

# Systematic Literature Review on Convolutional Neural Networks for Vascular Surgeries

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Javier Gamboa-Cruzado<sup>1</sup>(✉), Michelle Rojas-Morales<sup>2</sup>, Jefferson López-Goycochea<sup>3</sup>, Enrique Condor Tinoco<sup>4</sup>, Guillermo Paucar-Carlos<sup>5</sup>, Anibal Sifuentes Damián<sup>6</sup>

<sup>1</sup>Universidad Nacional Mayor de San Marcos, Lima, Perú

<sup>2</sup>Universidad Nacional Federico Villareal, Lima, Perú

<sup>3</sup>Universidad de San Martín de Porres, Lima, Perú

<sup>4</sup>Universidad Nacional José María Arguedas, Andahuaylas, Perú

<sup>5</sup>Universidad Nacional de San Antonio Abad del Cuzco, Cuzco, Perú

<sup>6</sup>Universidad Nacional José Faustino Sánchez Carrión, Huacho, Perú

jgamboa65@hotmail.com

**Abstract**—The development of computer systems supported by convolutional neural networks that help the vascular surgeries represents an important deviation from traditional approaches like the performance of surgical intervention, either through tomography verification or the way a surgeon ceases to participate in this type of surgical interventions. A systematic review of Literature (SRL) on convolutional neural networks for using in vascular surgeries was done from 2016 to 2021. The search strategy identified 15505 papers from different search sources such as ACM Digital Library, EBSCOhost, Google Scholar, IEEE Xplore, MDPI, Microsoft Academic, ProQuest, ScienceDirect, Scopus, Springer, Web of Science, and Wiley Online Library, from which only 70 papers were selected based on exclusion criteria. The SRL is focused on recent studies on convolutional neural networks where their use in vascular surgeries has been shown. This SRL provides a mapping of all identified findings for the readers, it is a possible way to compare by relevance regarding their own settings and possible scenarios. Therefore, it is hoped that this research will help other researchers to understand the current status of Convolutional Neural Networks and their application in Vascular Surgeries.

**Keywords**—Convolutional Neural Networks, vascular surgeries, Artificial Intelligence (AI), Systematic Literature Review

## 1 Introduction

Surgical interventions at the vascular level with the use of convolutional neural network technologies reduce the preoperative mortality rate. Artificial intelligence (AI) and machine learning (ML) are influencing healthcare, diagnosis, monitoring, and therapeutics. Although the AI field comes from the 1950s, there has been a recent resurgence of AI in cardiovascular medicine, including in the area of heart failure (HF) [1][2].

Multiple studies have used AI and ML-based models to identify new risk markers for coronary artery disease, distinguish various clinical phenotypes in HF, and facilitate risk stratification measures derived from large clinical datasets to support decision making [3][4]. The advent of electronic medical records and of technological platforms such as Google, Amazon, and Apple for health care, as well as the scope of “big data” analytics, have generated a unique opportunity to involve medical practice [5].

As it is known, there is not any SRL that has focused on the application of convolutional neural networks in vascular surgeries. However, the work done that were useful to define the approach for the use of convolutional neural networks in vascular surgeries will be shown. It is worth mentioning that the RAj (Research Assistant) and Mendeley tools were a great help.

E. Mangina, A. Almakys, and A. Campbell. propose a free tool for the segmentation of medical image, and also discuss about the free available software to do the same function. MIPAV1, MeVisLab2, 3D Slicer, Seg3D, Caret, and ITK-SNAP are mentioned in the paper to discuss how the proposed tool differs from other software and it explains how it solves typical problems that occur during the segmentation process, for example, leakage during segmentation when parts of the segmentation leak into the nearest structures. The tools kit also provides interpolation, which is used to speed up the segmentation process, particularly when it works with many slices. The software provides this as a suggestion that can be undone, if necessary, a functionality that is not implemented in other tools [6].

On the other hand, A. Fantazzini *et al.* describe in detail a method to reconstruct the abdominal aortic aneurysm (AAA) geometry applying images of Computed tomography (CT), trying to use economic resources and perform minimal user interventions. MATLAB was used to reconstruct the geometry through the implementation of the active contour technique to segment the focused region. The study describes another method used to segment the wall that involved the use of another snake (tool) with a rigid surface. The study says that the use of the SVM for smoothing the model ensures the curvature continuity, which is important for the development of automated and smooth meshes [7]. The objective of this systematic literature review (SLR) is to determine the worldwide progress of practical applications of convolutional neural networks in vascular surgeries in the last five years.

## 2 Review methodology

The applied review methodology centered its basis on the guidelines defined by Kitchenham [8] and considered for this SRL. For this reason, there have been defined research problems and objectives, search sources, search strategies, exclusion criteria, quality criteria, data extraction and synthesis (Figure 1).

