3.6 Quality Assessment

The quality rules helped to obtain a list of more specific results in the papers included for review. The quality criteria (QA's) that were formulated to evaluate the quality of the papers are:

QA1: Is the purpose of the research clearly explained?

QA2: Are the research findings detailed?

QA3: Is there a possibility to consult the researchers?

QA4: Is the research conducted in financial institutions?

QA5: Does the research detail unit tests?

QA6: Was the research conducted during the pandemic?

QA7: Does the investigator have a postgraduate degree?

During this stage, the quality of the research submitted by the 85 studies that had met the exclusion criteria was assessed. The investigators jointly conducted an analysis of the papers and applied each of the criteria to assess the quality of the papers. The primary studies evaluated met each of the QA's.
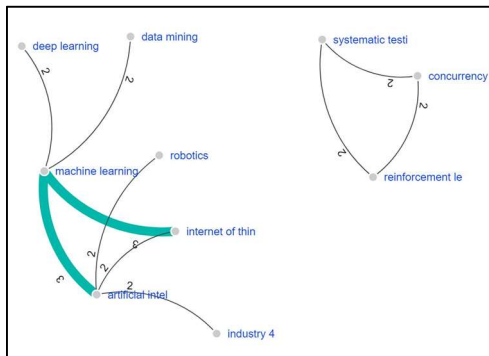
Fig. 6. Quantity of papers on Machine Learning Deployment in the last 5 years by Country
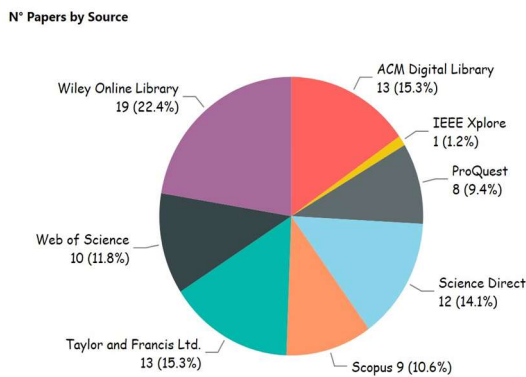
Fig. 7. Number of papers on Machine Learning by Source of Information

Fig. 8. Keywords with Cooccurrences in Machine Learning Research

3.7 Data Extraction Strategies

The final list of papers was used at this stage to extract the information needed to answer the set of research questions.

The information extracted from each paper included the following fields: paper ID and title, url, source, year, country, number of pages, authors, affiliation, number of citations, abstract, keywords, and sample size.

Not all the papers helped to answer all the research questions. Mendeley was used to perform the data extraction as shown in Figure 4.

3.8 Synthesis of Findings

The information extracted for research questions RQ1-RQ6 are presented as qualitative and quantitative data to perform a descriptive and inferential statistical analysis to obtain the research answers; on the other hand, the development or analysis of the statistics obtained allowed the finding of certain research patterns occurred during the last 5 years (2017-2021).

4 Results and Discussion

In this section, it is expected to address the key findings obtained through the systematic review of the literature, as well as an interpretative discussion on these findings in the context of the impact of machine learning on the implementation of APIs. Here is a general breakdown of what could be included in this section:

4.1 General Description of the Studies

The paper selection process resulted in a total of 85 papers, these were selected for data extraction and analysis. Figure 5 shows the chronological distribution of published studies from 2017 to 2022.

The graph represents the evolution when applying Machine Learning for processes involving deployments in both productive and pre-productive environments independent of the organization and how this technology has been growing in the IT domain.

According to author Yildiz [91] the most profitable year for Machine Learning publications in the current field, especially with the internet of things and new technologies emerging, was 2018 with a total of 2071 publications.

According to the authors Chai *et al*. [92], the year that could be leveraged the most in terms of

Table 4. Number of papers per publication and year

Name of Publication	2017	2018	2019	2020	2021	2022	Total
IET Software		3	6	3	7		**19**
Journal of Information and Telecommunication		2	4	1	6		**13**
Proceedings of the ACM on Programming Languages			3	5	5		**13**
Machine Learning with Applications					12		**12**
IEEE Transactions on Industrial Informatics		1		1	1		**3**
Sensors					3		**3**
Cybersecurity					2		**2**
IEEE Transactions on Control of Network Systems	1		1				**2**
Advanced Intelligent Systems					1		**1**
Computer Speech and Language						1	**1**
Control Engineering Practice				1			**1**
Electronic Markets					1		**1**
Electronics					1		**1**
Eurasip Journal on Wireless Communications and N…					1		**1**
Frontiers in Neuroscience					1		**1**
IEEE Transactions on Automation Science and Engineering				1			**1**
IEEE Transactions on Cybernetics				1			**1**
…							…
Total	**1**	**6**	**14**	**18**	**44**	**2**	**85**

machine learning papers on application development scenarios was 2020.

As time and technology progresses each year has significantly increased the productivity of papers regarding Machine Learning.

Figure 6 shows that the United States contributed the most papers on Machine Learning with respect to the set of questions of the present research, US contributed 20 papers followed by China with 12 papers.

According to the authors Salod and Singh [93] identified the US as the country that has published the most on Machine Learning in prediction processes in the last 5 years with 803 papers, followed by China with 394, UK with 209, Canada with 169 and Germany with 147.

Likewise, the authors Akbari and Do [94] validate that the US is the country that has published the most on Machine Learning in the last

decade on logistics process improvement, followed by Hong Kong, UK and Germany.

Figure 7 below shows the distribution of the sources that published the most papers on machine learning as a result of the search performed with the equations used.

As can be seen, Wiley Online Library is the bibliographic source that has made the greatest contribution to this research with 22.4% of the papers, followed by ACM Digital Library with 15.3%, Taylor and Francis Online with 15.3%, Scienci Direct with 14.1%, Web of Science with 11.8%, Scopus with 10.6%, Proquest with 9.4% and finally IEEE Xplore with 1.1% of the papers, respectively.

