April 2021

A Brief Bibliometric Survey of Explainable AI in Medical Field

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ABSTRACT

Background: This study aims to analyze the work done in the field of explainability related to artificial intelligence, especially in the medical field from 2004 onwards using the bibliometric methods.

Methods: different articles based on the topic leukemia detection were retrieved using one of the most popular database- Scopus. The articles are considered from 2004 onwards. Scopus analyzer is used for different types of analysis including documents by year, source, county and so on. There are other different analysis tools such as VOSviewer Version 1.6.15. This is used for the analysis of different units such as co-authorship, co-occurrences, citation analysis etc.

Results: In our study, the Scopus search has the outcome of a total of 91 articles on explainability of AI from 2004 onwards. The topic is so popular and is newly introduced. The maximum articles are published in the year 2020. Computer science area contributed the largest number of articles of 37% and United states contributed most of the articles in the field. Network analysis of different parameters shows a good potential of the topic in terms of research.

Conclusions: Scopus keyword search outcome has 91 articles with English language having the largest number of 90 and one is contributed in German language. Authors, documents, country, affiliation etc are statically analyzed and indicates the potential of the topic. Network analysis of different parameters indicates that, there is a lot of scope to contribute in the further research in terms of explainability in medical fields including diagnosis in imaging. There are advanced algorithms of computer vision, deep learning and machine learning are utilized in medical diagnosis as far as imaging is concerned. Explainable AI

frameworks will prove to increase the trustability in medical diagnosis.

Keywords: medical imaging, explainability, artificial intelligence, AI, citation, co-occurrence

I. INTRODUCTION

1.1 Major diagnosis techniques in medical imaging

1. X-ray imaging
2. Magnetic resonance imaging (MRI)
3. Computer tomography (CT)
4. Ultrasound imaging
5. Microscopic imaging

These are the imaging techniques used for the detection of a particular abnormality in the human body. The abnormality may be related to a particular organ also. The detection and diagnosis is always very critical as far as the imaging techniques are concerned. It requires a very trained and experienced radiologist or pathologist in this case.

There are many software frameworks for detection and diagnosis of abnormalities via medical imaging. MRI [36][38] and CT are used for different abnormalities related to brain, spinal cord and other organs. Ultrasound is also popular technique that detects the existence of abnormalities in different parts of the body. Popular organs include liver, kidney, abdomen etc. Moreover, microscopic imaging is very popular as it observes the images under microscope. This is generally popular for blood analysis by suing different morphological features [1-3]. Different cancerous tissues could be observed after the biopsies of a particular organ via microscope examination [21][25][41][51]. Various diseases could cause the blood parameters to change their morphologies, counts and other features. Microscopic examination of blood cells could give various ailments attack on human body. Different viral diseases such as, leukemia[4-8][12][14-15][20][29][31-34], sickle cell disease[16-18], blood cell detection and counting[13][22][26-27] could be detected by this examination.

1.2 Requirement of automated techniques

Although, there are a number of techniques for disease detection via medical imaging, the decision is crucial many times. So there is a need to have an automated framework for the detection and diagnosis purposes. There are different automated frameworks employing machine learning, deep learning, computer vision and image processing algorithms for detection of different diseases via medical imaging.

1.3 Unexplainable Nature: of the popular machine learning and deep learning is a challenge in many ways. Due to lack of explanation of what actually happens inside the classifier such as CNN, it is of very lesser use for commercial purposes. The classifiers are generally considered to be black-boxes as far as there training and output results are concerned [43][50]. So there nay the correct decision due to wrong inputs or wrong interpretation by classifier.

1.4 Explainable AI: This can play a very important role in these kinds of cases, especially diagnosis decision s in medical imaging. There are 3 stages in Explainable AI as shown in figure 1. Stage 1 consists of explainable building process. A stage 2 is the explainable decisions and stages 3 is the process of explainable decisions [35][37][42] [44-49][52]. There are many popular frameworks of explainable AI including SHAP, LIME, etc. These frameworks can explain how the decision of diagnosis is been taken by any of the deep leering and machine learning algorithms. This area is very popular in the research now a day. So the same area database is analyzed and the potential of research is explored in the same area.