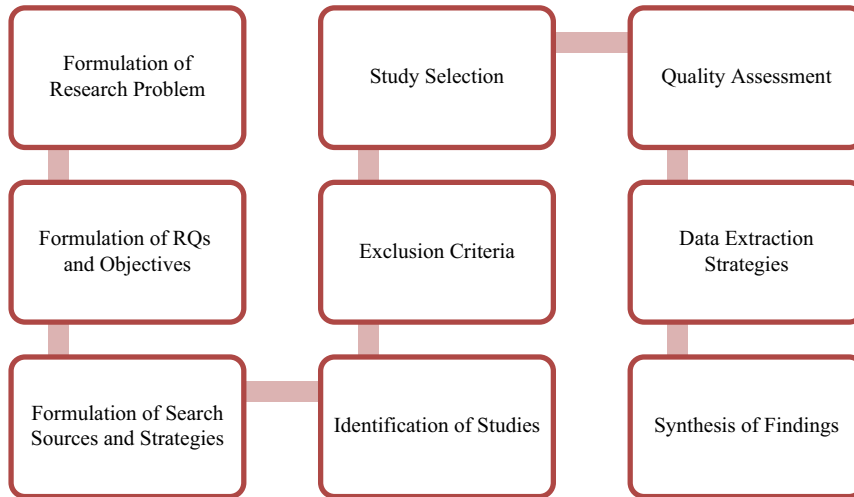


Fig. 1. Stages of a systematic literature review

### 2.1 Research problems and objectives

For this SRL, it is set the research questions; these have a fundamental role in the elaboration of the search strategy, then to do the extraction and synthesis of the data obtained. At formulating the research questions, the objectives of each question were acknowledged as shown in Table 1.

Table 1. Research questions and objectives

Research Questions	Objectives
RQ1: Who are the most productive authors related to vascular surgery research with the application of new technologies?	To identify the most productive authors researching on vascular surgeries with the application of new technologies.
RQ2: In which countries is scientific research on the topic being published?	To know the countries where scientific research on the topic is being published.
RQ3: What keywords co-occur in the research on convolutional neural networks and their influence on vascular surgeries?	To identify keywords that co-occur in research on convolutional neural networks and their influence on vascular surgeries.
RQ4: Which type of computational support exists for the use of convolutional neural networks in vascular surgery (framework or programming language)?	To identify which existing computational support exists for the use of convolutional neural networks in vascular surgery (framework or programming language).

### 2.2 Search sources and search strategy

The twelve selected search sources, which are repositories of a wide variety of scientific papers, are as follows: ACM Digital Library, EBSCOhost, Google Scholar, IEEE Xplore, MDPI, Microsoft Academic, ProQuest, ScienceDirect, Scopus, Springer, Web of Science, and Wiley Online Library.

Table 2 shows different search sources with their respective search equations.

**Table 2.** Sources and search equation

Source	Search Equation
ACM Digital Library	[[All: “convolutional neural network*”] OR [All: “neuronal network*”] OR [All: “artificial intelligence”] OR [All: “machine learning”] OR [All: “big data”]] AND [[All: methodology] OR [All: method] OR [All: model]] AND [[All: “vascular surgery”] OR [All: “vascular operation”]]
EBSCOhost	TX (“convolutional neural network*” OR “neuronal network*” OR “artificial intelligence” OR “machine learning” OR “big data”) AND TX (methodology OR method OR model) AND TX (“vascular surgery” OR “vascular operation”)
Google Scholar	(“convolutional neural networks” OR “neuronal networks” OR “artificial intelligence” OR “machine learning” OR “big data”) AND (methodology OR method OR model) AND (“vascular surgery” OR “vascular operation”)
IEEE Xplore	(“All Metadata”.:“convolutional neural network*” OR “All Metadata”.:“neuronal network*” OR “All Metadata”.:“artificial intelligence” OR “All Metadata”.:“machine learning” OR “All Metadata”.:“big data”) AND (“All Metadata”.: methodology OR “All Metadata”.: method OR “All Metadata”.: model) AND (“All Metadata”.:“vascular surgery” OR “All Metadata”.:“vascular operation”)
MDPI	(“convolutional neural network*” OR “neuronal network*” OR “artificial intelligence” OR “machine learning” OR “big data”) AND (methodology OR method OR model) AND (“vascular surgery” OR “vascular operation”)
Microsoft Academic	(“convolutional neural network” OR “neuronal network” OR “artificial intelligence” OR “machine learning” OR “big data”) AND (methodology OR method OR model) AND (“vascular surgery” OR “vascular operation”)
ProQuest	(“convolutional neural network” OR “neuronal network” OR “artificial intelligence” OR “machine learning” OR “big data”) AND (methodology OR method OR model) AND (“vascular surgery” OR “vascular operation”)
ScienceDirect	(“convolutional neural network” OR “neuronal network” OR “artificial intelligence” OR “machine learning” OR “big data”) (methodology OR method OR model) (“vascular surgery” OR “vascular operation”)
Scopus	(ALL (“convolutional neural network*” OR “neuronal network*” OR “artificial intelligence” OR “machine learning” OR “big data”) AND ALL (methodology OR method OR model) AND ALL (“vascular surgery” OR “vascular operation”))
Springer	(“convolutional neural network*” OR “neuronal network*” OR “artificial intelligence” OR “machine learning” OR “big data”) AND (methodology OR method OR model) AND (“vascular surgery” OR “vascular operation”)
Web of Science	(“convolutional neural network*” OR “neuronal network*” OR “artificial intelligence” OR “machine learning” OR “big data”) (All Fields) and (methodology OR model OR method) (All Fields) and (“vascular surgery” OR “vascular operation”) (All Fields)
Wiley Online Library	(“convolutional neural network*” OR “neuronal network*” OR “artificial intelligence” OR “machine learning” OR “big data”) anywhere and (“methodology OR method OR model”) anywhere and (“vascular surgery” OR “vascular operation”) anywhere

### 2.3 Identified studies

Once the search equations have been applied in their respective search engines, the quantity of studies identified in each search source is disclosed.