The authors Nair *et al*. [95] consider Scopus as one of the largest databases for searching papers as they have papers whose publishers are internationally renowned.

Table 5. Most used algorithms using machine learning

Algorithm	Reference	Qty. (%)
Linear regression	[10] [23] [26] [29] [69] [70]	6 (7.5)
Logistic regression	[2] [10] [22] [23] [24] [25] [26] [27] [29] [46] [57] [66] [70] [84]	14 (17.5)
Decision tree	[1] [10] [22] [23][26] [28] [29] [30] [33] [36] [55] [66] [70] [78] [79] [80] [84]	17 (21.25)
SVM	[7] [10] [79]	3 (3.75)
Naive Bayes	[33]	1 (1)
KNN	[79]	1 (1)
K-means	[4] [11] [12] [22] [28] [29] [33] [36] [53] [66] [68] 77] [78] [79] [83] [84]	16 (20)
Random forest	[27]	1 (1)
Dimensionality reduction	[3] [24] [29] [30] [33] [36] [57] [75] [77] [84] [85]	11 (13.75)
Gradient boosting	[10] [23] [26] [27] [28] [29] [30] [47] [69] [79]	10 (12.5)

Likewise, the authors Huang et al [96] use Web of Science as a bibliometric source; they consider this source for its quality of published papers because it helped them in their research.

Table 4 shows the number of papers by publication name (Journal or Congress) and by year in ascending order, detailing the number of research papers on Machine Learning from 2017 to 2022.

IET Software leads with 19 papers, followed by Journal of Information and Telecommunication with 13 papers and Proceedings of the ACM on Programming Languages; Machine learning with Applications with 12 papers, IEEE Transactions on Control of Network Systems and Sensors with 3.

The authors Kousis and Tjortjis [97] mention that the publication media where Machine Learning publications were made, elaborated a ranking where IEEE Access leads followed by Sensors in second place, and Sustainable Cities and Society and Wiley Disciplinary Reviews are in the last positions.

Likewise, the authors [96] detail that the publication media that most helped their paper on Machine Learning in improving implementation in a pre-production environment was the International Journal of Production Research followed by Expert Systems with Applications.

4.2 Answers to the Research Questions

In this section, clear and well-founded answers to the posed research questions are provided. This segment is crucial for demonstrating how the carried-out research has addressed the proposed questions.

Principio del formulario.

RQ1: What are the most widely used algorithms in Machine Learning research?

According to the results of the literature review, Table 5 shows the most used algorithms on machine learning, highlighting Decision tree with
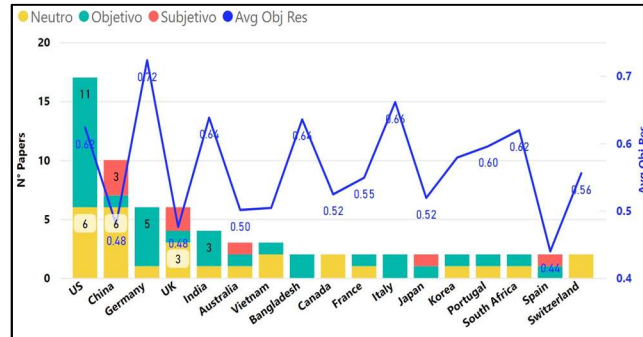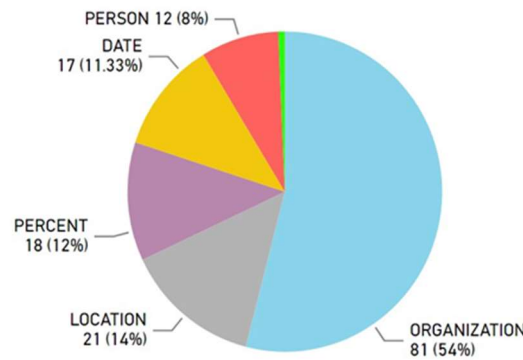
Fig. 9. Objectivity in the Abstracts of papers by Country

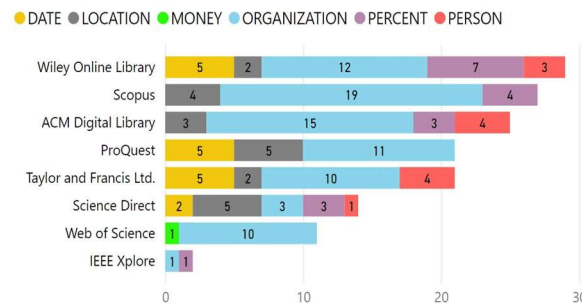**Fig. 10.** Type and number of NERs in Abstracts

Fig. 11. Type of NER's in Abstracts of papers by Source

17 papers, followed by K-means with 16 papers, Logistic regression with 14 papers, Gradient Boosting with 10 papers. The other algorithms are also used but in a lower percentage.

According to the authors Udayakumar et al. [98], the algorithm that gave them the highest accuracy in their research results was the SVM with 86.80% and the least accurate was the Randon Forest.

RQ2: What are the Cooccurring Keywords in Machine Learning Research and their Impact on API Deployment?