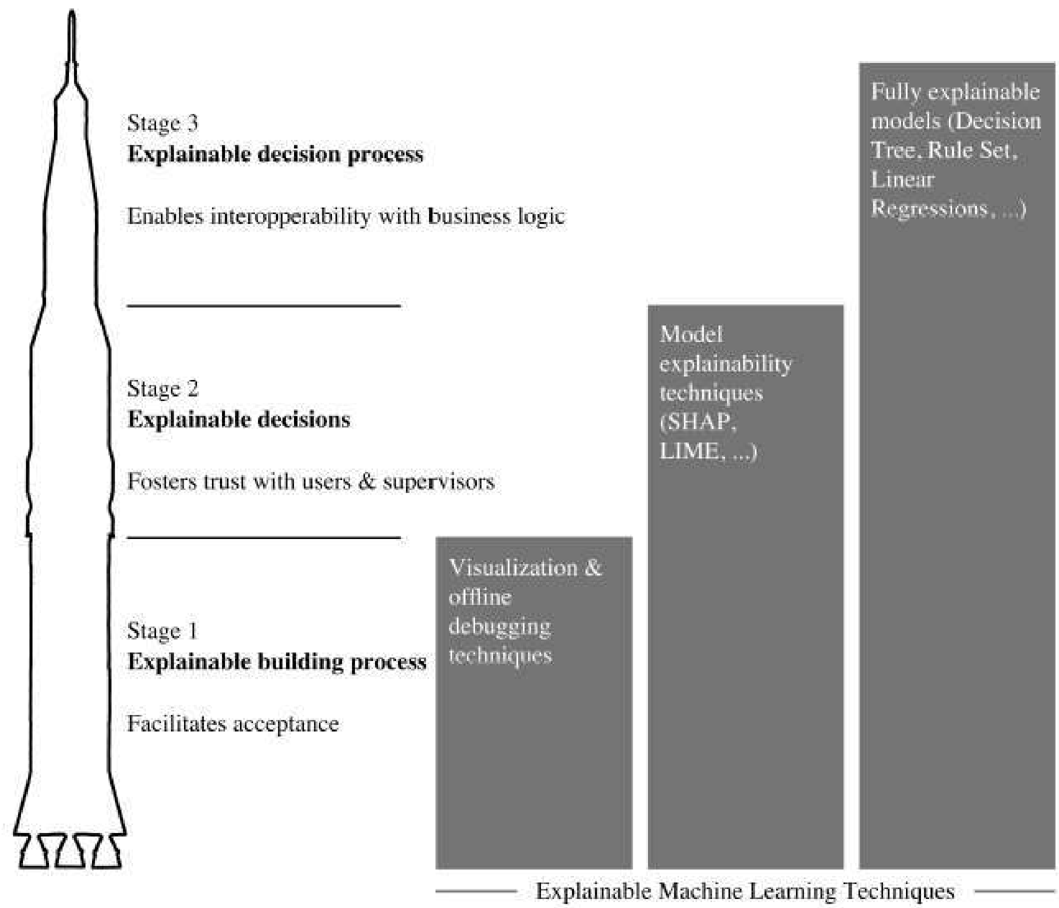


Figure 1: Three stages of Explainable AI (35)

II. MATERIALS AND METHODS

2.1 Primary Database Collection

There are certain popular databases worldwide those include the research articles, such as scopus, web of science, google scholar, scimago etc. A very wide range of publications are covered by these databases. Scopus is the most popular databases and is one of the largest. So we have used Scopus database for our analysis. The keywords search has given a total of 91 number of publication as output. The different keywords are used for the searching of the databases across the world. There is no any restriction on country, language etc. Each publication has the information such as author, country, citations, documents, sources etc. This information is used for the analysis.

Fundamental Keywords

Table 1: List of Primary and Secondary Keywords

Fundamental Keyword	**Explainable AI in Medical**
Primary Keywords using (AND)	**Explainable AND AI AND Medical**

Thus the query for searching the documents in Scopus is:

(TITLE-ABS-KEY (explainable) AND TITLE-ABS-KEY (ai) AND TITLE-ABS-KEY (medical))

2.2 Initial Search Outcomes

On the Scopus database, using the different keywords related to our work, the publications are obtained. These are analyzed according to the language. It is found that, English language has the highest number of publications of 606, followed by Chinese.

Table 2: Language Trends of Publications

Language of publishing	Publication count
English	90
German	01
Total	91

Source: http://www.scopus .com (assessed on 9th Feb. 2021)

2.3 Publication outcome based on Top 15 Keywords

During the search, many keywords are found in addition to the fundamental keywords. Top 15 keywords are listed here in the table. Disease is the keyword having the highest publications. Generally all these keywords are found to be related to health and technology.