### 2.4 Selection criteria

Nine exclusion criteria allowed selecting the articles that fit the needs of this research:

- EC1: Papers are more than 5 years old.
- EC2: Papers are not written in English OR Spanish language
- EC3: Documents are not papers
- EC4: Papers were not published in conferences OR peer-reviewed journals.
- EC5: Papers do not mention a methodology, model, or method.
- EC6: Papers do not have a title or keywords or abstract related to our criteria.
- EC7: Papers are not unique
- EC8: The proposed solution does not apply to convolutional neural networks OR neural networks OR artificial intelligence OR machine learning OR big data
- EC9: Papers do not propose a solution related to vascular surgery.

### 2.5 Studio selection

Initially, a total of 15505 articles were obtained from all the search sources. After applying the stages of the PRISMA graph, 70 papers were obtained (Figure 2).

### 2.6 Quality assessment

After selecting the papers, the quality assessment criteria known as QAs were applied to evaluate the papers obtained. In this SRL, six quality assessment criteria are considered:

- QA1: Does the paper consider pure research?
- QA2: Is there a possibility to consult the researcher?
- QA3: Does the research detail how the sample extraction was conducted?
- QA4: Are the methods used to analyze the results appropriate?
- QA5: Is the full text of the document available?
- QA6: Are the research objectives clearly identified in the document?

The authors reviewed methodically each article to certify quality. They evaluated each article based on each of the QAs, thus they verified the quality of the initial 70 studies.

The impact factor of the publication media of these articles, in Web of Science (JIF) are: *Predicting Future Cardiovascular Events in Patients with Peripheral Artery Disease Using Electronic Health Record Data* (5.882), *Fully automatic volume segmentation of infrarenal abdominal aortic aneurysm computed tomography images with deep learning approaches versus physician controlled manual segmentation* (4.268), *CNN-G: Convolutional Neural Network Combined with Graph for Image Segmentation*

with *Theoretical Analysis* (3.379), *Machine Learning to Predict the Rapid Growth of Small Abdominal Aortic Aneurysm* (1.826), *Using multiple classifiers for predicting the risk of endovascular aortic aneurysm repair re-intervention through hybrid feature selection* (1.617), among others; and for Scopus (SJR): *Deep-learned placental vessel segmentation for intraoperative video enhancement in fetoscopic surgery* (1.0), *Machine Learning Offers Exciting Potential for Predicting Postprocedural Outcomes: A Framework for Developing Random Forest Models in IR* (0.91), *Effective blood vessels reconstruction methodology for early detection and classification of diabetic retinopathy using OCTA images by artificial neural network* (0.79), *3D Automatic Segmentation of Aortic Computed Tomography Angiography Combining Multi-View 2D Convolutional Neural Networks* (0.53), *Clinical management of cardiovascular care on the basis of big Data: Electronic medical records* (0.21), etc.