Table 6. Most used types of machine learning

Types of Machine Learning	Reference	Cant. (%)
Supervised Learning	[5] [10] [22] [24] [29] [30] [31] [32] [33] [36] [40] [47] [54] [58] [62] [66] [70] [71] [75] [77] [79] [78] [80] [84]	24 (62)
Unsupervised Learning	[5] [22] [24] [29] [40] [57] [62] [63] [66] [68] [70] [78] [79] [80] [82]	15 (38)
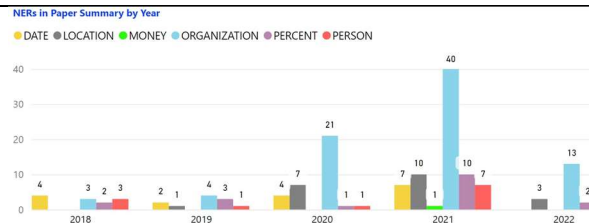
Fig. 12. Number of NERs in abstracts of papers per year
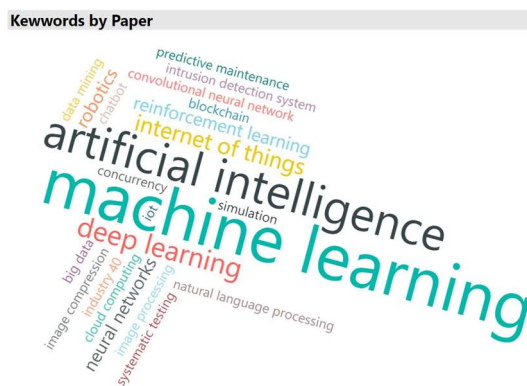
Fig. 13. Most used keywords for the search of solutions with Machine Learning

According to the results of the literature review, the keywords such as "artificial intelligence", "machine learning", "internet of things" and "industry 4.0" are the ones that presented 3 concurrences each. (See Figure 8).

Keywords such as "artificial intelligence", "machine learning", "internet of things" and "industry 4.0" presented higher co-occurrences in the papers, but keywords such as "deep learning", "data mining", "finance", "digital financial", "systematic testing", "reiforcement learning" and "robotics" had 2 co-occurrences.

Authors Monteiro and Barata [99] detail that the keywords most commonly used to obtain papers on Machine Learning are: "artificial intelligence", "machine learning", "deep learning", and "neural networks".

RQ3: Which are the publications with the highest Objectivity in their Abstracts, by country, on Machine Learning and its impact on the Deployment of API's?

According to the results of the literature review, Figure 9 shows the United States (US) and China as the countries with the highest objectivity in the abstracts of their papers which shows that it is in line with their technological advancement over the other countries; this study was conducted between the year 2017 to 2022.

Keyword repetitions
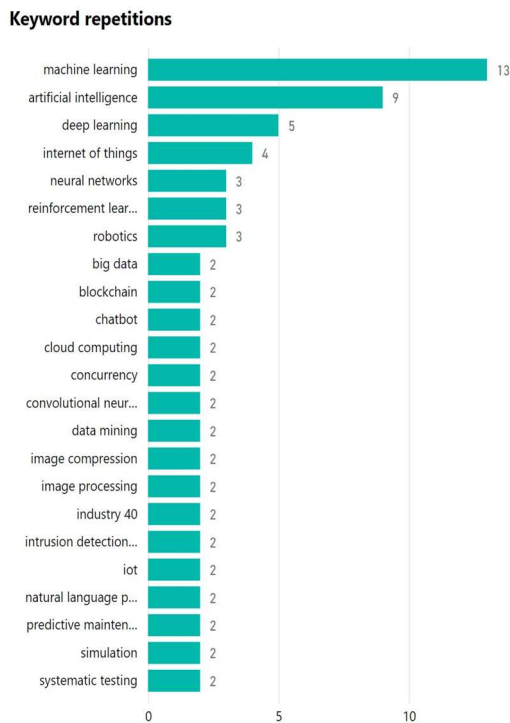
Fig. 14. Number of most used keyword repetitions

The authors Rejeb et al. [87] detail that the country that published the most on Machine Learning with respect to API, software, error detection deployments in the last 4 years was the US with 29% followed by China with 10% leaving Switzerland and Finland with a 2% share.

RQ4: Which types of Machine Learning are most commonly used in experimental research?

According to the results of the literature review, Table 6 shows the most used machine learning algorithms.

The most commonly used type of machine learning is Supervised Learning, according to Sharifi *et al*. [90] implemented in their paper on Signal Detection Robot with constrained computational resources.

RQ5: What are the Named Entities (NER): people, organizations, places, time expressions and quantities that are most frequently presented in Machine Learning Research Abstracts and their impact on API Deployment?

After performing a detailed analysis of the abstracts of the papers reviewed, using natural language processing (NLP) techniques, a series of NERs were obtained. The most frequent ones are shown in Figure 10.

According to the results of the literature review, the Organization type NERs were found very frequently in the abstracts of the papers with 54%, the Location type with 21%, the Percentage type with 18%, the Date type with 11.3% and the Person type with 8% of the total percentage.

It is considered necessary to emphasize that the answer to this type of question cannot be compared with other papers since it is considered unique, this in order to be able to contribute to the research on Machine Learning so that it can be used as a reference in future papers.

On the other hand, Figure 11 shows the NERs that were identified in the paper abstracts. They are shown ordered by bibliographic source, and the bibliographic source whose papers have the most NERs is Wiley Online Library, followed by Scopus. IEEE Xplore is the source with the fewest NERs in the abstracts of its publications.

Finally, Figure 12 shows that in the years 2020 and 2021 the NERs of type Organization were presented more frequently in 21 and 40 abstracts of their papers respectively.

RQ6: What are the most used and relevant Machine Learning keywords and their impact on API Deployment?

According to the results of the literature review, Figure 13 shows the main keywords used in the research on machine learning solutions and their impact on API Deployment. To detail this, Figure 14 shows the number of keyword repetitions.

In the authors' paper Hasan *et al*. [100] include the keywords such as "machine learning", "big data analytics", "predictive analytics" among others.

Also [94] state that the most used keywords in their research were "machine learning", "artificial intelligence", "logistic", among others.

After the analysis of these 2 randomly selected systematic literature review papers, it is observed that the most repeated keyword is "machine learning" and "artificial intelligence" and it is found within the evaluation carried out.