Table 3: Publication Analysis based on Top 15 keyword Analysis

Source: http://www.scopus.com (assessed on 9th Feb. 2021)

Sr. No.	Keyword	Publications
1.	Explainable AI	43
2.	Deep Learning	29
3.	Diagnosis	29
4.	Artificial Intelligence	26
5.	Machine Learning	26
6.	Learning Systems	21
7.	Medical Imaging	18
8.	Human	16
9.	Decision Making	11
10.	Interpretability	11
11.	Convolutional Neural Networks	10
12.	Explainable Artificial Intelligence	9
13.	Neural Networks	9
14.	Classification (of Information)	8
15.	Deep Neural Networks	8
16.	Explainability	8
17.	XAI	8

II. PERFORMANCE ANALYSIS

VOSviewer 1.6.15 [19][28] is the software that is used for the database analysis in addition to the analysis form Scopus. It provides a very effective way to analyze the co-citations, co-occurrences, bliometric couplings etc.

Following types of analysis is performed.

Statistical Analysis of Databases

1. Documents by Source
2. Documents by year
3. Documents by subject area
4. Documents by Type
5. Documents by Country
6. Documents by author
7. Documents by affiliation
8. Documents by top funding agencies

Network Analysis of Databases

1. Co-authorship: Authors, organizations, country
2. Co-occurrence: All keywords, Author keywords, Index keywords
3. Citation Analysis: Sources, authors, organizations, country
4. Bibliographic coupling: Documents, Authors

III. RESULTS AND DISCUSSION

Analysis is performed by two different ways, statistical analysis of database and network analysis.

4.1 Statistical Analysis

4.1.1 Document Analysis by Sources

Database indicates different sources such as conferences, journal, book chapter, notes, and reviews and so on. Year-wise publication statistics are shown in the table. Figure shows the graphical representation of the different sources with number of documents published year-wise.

Lecture Notes In Computer Science Including Subseries Lecture Notes In Artificial Intelligence And Lecture Notes In Bioinformatics 21 documents and Ceur Workshop Proceedings 5 documents

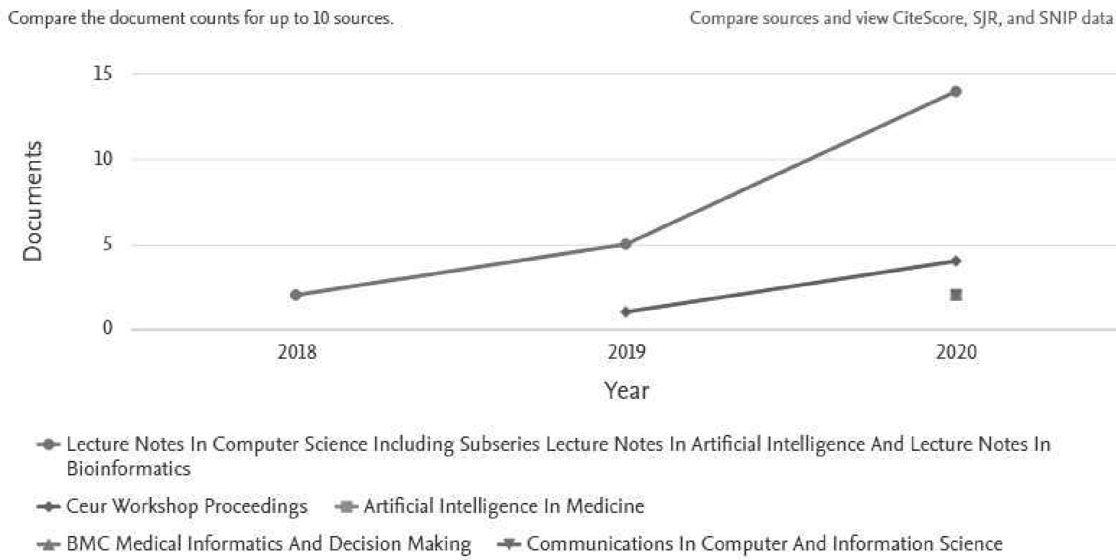


Figure 2: Analysis of Documents by Sources

Source: http://www.scopus .com (assessed on 9th Feb. 2021)