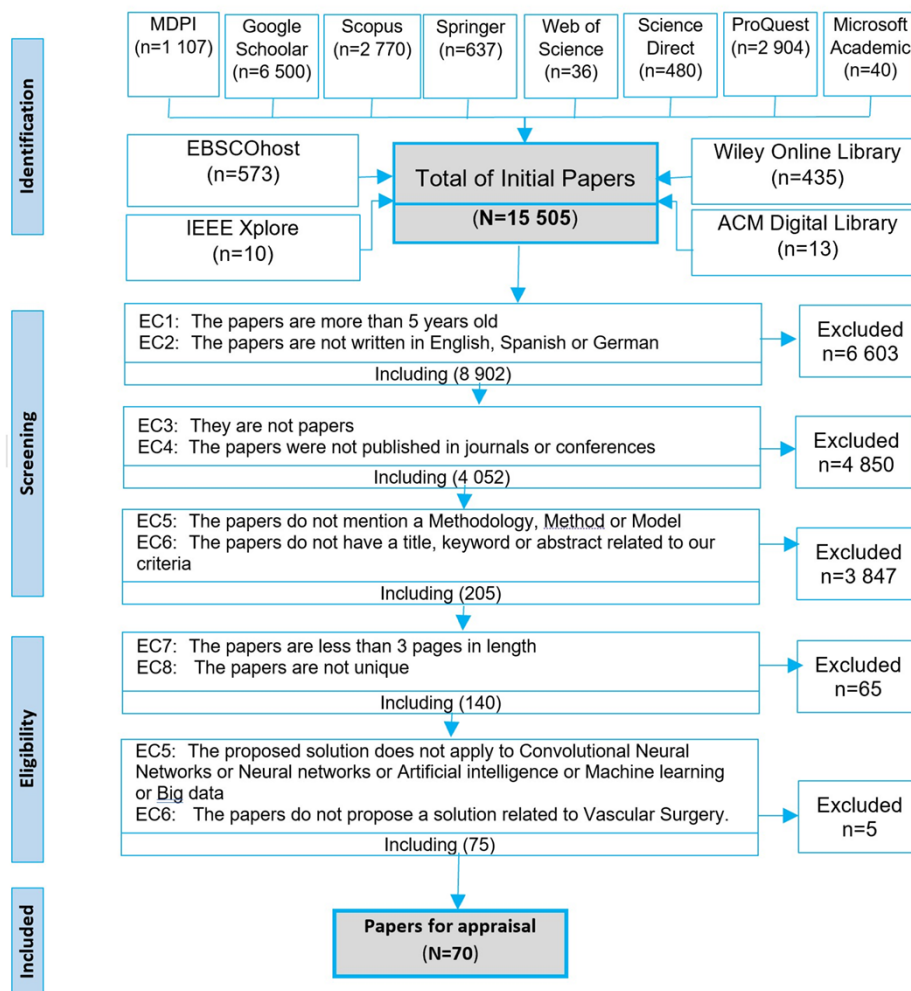


Fig. 2. PRISMA chart to obtain the items to be reviewed

## 2.7 Strategies of data extraction

From the final studies, relevant information was extracted to respond to each RQ in Table 1. The information of each paper, which aids in answering the RQs, refers to the following: Article reference ID, title, URL, search source, year of publication, authors' country, number of pages, language, publication type, publication name, research methodology, authors, affiliations, number of citations, summary or abstract, keywords, paper body, discussion and/or conclusion, the size of the sample, and pages that aid in answering each RQ. It should be noted that not all papers helped in answering the different RQs.

## 2.8 Synthesis of findings

The information extracted to answer the RQs was tabulated and presented as quantitative and qualitative data, they were used to produce a statistical parity between the various data answering each RQ. The statistical results helped to identify the research patterns during the last five years.

# 3 Results and discussion

## 3.1 General description of studies

During the selection process, 70 studies were obtained, from which data were extracted to perform the statistical analysis. Figure 3 shows the distribution of studies by source from 2016 to 2021, considering 2019 as the year with the most published articles related to the central topic of convolutional neural networks for vascular surgeries.

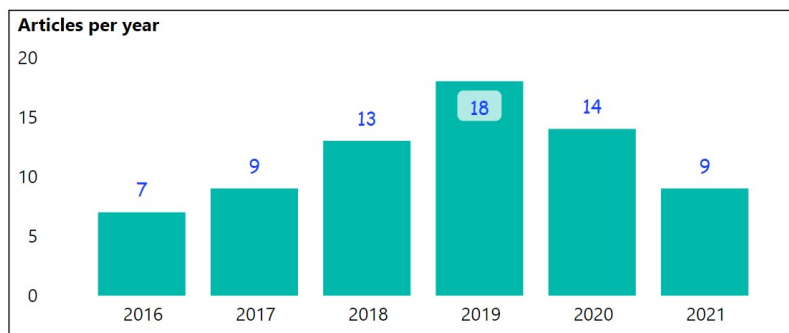


Fig. 3. Distribution of papers by year

According to J. Raffort *et al.*, in their paper “Fundamentals in Artificial Intelligence for Vascular Surgeons” [9], they argue that there is an increasing interest in AI applications in medicine, covering all medical and surgical specialties. While many publications are available on the topic related to cancerology, radiology, cardiology, or even neurology, AI is less reported for vascular disease management. However, the increase

in AI-related publications for vascular diseases has been estimated at 147% over a 17-year evaluation period (2000–2016), which suggest real potential for future use in medical practice.

Of the 13 sources used for the study, 20% of the papers were obtained from Science Direct and another 20% from Springer, both search sources are the ones that contributed the most to this SRL, followed by Google Scholar and Web of Science with a percentage of 11.43% respectively (See Figure 4).

According to S. Bodenstedt *et al.*, in their paper “Artificial Intelligence-Assisted Surgery: Potential and Challenges” [10], agree that ScienceDirect, Springer, and Web of Science are among the top productive sources for answering RQs due to the large number of quality papers that can be found, and its ability to enable the application of various filters.