5 Conclusions and Future Research

In conclusion, this study applies systematic literature review (SRL), which is an iterative process that combines the existing literature on a specific topic.

The objective was to address the issues by identifying, critically evaluating, and integrating the findings of all relevant individual high-quality studies that address one or more research questions.

This review has determined how far current studies on the use of machine learning have progressed in organizations that have successfully implemented it. It has also helped to formulate general statements, develop theoretical and practical implications, and make suggestions for future research.

We have answered, in detail, each of the RQs formulated, based on a thorough review of the 96 papers selected, discussed gaps and future directions. This review has some limitations that future research can address as it has a time limit for the papers that were reviewed from 2017 to 2021.

Therefore, future research should consider more recent publications to keep up with new technologies, methods, algorithms, and frameworks that may come out for machine learning in the future.

References

1. **Syed, N. F., Baig, Z., Ibrahim, A., Valli, C. (2020).** Denial of service attack detection through machine learning for the IoT. Journal of Information and Telecommunication, Vol. 4, No. 4, pp. 482–503. DOI: 10.1080/24751839. 2020.1767484.

2. **Paul, A., Latif, A. H., Adnan, F. A., Rahman, R. M. (2019).** Focused domain contextual ai chatbot framework for resource poor languages. Journal of Information and Telecommunication, Vol. 3, No. 2, pp. 248–269. DOI: 10.1080/24751839.2018.1558378.

3. **Osman, T., Psyche, S. S., Deb, T., Firoze, A., Rahman, R. M. (2019).** An algorithmic approach to estimate cognitive aesthetics of images relative to ground truth of human psychology through a large user study. Journal of Information and Telecommunication, Vol. 3, No. 2, pp. 156–179. DOI: 10.1080/24751839.2018.1542574.

4. **Nguyen-Mau, T., Inoguchi, Y. (2018).** Audio fingerprint hierarchy searching strategies on GPGPU massively parallel computer. Journal of Information and Telecommunication, Vol. 2, No. 3, pp. 265–290. DOI: 10.1080/24751839. 2018.1423790.

5. **Morozkin, P., Swynghedauw, M., Trocan, M. (2019).** Image compression in resource-constrained eye tracking devices. Journal of Information and Telecommunication, Vol. 3, No. 3, pp. 342–360. DOI: 10.1080/24751839. 2019.1573395.

6. **Dang, N. T., Tran, H. M., Nguyen, S. V., Maleszka, M., Le, H. D. (2021).** Sharing secured data on peer-to-peer applications using attribute-based encryption. Journal of Information and Telecommunication, Vol. 5, No. 4, pp. 440–459. DOI: 10.1080/24751839. 2021.1941574.

7. **Vu, H., Le, T. L., Nguyen, V. G., Dinh, T. H. (2018).** Semantic regions segmentation using a spatio-temporal model from an UAV image sequence with an optimal configuration for data acquisition. Journal of Information and Telecommunication, Vol. 2, No. 2, pp. 126–146. DOI: 10.1080/24751839.2017.1390654.

8. **Indoonundon, M., Pawan-Fowdur, T. (2021).** Overview of the challenges and solutions for 5G channel coding schemes. Journal of Information and Telecommunication, Vol. 5, No. 4, pp. 460–483. DOI: 10.1080/24751839.2021.1954752.

9. **Tahsin-Mayeesha, T., Md-Sarwar, A., Rahman, R. M. (2021).** Deep learning-based question answering system in Bengali. Journal of Information and Telecommunication, Vol. 5, No. 2, pp, 145–178. DOI: 10.1080/24751839.2020.1833136.

10. **Nguyen, N. H., Nguyen, D. T. A., Ma, B., Hu, J. (2022).** The application of machine learning and deep learning in sport: predicting NBA players' performance and popularity. Journal of Information and Telecommunication, Vol. 6,

No. 2, pp. 217–235. DOI: 10.1080/24751839. 2021.1977066.

11. **Ikemoto, Y., Asawavetvutt, V., Kuwabara, K., Huang, H. H. (2019).** Tuning a conversation strategy for interactive recommendations in a chatbot setting. Journal of Information and Telecommunication, Vol. 3, No. 2, pp. 180–195. DOI: 10.1080/24751839.2018.1544818.

12. **Medrano-Berumen, C., Akbaş, M. I. (2021).** Validation of decision-making in artificial intelligence-based autonomous vehicles. Journal of Information and Telecommunication, Vol. 5, No. 1, pp. 83–103. DOI: 10.1080/24751839.2020.1824154.

13. **Afzal, M., Hussain, M., Hussain, J., Bang, J., Lee, S. (2021).** COVID-19 knowledge resource categorization and tracking: Conceptual framework study. Journal of Medical Internet Research, Vol. 23, No. 6. DOI: 10.2196/29730.

14. **Bogdan, R., Tatu, A., Crisan-Vida, M. M., Popa, M., Stoicu-Tivadar, L. (2021)**. A practical experience on the amazon Alexa integration in smart offices. Sensors (Switzerland), Vol. 21, No. 3, pp. 1–21. DOI: 10.3390/s21030734.

15. **Mhlanga, D. (2020).** Industry 4.0 in finance: the impact of artificial intelligence (ai) on digital financial inclusion. International Journal of Financial Studies, Vol. 8, No. 3, pp. 1–14. DOI: 10.3390/ijfs8030045.

16. **Rambe, P., Chipunza, C., Ng'ambi, D. (2020).** Using whatsapp for co-creation of learning resources: A case of a South African university. The Journal for Transdisciplinary Research in Southern Africa, Vol. 16, No. 1, pp. 1–16. DOI: 10.4102/td.v16i1.791.

17. **Drury, R. L., Jarczok, M., Owens, A., Thayer, J. F. (2021).** Wireless heart rate variability in assessing community COVID-19. frontiers in neuroscience, pp. 1–5. DOI: 10.33 89/fnins.2021.564159.