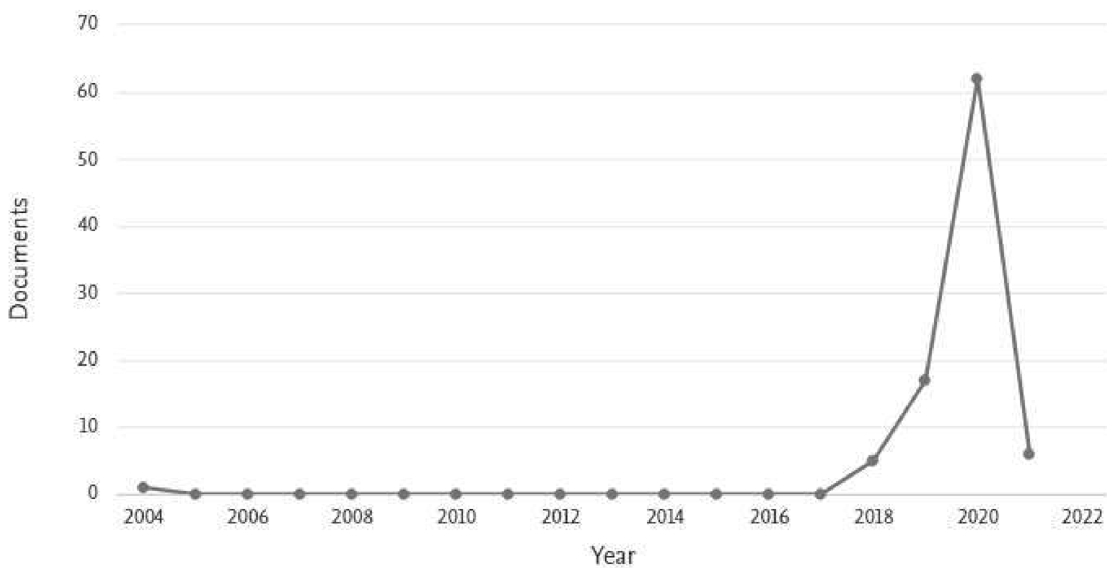


Figure 3: Analysis of Documents by year

Source: http://scopus.com, (assessed on 9th Feb. 2021)

4.1.2 Documents Analysis by year

Documents are collected from scopus database in the year 2011 to 2021 including different sources such as conferences, journal, book chapter etc. The table shows the statistical information and graphical representation is as shown in figure. It is observed from the analysis that, highest number of publication is in the year of 2019 followed by 2020. This shows that, there is a good scope for working in this area in the preceding years.

Table 4: Number of Publication by Year

Year	Number of Publications
2021	06
2020	62
2019	17
2018	05
2017- 2005	0
2004	01
Total	**91**

Source: http://www.scopus.com (assessed on 9th Feb. 2021)

4.1.3 Documents by Subject Area

Explainable AI is the area that is covered mostly in computer science field. About 37.1 % of papers in databases are from computer science followed by mathematics having 14.5% and 11.3 % in engineering area.

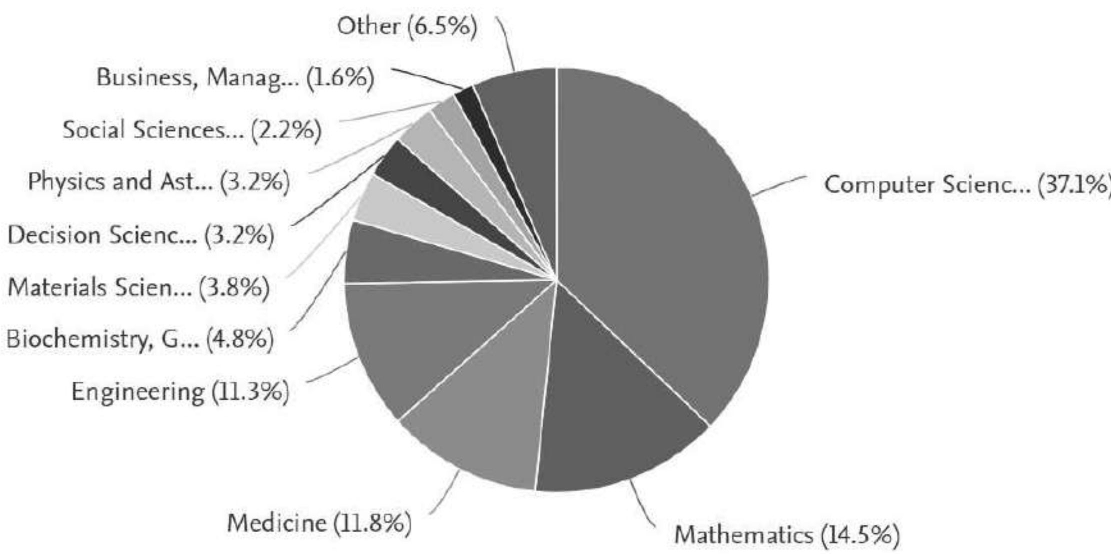


Figure 4: Analysis of Documents by Subject Area

Source: http://www.scopus .com (assessed on 9th Feb. 2021)