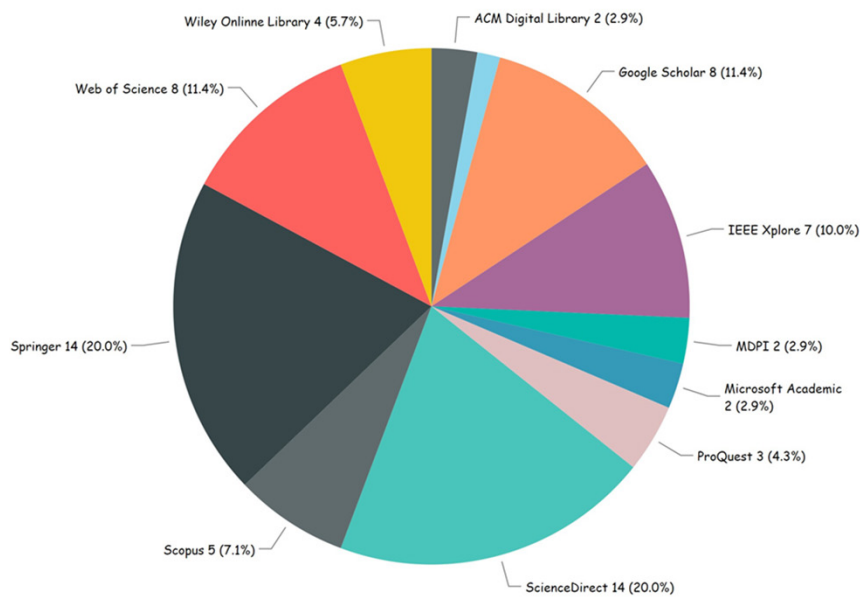


Fig. 4. Percentage of papers by source

### 3.2 Answers to research questions

*RQ1: Who are the most productive authors in research of vascular surgery with the application of new technologies?*

According to the results, Table 3 shows a list of the most productive authors, i.e., those with the most published papers on the use of new technologies in vascular surgery, where Michael W. Gee is the most productive author with five papers: “A methodology for in silico endovascular repair of abdominal aortic aneurysms” [11], “Patient-specific



in silico endovascular repair of abdominal aortic aneurysms: application and validation” [12], “In silico study of vessel and stent-graft parameters on the potential success of endovascular aneurysm repair” [13], “Probabilistic noninvasive prediction of wall properties of abdominal aortic aneurysms using Bayesian regression” [14], and “Bio-mechanical rupture risk assessment of abdominal aortic aneurysms using clinical data: A patient-specific, probabilistic framework and comparative case-control study” [15]. Christian Reeps follows as the second most productive author with four published papers.

**Table 3.** Authors with the most published papers

Authors	2016	2017	2018	2019	2020	2021	Total
Michael W. Gee	1		1	2	1		5
Christian Reeps	1		1	2			4
André Hemmler			1	2			3
Brigitta Lutz			1	2			3
Cédric Adam				1	1	1	3
Fabien Lareyre				1	1	1	3
Jinxin Cui				2	1		3
Juliette Raffort				1	1	1	3
Marion Carrier				1	1	1	3
Shuxiang Guo				2	1		3
Yan Zhao				2	1		3
Yuxin Wang				2	1		3
Ainhoa García Familiar	1	1					2
Ali Alaraj	1	1					2
Andreas Linninger	1	1					2
Celia Riga			2				2
Chih-Yang Hsu	1	1					2

According to D. C. Sutzko *et al.*, in their paper “Big data in vascular surgery: registries, international collaboration and future directions” [16], indicate in their research that Alexander Behrendt is the most productive author, with four published papers.

And G. Litjens *et al.*, in their paper “State-of-the-Art Deep Learning in Cardiovascular Image Analysis” [17] hold Jelmer Wolterink as the most productive author between the years 2014 and 2019, having conducted extensive research regarding the use of artificial intelligence in 3D modeling of surgical procedures.

For more detail, Figure 5 shows co-authorship in primary studies, where Michael Gee and Christian Reeps had a co-authorship relationship in four investigations.

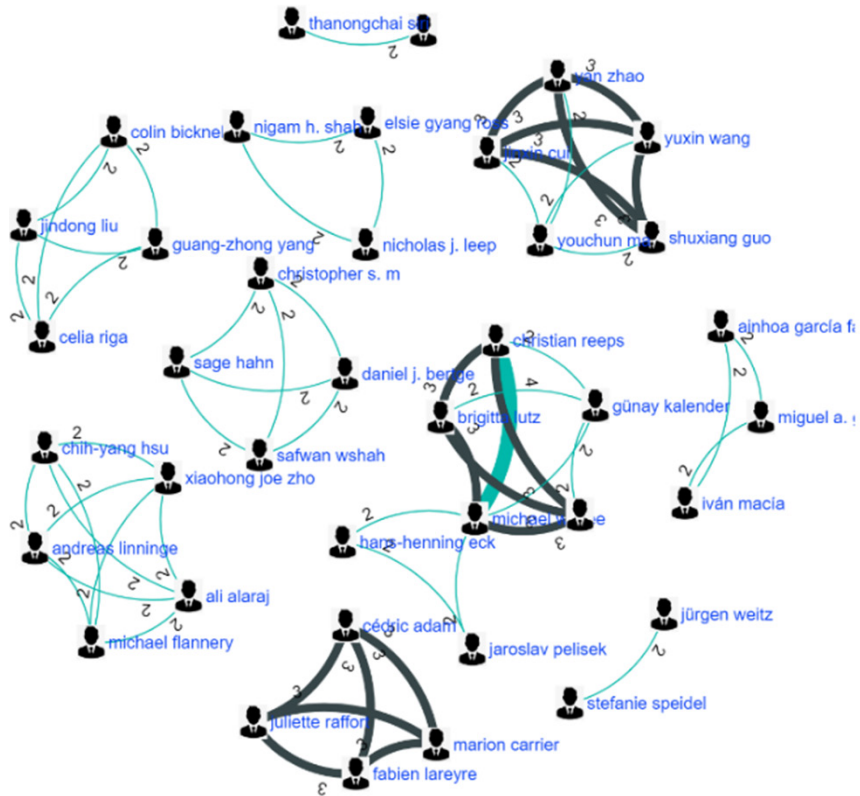


Fig. 5. Bibliometric co-author networks

According to A. A. Gumbs, *et al.*, in their paper “Artificial intelligence surgery: How do we get to autonomous actions in surgery?” [18], argue that Croner and Elie Chouillard are the most productive and most cited authors with a total of nine papers.