18. **Miedes-Ugarte, B., Flores-Ruiz, D., Wanner, P. (2020).** Managing tourist destinations according to the principles of the social economy: The case of the Les Oiseaux de Passage cooperative platform. Sustainability (Switzerland), Vol. 12, No. 12. DOI: 10.3390/su12124837.

19. **Sahoo, S., Halder, R. (2021).** Traceability and ownership claim of data on big data marketplace using blockchain technology. Journal of Information and Telecommunication, Vol. 5, No. 1, pp. 35–61. DOI: 10.1080/24751839.2020.1819634.

20. **Melluso, N., Bonaccorsi, A., Chiarello, F., Fantoni, G. (2020).** Rapid detection of fast innovation under the pressure of COVID-19. PLoS ONE, Vol. 15, No. 12, pp. 1–27. DOI: 10.1371/journal.pone.0244175.

21. **Osterhaus, A. D. M. E., Vanlangendonck, C., Barbeschi, M., Bruschke, C. J. M., Christensen, R., Daszak, P., de Groot, F., Doherty, P., Drury, P., Gmacz, S., Hamilton, K., Hart, J., Katz, R., Longuet, C., McLeay, J., Morelli, G., Schlundt, J., Smith, T., Suri, S., Wagenaar, J. A. (2020).** Make science evolve into a One Health approach to improve health and security: a white paper. One Health Outlook, Vol. 2, No. 1, pp. 1–33. DOI: 10.11 86/s42522-019-0009-7.

22. **Saeed, A., Ungureanu, V., Gfeller, B. (2021).** Sense and Learn: Self-supervision for omnipresent sensors. Machine Learning with Applications, pp. 100152. DOI: 10.1016/j.m lwa.2021.100152.

23. **Oyedele, A. O., Ajayi, A. O., Oyedele, L. O. (2021).** Machine learning predictions for lost time injuries in power transmission and distribution projects. Machine Learning with Applications, pp. 100158. DOI: 10.1016/j.ml wa.2021.100158.

24. **Amara, A., Hadj-Taieb, M. A., Ben-Aouicha, M. (2021)**. Network representation learning systematic review: Ancestors and current development state. Machine Learning with Applications, pp. 100130. DOI: 10.1016/j.ml wa.2021.100130.

25. **Singh, S., Sharma, A., Chauhan, V. K. (2021).** Online handwritten Gurmukhi word recognition using fine-tuned deep convolutional neural network on offline features. Machine Learning with Applications, pp. 100037. DOI: 10.1016/j.mlwa.2021. 100037.

26. **Amram, M., Dunn, J., Toledano, J. J., Zhuo, Y. D. (2021)**. Interpretable predictive maintenance for hard drives. Machine Learning with Applications, pp. 100042. DOI: 10.1016/j.mlwa.2021.100042.

27. **Saha, P., Sircar, R., Bose, A. (2021).** Using hospital admission, discharge & transfer (ADT) data for predicting readmissions. Machine Learning with Applications, pp. 100055. DOI: 10.1016/j.mlwa.2021.100055.

28. **Batarseh, F. A., Gopinath, M., Monken, A., Gu, Z. (2021)**. Public policymaking for international agricultural trade using association rules and ensemble machine learning. Machine Learning with Applications, pp. 100046. DOI: 10.1016/j.mlwa.2021. 100046.

29. **Ray, A., Chaudhuri, A. K. (2021).** Smart healthcare disease diagnosis and patient management: Innovation, improvement and skill development. Machine Learning with Applications, pp. 100011. DOI: 10.1016/j.mlwa.2020.100011.

30. **Nguyen, B., Coelho, Y., Bastos, T., Krishnan, S. (2021).** Trends in human activity recognition with focus on machine learning and power requirements. Machine Learning with Applications, pp. 100072. DOI: 10.1016/j.mlwa.2021.100072.

31. **Ott, J., Bruyette, D., Arbuckle, C., Balsz, D., Hecht, S., Shubitz, L., Baldi, P. (2021).** Detecting pulmonary coccidioidomycosis with deep convolutional neural networks. Machine Learning with Applications, pp. 100040. DOI: 10.1016/j.mlwa.2021.100040.

32. **Teague, S., Chahl, J. (2021).** Time series classification of radio signal strength for qualitative estimate of UAV motion. Machine Learning with Applications, pp. 100027. DOI: 10.1016/j.mlwa.2021.100027.

33. **Onah, J. O., Abdulhamid, S. M., Abdullahi, M., Hassan, I. H., Al-Ghusham, A. (2021).** Genetic algorithm-based feature selection and Naïve Bayes for anomaly detection in fog computing environment. Machine Learning with Applications, pp. 100156. DOI: 10.1016/j.mlwa.2021.100156.

34. **Higgins, D. C. (2021).** OnRAMP for regulating artificial intelligence in medical products. Advanced Intelligent Systems, Vol. 3, No. 11, pp. 2100042. DOI: 10.1002/aisy.202100042.

35. **Kim, U. H., Park, J. M., Song, T. J., Kim, J. H. (2020).** 3-D scene graph: A sparse and semantic representation of physical environments for intelligent agents. IEEE Transactions on Cybernetics, Vol. 50, No. 12, pp. 4921–4933. DOI: 10.1109/TCYB.2019. 2931042.

36. **Maddalena, E. T., Lian, Y., Jones, C. N. (2020).** Data-driven methods for building control — A review and promising future directions. Control Engineering Practice, Vol. 95, pp. 1–24. DOI: 10.1016/j.conengprac. 2019.104211.

37. **Song, Y., Liu, T., Wei, T., Wang, X., Tao, Z., Chen, M. (2021).** FDA3: Federated defense against adversarial attacks for cloud-based IIoT applications. IEEE Transactions on Industrial Informatics, Vol. 17, No. 11, pp. 7830–7838. DOI: 10.1109/TII.2020.3005969.