4.1.4. Documents by Type

It is seen form the analysis that, most of the publications are journal articles followed by conference papers.

Table 5: Analysis by Document Types

Sr. No.	Document type	Publications
1.	Article	27
2.	Conference Paper	45
3.	Conference Review	4
4.	Review	10
5.	Book Chapter	4
6.	Undefined	1
Total		**91**

Source: http://www.scopus .com (assessed on 9th Feb. 2021)

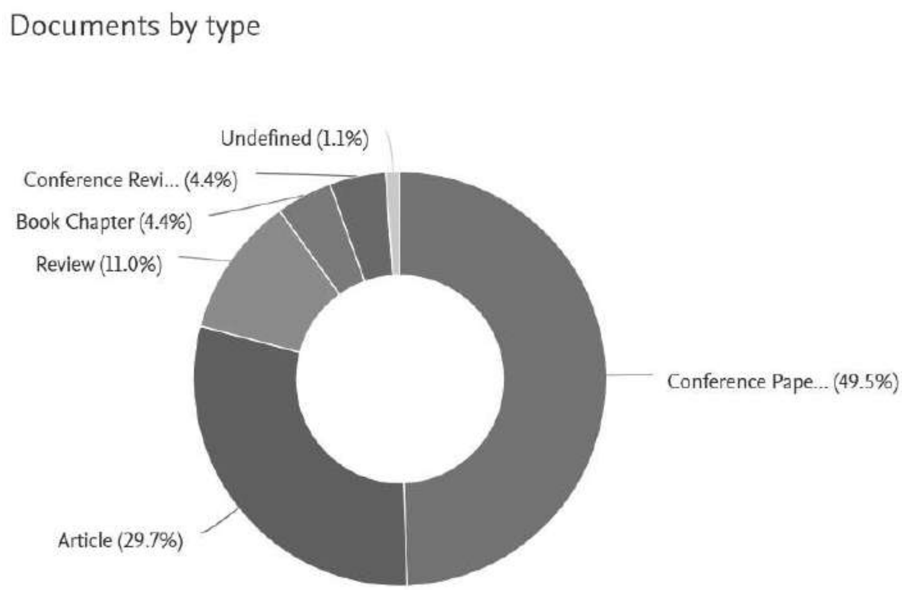


Figure 5: Analysis of Publications by Document Type

Source: http://www.scopus .com (assessed on 9th Feb. 2021)

4.1.5 Analysis of Publications by Country or Territory

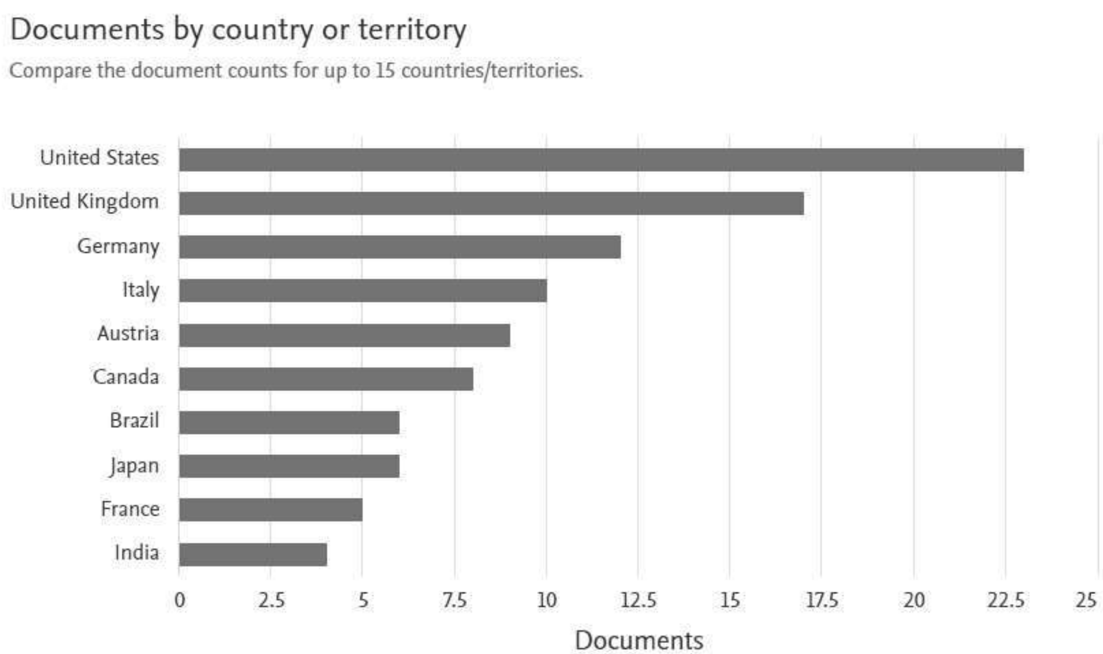
Scopus database is analyzed for countries by considering the number of documents published. It shows that India has the highest number of documents published between the elected timeline. It is followed by United States and then China.