Among the authors analyzed, it was found that those with the most published papers, such as Michael W. Gee (5 papers), Christian Reeps (4 papers) and André Hemmler (3 papers) are those with a strong coordination in their production, as shown in the bibliometric network. It is relevant for those authors who want to develop applications of Convolutional Neural Networks for vascular surgery or other health topics to do so jointly with other researchers.

*RQ2: In which countries is scientific research on the topic being published?*

Figure 6 shows the countries that have published articles, and the greater the circumference radius, the greater the number of papers published. At a first glance, the US is the country with the largest number of published papers.

For more detail, on the right side of the figure shows the number of articles published by country, where the US confirmed the highest number of papers published, with 18 papers; in second place is Germany with 14 papers, and in third place is the United Kingdom with 10 papers.

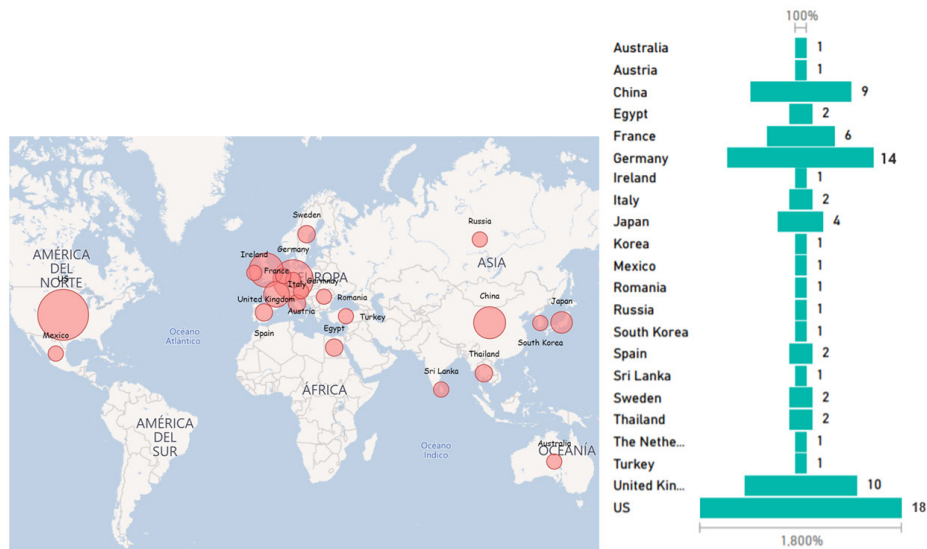


Fig. 6. Georeferential map of countries with published papers

According to J. Raffort *et al.*, in their paper “Fundamentals in Artificial Intelligence for Vascular Surgeons” [9], agree with our results by claiming that at the end of 2018, in the Web of Science database, the most prolific countries regarding AI-related research in health and medicine were the United States with 30.8%, followed by China, European countries, and India. In addition, they comment that Western countries appear to have a clinical focus on projects targeting specific diseases such as cancer or cardiovascular diseases. On the other hand, low- and middle-income countries develop applications aimed at the public health sector.

According to J. T. Senders *et al.*, in their paper “An introduction and overview of machine learning in neurosurgical care” [20], claim that China is the country with the highest number of publications, with 31 papers published between the years 2014 and 2019.

On the other hand, P. Sardar, *et al.*, in their paper “Impact of artificial intelligence on interventional cardiology: From decision-making aid to advanced interventional procedure assistance” [21], state that India is the country with the largest number of research papers on software development related to ML, deep learning, convolutional neural networks, and AI technologies in the medical field.

The practical utility that other researchers can give to these results is that they should review the practical research carried out in the United States, Germany, the United Kingdom or China, as these are the countries with the greatest production and experience in the application of Convolutional Neural Networks for vascular surgery, and thus be able to apply them to other projects in health or in other business sectors.

*RQ3: What keywords co-occur in the research on convolutional neural networks and their influence on vascular surgeries?*

Figure 7 shows a bibliometric network of the keywords that co-occur in the research on convolutional neural networks and their influence on vascular surgeries.