38. **Douer, N., Meyer, J. (2020).** The responsibility quantification model of human interaction with automation. IEEE Transactions on Automation Science and Engineering, Vol. 17, No. 2, pp. 1044–1060. DOI: 10.1109/TASE.2020.2965466.

39. **Tabatabai, D., Ajina, M., Nowzari, C. (2021).** Self-triggered distributed K-order coverage control. IEEE Transactions on Control of Network Systems, Vol. 8, No. 3, pp. 1059–1068. DOI: 10.1109/TCNS.2021.3074241.

40. **Pasquale, G., Ciliberto, C., Odone, F., Rosasco, L., Natale, L. (2019).** Are we done with object recognition? The iCub robot's perspective. Robotics and Autonomous Systems, Vol. 112, pp. 260–281. DOI: 10.1016/j.robot.2018.11.001.

41. **Çavdar, T., Günay, F. B., Ebrahimpour, N., Kakiz, M. T. (2022).** An optimal anchor placement method for localization in large-scale wireless sensor networks. Intelligent Automation and Soft Computing, Vol. 31, No. 2, pp. 1197–1222. DOI: 10.32604/iasc.2022. 020127.

42. **Cao, B., Zhao, J., Yang, P., Yang, P., Liu, X., Zhang, Y. (2019).** 3-D deployment optimization for heterogeneous wireless directional sensor networks on smart city. IEEE Transactions on Industrial Informatics, Vol. 15, No. 3, pp. 1798–1808. DOI: 10.1109/TII.2018.2884951.

43. **Taylor, A. T., Berrueta, T. A., Murphey, T. D. (2021).** Active learning in robotics: A review of control principles. Mechatronics, Vol. 77. DOI: 10.1016/j.mechatronics.2021.102576.

44. **Barik, R., Sridharan, M., Ramanathan, M. K., Chabbi, M. (2019)**. Optimization of swift protocols. Proceedings of the ACM on Programming Languages, 3 (OOPSLA). https://doi.org/10.1145/3360590.

45. **Greenberg, M., Blatt, A. J. (2020).** Executable formal semantics for the POSIX shell. Proceedings of the ACM on Programming Languages, 4 (POPL), pp. 1–30. DOI: 10.1145/3371111.

46. **Near, J. P., Darais, D., Abuah, C., Stevens, T., Gaddamadugu, P., Wang, L., Somani, N., Zhang, M., Sharma, N., Shan, A., Song, D. (2019).** Duet: An expressive higher-order language and linear type system for statically enforcing differential privacy. Proceedings of the ACM on Programming Languages, 3 (OOPSLA). DOI: 10.1145/3360598.

47. **Urban, C., Christakis, M., Wüstholz, V., Zhang, F. (2020).** Perfectly parallel fairness certification of neural networks. Proceedings of the ACM on Programming Languages, 4 (OOPSLA). DOI: 10.1145/3428253.

48. **Hameer, A., Pientka, B. (2019).** Teaching the art of functional programming using automated grading (experience report). Proceedings of the ACM on Programming Languages, 3 (ICFP). DOI: 10.1145/3341719.

49. **Atkinson, E., Carbin, M. (2020).** Programming and reasoning with partial observability. Proceedings of the ACM on Programming Languages, 4 (OOPSLA). DOI: 10.1145/3428268.

50. **Majumdar, R., Yoshida, N., Zufferey, D. (2020).** Multiparty motion coordination: From choreographies to robotics programs. Proceedings of the ACM on Programming Languages, 4 (OOPSLA). DOI: 10.1145/3428202.

51. **Atkinson, E., Baudart, G., Mandel, L., Yuan, C., Carbin, M. (2021).** Statically bounded-memory delayed sampling for probabilistic streams. Proceedings of the ACM on Programming Languages, 5 (OOPSLA). DOI: 10.1145/3485492.

52. **Muller, S. K., Hoffmann, J. (2021).** Modeling and analyzing evaluation cost of CUDA kernels. Proceedings of the ACM on Programming Languages, 5 (POPL). DOI: 10.1145/3434306.

53. **Iorga, D., Donaldson, A. F., Sorensen, T., Wickerson, J. (2021).** The semantics of shared memory in Intel CPU/FPGA systems. Proceedings of the ACM on Programming Languages, 5 (OOPSLA). DOI: 10.1145/3485497.

54. **Mukherjee, S., Deligiannis, P., Biswas, A., Lal, A. (2020).** Learning-based controlled concurrency testing. Proceedings of the ACM on Programming Languages, 4 (OOPSLA). DOI: 10.1145/3428298.

55. **Moreira, A. A., Ottoni, G., Quintão-Pereira, F. M. (2021).** VESPA: Static profiling for binary optimization. Proceedings of the ACM on Programming Languages, 5 (OOPSLA). DOI: 10.1145/3485521.

56. **Pitchanathan, A., Ulmann, C., Weber, M., Hoefler, T., Grosser, T. (2021).** FPL: Fast Presburger arithmetic through transprecision. Proceedings of the ACM on Programming Languages, 5 (OOPSLA). DOI: 10.1145/3485539.

57. **Chen, X., Yuan, Z., Cui, Z., Zhang, D., Ju, X. (2021).** Empirical studies on the impact of filter-based ranking feature selection on security vulnerability prediction. IET Software, Vol. 15, No. 1, pp. 75–89. DOI: 10.1049/sfw2.12006.

58. **Pereira, A., Trifan, A., Lopes, R. P., Oliveira, J. L. (2022).** Systematic review of question answering over knowledge bases. IET Software, Vol. 16, No. 1, pp. 1–13. DOI: 10.1049/sfw2.12028.