4.1.6 Documents by Author

In this analysis, authors with the number of publications are considered. Publications with a very large number of authors (15) are excluded. Top 10 authors with this comparison are shown here. It is found that Mashor M.Y [5-7] has the highest number of publications of 14 in this area. Maximum authors have an approximate average publication count 4 to 6.

4.1.7Documents by Affiliations

In this analysis, top 10 affiliations are considered. It is found that, University Saries Malaysis, Health Campus. More than half of the affiliations have at least 5 publications related to this field.



4.1.8 Analysis by Funding Sponsors

Figure 6: Analysis by Country

Source: http://www.scopus .com (assessed on 9th Feb. 2021)

In this case, China is ahead amongst all, with highest funding to the National Nature Science Foundation, China. Analysis found most of the funding institutes are form health science field.

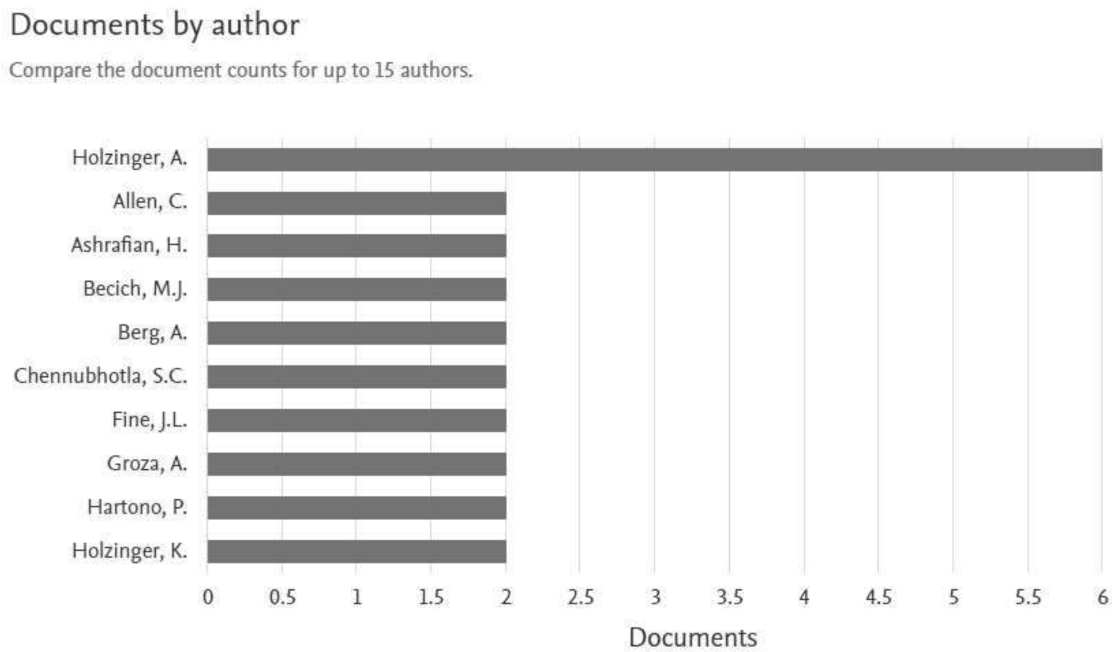


Figure 7: Analysis of Documents by Author
Source: http://scopus.com, (assessed on 9th Feb. 2021)