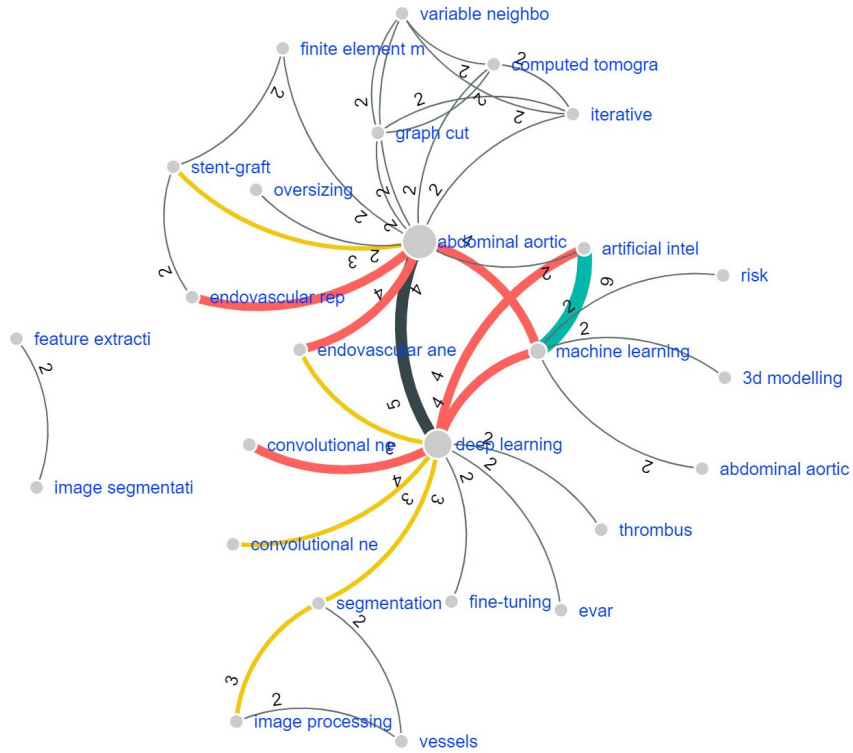
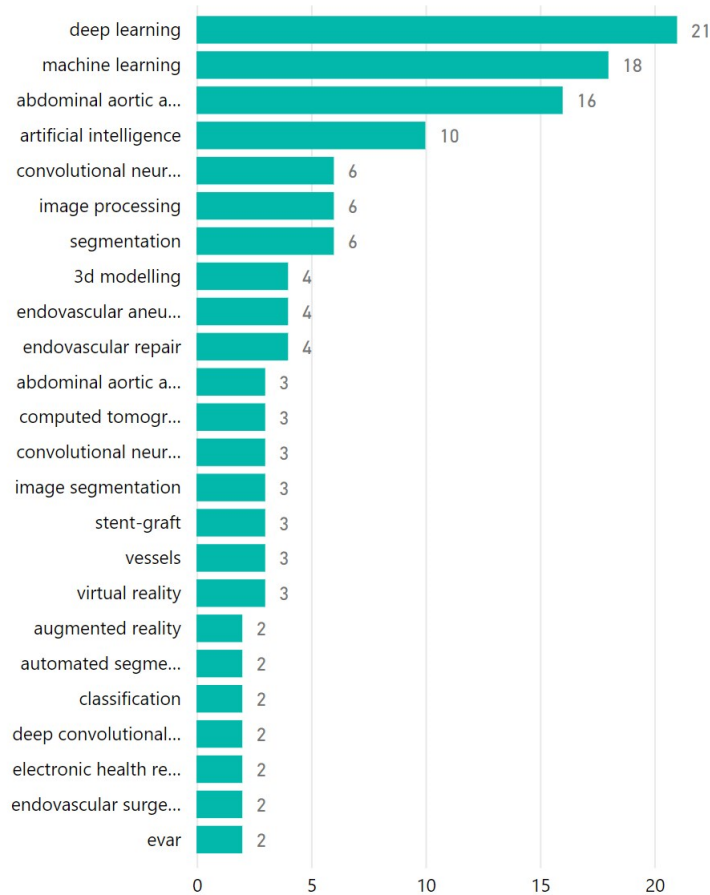


Fig. 7. Bibliometric network of co-occurring keywords in studies

For more details, Figure 8 shows the number of repetitions for each keyword.



**Fig. 8.** Keyword repetitions

According to C. Krittanawong, *et al.*, “Artificial intelligence in precision cardiovascular medicine” [22], “convolutional neural network” and “deep learning” were the most repeated words in the studies they carried out, coinciding with our study. Other words co-occur in both papers, although in fewer cases.

According to B. J. Park, *et al.*, in their paper “Augmented and mixed reality: Technologies for enhancing the future of IR” [23], observed in their studies words related to the AI field, but these were not classified because of their co-occurrence in the research.

According to A. A. Gumbs, *et al.*, in their paper “Artificial intelligence surgery: How do we get to autonomous actions in surgery?” [18], in most of their research, they found software developments capable of segmentation of image in which a deep learning process for the creation of a 3D modeling was performed.

The reviewed literature has allowed to determine that the most used keywords such as “deep learning”, “machine learning”, “abdominal aortic”, “artificial intelligence” should be used by researchers when consulting practical research in order to help them

carry out applications of Convolutional Neural Networks for vascular surgeries or in other projects in health or other business sectors.

*RQ4: What are the programming languages for developing convolutional neural networks?*

Table 4 shows the programming languages used to develop convolutional neural networks, of which R project, Python, Java, JavaScript, and C# have been identified. For each one, the papers that have referenced them, indicate the application of that programming language.