59. **Fard, M. V., Sahafi, A., Rahmani, A. M., Mashhadi, P. S. (2020).** Resource allocation

mechanisms in cloud computing: A systematic literature review. IET Software, Vol. 14, No. 6, pp. 638–653. DOI: 10.1049/iet-sen.2019.0338.

60. **Zhuo, Z., Cai, T., Zhang, X., Lv, F. (2021).** Long short-term memory on abstract syntax tree for SQL injection detection. IET Software, Vol. 15, No. 2, pp. 188–197. DOI: 10.1049/sfw2.12018.

61. **Akbar, M. A., Naveed, W., Mahmood, S., Rafi, S., Alsanad, A., Alsanad, A. A. A., Gumaei, A., Alothaim, A. (2021).** Prioritization of global software requirements' engineering barriers: An analytical hierarchy process. IET Software, Vol. 15, No. 4, pp. 277–291. DOI: 10.1049/sfw2.12022.

62. **Tsimpourlas, F., Rooijackers, G., Rajan, A., Allamanis, M. (2022).** Embedding and classifying test execution traces using neural networks. IET Software, Vol. 16, No. 3, pp. 301–316. DOI: 10.1049/sfw2.12038.

63. **Demi, S., Sanchez-Gordon, M., Colomo-Palacios, R. (2021).** What have we learnt from the challenges of (semi-) automated requirements traceability? A discussion on blockchain applicability. IET Software, Vol. 15, No. 6, pp. 391–411. DOI: 10.1049/sfw2.12035.

64. **Bhandari, G. P., Gupta, R. (2018).** Fault analysis of service-oriented systems: A systematic literature review. IET Software, Vol. 12, No. 6, pp. 446–460. DOI: 10.1049/iet-sen.2018.5249.

65. **Larrucea, X., Santamaría, I., Graña Romay, M. (2021).** Towards a privacy debt. IET Software, Vol. 15, No. 6, pp. 453–463. DOI: 10.1049/sfw2.12044.

66. **Mutanu, L., Kotonya, G. (2019).** State of runtime adaptation in service-oriented systems: what, where, when, how and right. IET Software, Vol. 13, No. 1, pp. 14–24. DOI: 10.1049/iet-sen.2018.5028.

67. **Zhao, J., Liu, Y. (2019).** APIUaaS: A reference architecture for facilitating API usage from a data analytics perspective. IET Software, Vol. 13, No. 5, pp. 466–478. DOI: 10.1049/iet-sen.2018.5355.

68. **Hidayah, I., Adji, T. B., Setiawan, N. A. (2019).** Development and evaluation of adaptive metacognitive scaffolding for algorithm-learning system. IET Software, Vol. 13, No. 4, pp. 305–312. DOI: 10.1049/iet-sen.2018.5072.

69. **Cerón-Figueroa, S., López-Martín, C., Yáñez-Márquez, C. (2020).** Stochastic gradient boosting for predicting the maintenance effort of software-intensive systems. IET Software, Vol. 14, No. 2, pp. 82–87. DOI: 10.1049/iet-sen.2018.5332.

70. **Li, Z., Jing, X. Y., Zhu, X. (2018).** Progress on approaches to software defect prediction. IET Software, Vol. 12, No. 3, pp. 161–175. DOI: 10.1049/iet-sen.2017.0148.

71. **Liu, Y., Yi, X., Chen, R., Zhai, Z., Gu, J. (2018).** Feature extraction based on information gain and sequential pattern for English question classification. IET Software, Vol. 12, No. 6, pp. 520–526. DOI: 10.1049/iet-sen.2018.0006.

72. **Abdelhamid, A. A., Alotaibi, S. R. (2021).** Adaptive multi-agent smart academic advising framework. IET Software, Vol. 15, No. 5, pp. 293–307. DOI: 10.1049/sfw2.12021.

73. **Chaintoutis, C., Akriotou, M., Mesaritakis, C., Komnios, I., Karamitros, D., Fragkos, A., Syvridis, D. (2019).** Optical PUFs as physical root of trust for blockchain-driven applications. IET Software, Vol. 13, No. 3, pp. 182–186. DOI: 10.1049/iet-sen.2018.5291.

74. **Ramanayaka, K. H., Chen, X., Shi, B. (2019).** Application of extent analysis FAHP to determine the relative weights of evaluation indices for library website usability acceptance model. IET Software, Vol. 13, No. 1, pp. 86–95. DOI: 10.1049/iet-sen.2018.5185.

75. **Unnikrishnan, S., Donovan, J., MacPherson, R., Tormey, D. (2020).** An integrated histogram-based vision and machine-learning classification model for industrial emulsion processing. IEEE Transactions on Industrial Informatics, Vol. 16, No. 9, pp. 5948–5955. DOI: 10.1109/TII.2019.2959021.

76. **Zhao, J., Liu, Y. (2019).** APIUaaS: A reference architecture for facilitating API usage from a data analytics perspective. IET Software, Vol. 13, No. 5, pp. 466–478. DOI: 10.1049/iet-sen.2018.5355.

77. **Escobar, C. A., McGovern, M. E., Morales-Menendez, R. (2021).** Quality 4.0: a review of big data challenges in manufacturing. Journal of Intelligent Manufacturing, Vol. 32, No. 8, pp. 2319–2334. DOI: 10.1007/s10845-021-01765-4.

78. **Khraisat, A., Alazab, A. (2021).** A critical review of intrusion detection systems in the internet of things: techniques, deployment strategy, validation strategy, attacks, public datasets and challenges. Cybersecurity, Vol. 4, No. 1. DOI: 10.1186/s42400-021-00077-7.

79. **Alzoman, R. M., Alenazi, M. J. F. (2021).** A comparative study of traffic classification techniques for smart city networks. Sensors, Vol. 21, No. 14, pp. 1–17. DOI: 10.3390/s21144677.