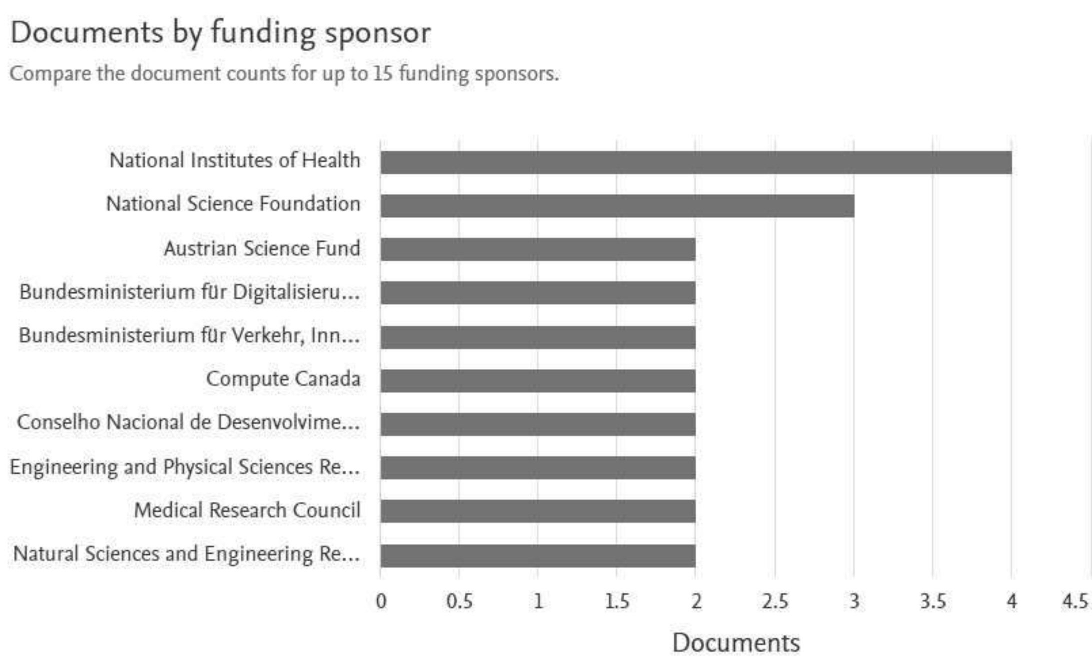


Figure 9: Analysis of Documents by Funding Sponsor

Source: http://scopus.com, (assessed on 9th Feb. 2021)