**Table 4.** Programming languages for developing convolutional neural networks

Programming Language	Reference	Quantity (%)
R Project	[6] [25] [77] [86] [74] [30] [36] [5] [39] [47] [48] [55] [65] [15] [72]	15 (27.3)
Python	[7] [73] [13] [80] [86] [42] [1] [24] [61] [67] [68] [72]	12 (21.8)
JavaScript (JS)	[71] [25] [3] [35] [69] [70]	6 (10.9)
C#	[48]	1 (1.8)
Node JS	[38] [71] [78] [75] [11] [12] [26] [30] [31] [33] [5] [40] [42] [47] [48] [52] [59] [61] [64] [69] [70]	21 (38.2)

The R language has been identified with the highest number of research references between the years 2016 and 2021 with 23 references, followed by Python with 12 references.

According to F. Lareyre, *et al.*, in their article “Automated segmentation of the human abdominal vascular system using a hybrid approach combining expert system and supervised deep learning” [24], say that Python programming language provides a greater impact on the early diagnosis of the development of an AAA.

On the other hand, K. López-Linares, *et al.*, in their paper “3D convolutional neural network for abdominal aortic aneurysm segmentation” [25], developed a convolutional neural network that helps the image segmentation using R and JavaScript programming languages.

According to Y. Lu, *et al.* in their paper “CNN-G: Convolutional neural network combined with graph for image segmentation with theoretical analysis” [26], say that the NodeJS language provides learning facilities for a higher probability of diagnosing cardiovascular diseases.

As can be seen from the results obtained, the programming languages most commonly used in successful neural convolutional neural network solutions for vascular surgery are: R Project, Python and JavaScript (JS) which should be considered for new Convolutional Neural Networks projects in other areas of health or other organizational sectors.

## 4 Conclusion

This SRL provides a statistical analysis on the use of convolutional neural networks in vascular surgeries by extracting data from 70 published studies in 2016. Most identified studies were found in ScienceDirect, Springer, Google Scholar, Web of Science, IEEE, and Scopus. In terms of the number of publications by country, the United States (US) has the highest number of published papers with 18 papers, followed by Germany with 14 papers, and the United Kingdom with 10 papers. Regarding co-occurrence of keyword, it is observed that deep learning and ML have the greatest co-occurrence in this study.

Regarding the programming languages used for the development of convolutional neural networks, R, Python, Java, JavaScript, and C# were found, being R project the most used. For future research, state and private organizations should promote scientific research by using technologies such as convolutional neural networks, deep Learning, ML, among other learning techniques to start a disruptive change from traditional approaches.

This research has a main limitation, it is known that the publications with the most significant impact belong to Q1 quartile or Q2; however, this detail has not been considered. This research aims to motivate future research can consider the inclusion of this information.

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## 6 Authors

**Dr. Javier Gamboa-Cruzado** works at the Faculty of Systems Engineering of the Universidad Nacional Mayor de San Marcos, Lima, Peru. He is Doctor in Systems Engineering and Doctor in Administrative Sciences. He has published several articles in international journals and conferences. His research interests are in machine learning, big data, the internet of things, natural language processing, and business intelligence (email: [jgamboa65@hotmail.com](mailto:jgamboa65@hotmail.com)).

**Michelle Rojas-Morales** is graduate of the Faculty of Industrial and Systems Engineering of the Federico Villarreal National University, Peru. His research interests are in web systems, parallel computing, and big data (email: [giovanni.rm.unfv@gmail.com](mailto:giovanni.rm.unfv@gmail.com)).

**Dr. Jefferson López-Goycochea** works at the Faculty of Engineering and Architecture of the Universidad de San Martín de Porres, Perú. He is Doctor in Education and a PhD candidate in Information Systems Engineering, he is Industrial Engineer and has a Master’s degree in Computer and Systems Engineering. His research interests are in cloud computing, knowledge management, and machine learning (email: [jlopezg@usmp.pe](mailto:jlopezg@usmp.pe)).

**Mg. Enrique Condor Tinoco** works at the Faculty of Engineering of the Universidad José María Arguedas, Apurímac, Peru. He is a Systems Engineer and has a Master’s Degree in Teaching at the Higher Level. He has published articles in international journals and conferences. His research interests are business intelligence, business process learning, the internet of things, and blockchain (email: [enricoti@unajma.edu.pe](mailto:enricoti@unajma.edu.pe)).

**Dr. Guillermo Paucar-Carlos** works at the Department of Mathematics and Statistics of the National University of San Antonio Abad del Cusco, Cusco, Peru. He is a Doctor in Mathematical Statistics, he has published some scientific articles in the International Business Information Management Association. His research is in data science and data mining (email: [guillermo.paucar@unsaac.edu.pe](mailto:guillermo.paucar@unsaac.edu.pe)).

**Mg. Anibal Sifuentes Damián** works at the Faculty of Sciences of the José Faustino Sánchez Carrión National University, Huacho, Huaura, Lima, Peru. He has a Master’s in Economics with a mention in Business Management. He has published several articles in magazines and national conferences. His research interests are machine learning, elaboration of socio-economic and demographic indicators (email: [anibalpsd@gmail.com](mailto:anibalpsd@gmail.com)).

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