80. **Gauthama, G. R., Ahmed, C. M., Mathur, A. (2021).** Machine learning for intrusion detection in industrial control systems: challenges and lessons from experimental evaluation. Cybersecurity, Vol. 4, No. 1. DOI: 10.1186/s42400-021-00095-5.

81. **Hu, Y., Bai, F., Yang, X., Liu, Y. (2021).** IDSDL: a sensitive intrusion detection system based on deep learning. Eurasip Journal on Wireless Communications and Networking, Vol. 2021, No. 1. DOI: 10.1186/s13638-021-01900-y.

82. **van der Westhuizen, E., Kamper, H., Menon, R., Quinn, J., Niesler, T. (2022).** Feature learning for efficient ASR-free keyword spotting in low-resource languages. Computer Speech and Language, pp. 101275. DOI: 10.1016/j.csl.2021.101275.

83. **Resende, C., Folgado, D., Oliveira, J., Franco, B., Moreira, W., Oliveira-Jr, A., Cavaleiro, A., Carvalho, R. (2021).** TIP4.0: industrial internet of things platform for predictive maintenance. Sensors, Vol. 21, No. 14, pp. 4676. DOI: 10.3390/s21144676.

84. **Abdel-Karim, B. M., Pfeuffer, N., Hinz, O. (2021).** Machine learning in information systems - a bibliographic review and open research issues. Electronic Markets, Vol. 31, No. 3, pp. 643–670. DOI: 10.1007/s12525-021-00459-2.

85. **Flamis, G., Kalapothas, S., Kitsos, P. (2021).** Best practices for the deployment of edge inference: the conclusions to start designing. Electronics (Switzerland), Vol. 10, No. 16. DOI: 10.3390/electronics10161912.

86. **Kitchenham, B. A., Charters, S. (2007).** Guidelines for performing Systematic Literature Reviews in Software Engineering. pp. 1–57. https://www.researchgate.net/publication/302924724.

87. **Rejeb, A., Simske, S., Rejeb, K., Treiblmaier, H., Zailani, S. (2020).** Internet of things research in supply chain management and logistics: A bibliometric analysis. Internet of Things (Netherlands), Vol. 12. DOI: 10.1016/j.iot.2020.100318.

88. **Osegi, E. N., Jumbo, E. F. (2021).** Comparative analysis of credit card fraud detection in simulated annealing trained artificial neural network and hierarchical temporal memory. Machine Learning with Applications, pp. 100080. DOI: 10.1016/j.mlwa.2021.100080.

89. **Wee, C. K., Nayak, R. (2019).** A novel machine learning approach for database exploitation detection and privilege control. Journal of Information and Telecommunication, Vol. 3, No. 3, pp. 308–325. DOI: 10.1080/24751839.2019.1570454.

90. **Sharifi, A., Zibaei, A., Rezaei, M. (2021).** A deep learning based hazardous materials (HAZMAT) sign detection robot with restricted computational resources. Machine Learning with Applications, pp. 100104. DOI: 10.1016/j.mlwa.2021.100104.

91. **Yildiz, T. (2019).** Examining the concept of industry 4.0 studies using text mining and scientific mapping method. Procedia Computer Science, Vol. 158, pp. 498–507. DOI: 10.1016/j.procs.2019.09.081.

92. **Chai, J., Zeng, H., Li, A., Ngai, E. W. T. (2021).** Deep learning in computer vision: A critical review of emerging techniques and application scenarios. Machine Learning with

Applications, pp. 100134. DOI: 10.1016/j.mlwa.2021.100134.

93. **Salod, Z., Singh, Y. (2020).** A five-year (2015 to 2019) analysis of studies focused on breast cancer prediction using machine learning: A systematic review and bibliometric analysis. Journal of Public Health Research, Vol. 9, No. 1, pp. 65–75. DOI: 10.4081/jphr.2020.1772.

94. **Akbari, M., Do, T. N. A. (2021).** A systematic review of machine learning in logistics and supply chain management: current trends and future directions. Benchmarking, Vol. 28, No. 10, pp. 2977–3005. DOI: 10.1108/BIJ-10-2020-0514.

95. **Nair, R. S., Agrawal, R., Domnic, S., Kumar, A. (2021).** Image mining applications for underwater environment management - A review and research agenda. International Journal of Information Management Data Insights, Vol. 1, No. 2, pp. 100023. DOI: 10.1016/j.jjimei.2021.100023.

96. **Huang, J., Mao, L. X., Liu, H. C., Song, M. S. (2022).** Quality function deployment improvement: A bibliometric analysis and literature review. Quality and Quantity, Vol. 56, No. 3, pp. 1347–1366. DOI: 10.1007/s11135-021-01179-7.

97. **Kousis, A., Tjortjis, C. (2021).** Data mining algorithms for smart cities: A bibliometric analysis. Algorithms, Vol. 14, No. 8, pp. 242. DOI: 10.3390/a14080242.

98. **Udayakumar, S., Senadeera, D. C., Yamunarani, S., Cheon, N. J. (2018).** Demographics analysis of twitter users who tweeted on psychological articles and tweets analysis. Procedia Computer Science, Vol. 144, pp. 96–104. DOI: 10.1016/j.procs.2018.10.509.

99. **Monteiro, J., Barata, J. (2021).** Artificial intelligence in extended agri-food supply chain: A short review based on bibliometric analysis. Procedia Computer Science, Vol. 192, pp. 3020–3029. DOI: 10.1016/j.procs.2021.09.074.

100. **Hasan, M. M., Young, G. J., Patel, M. R., Modestino, A. S., Sanchez, L. D., Noor-E-Alam, M. (2021).** A machine learning framework to predict the risk of opioid use disorder. Machine Learning with Applications, pp. 100144. DOI: 10.1016/j.mlwa.2021.100144.