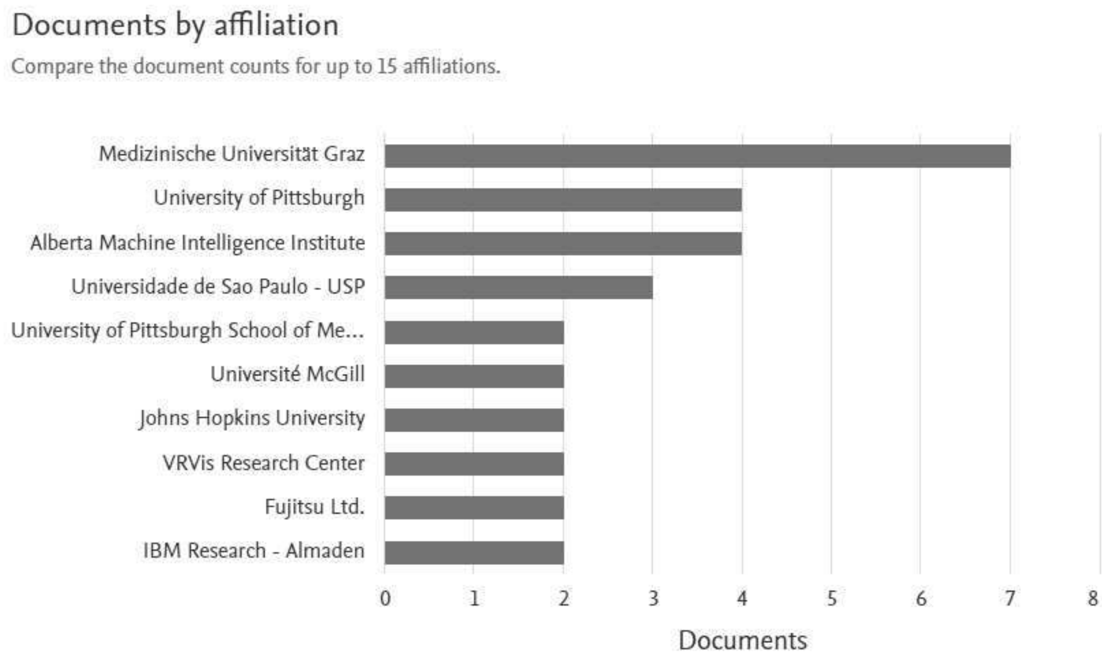


Figure 8: Analysis of Documents by Affiliation

Source: http://scopus.com, (assessed on 9th Feb. 2021)

4.2 Network Analysis

4.2.1 Co-authorship Analysis

A) Co-authorship in terms of Authors

This parameter of analysis is considered with 03 different parameters related to it. The authors, organizations, and countries are considered for analyzing this parameter.

Documents with a very large number of authors are ignored in this analysis. This number is considered to be 25. Threshold is considered as 2 for minimum number of documents of an author.

It is seen that out of 333 authors, 24 authors met the criteria. The total strength of the co-authorship is calculated with other authors. By this method, the link strengths are obtained. Holziger A. found the highest link strength of 14 with the total number of citations to be 116 for 7 different documents. Here total of 24 authors found to have the relation in terms of co-authorship. So these are only shown in the figure.

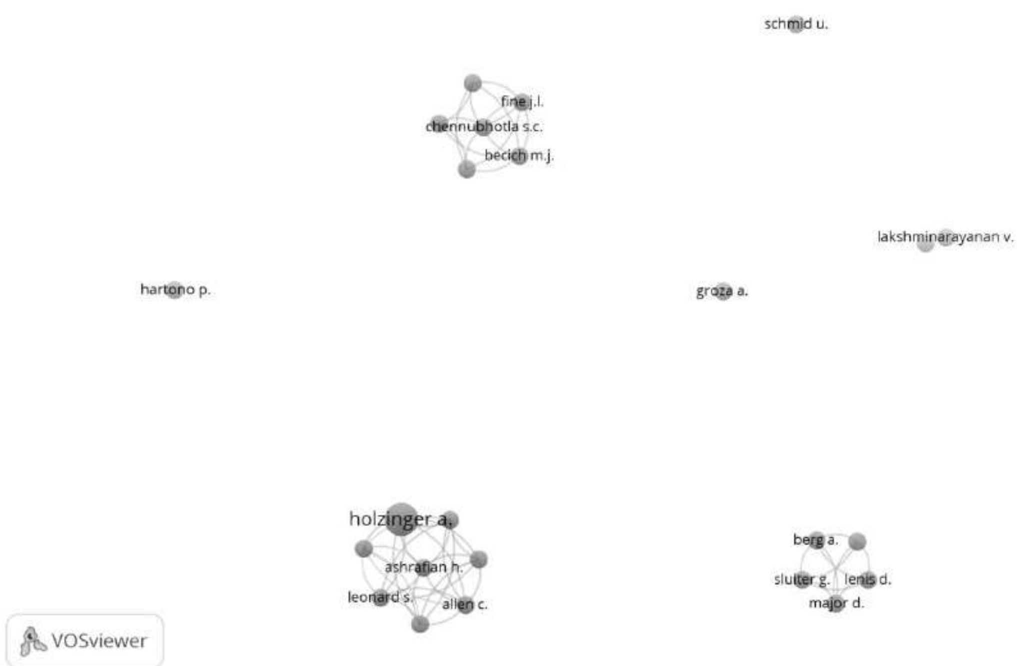


Figure 10: Co-authorship Network Analysis in Terms of Authors

Source: http://scopus.com, (assessed on 9th Feb. 2021)

B) CO-authorship in terms of Organizations

Co-authorship in the unit of organizations is calculated considering minimum 02 documents in organizations with neglecting the citation of the same,

4 organizations meet the criteria out of 228 numbers of total organizations, which are shown in the figure. The organizations include Department of electrical engineering, pontifical catholic university of rio de janeiro, rio de janeiro, Brazil, Department of pathology, faculdade de medicina, universidade de são paulo, são paulo, Brazil, UPMC magee-womens hospital, pittsburgh, pa, United States, and VRVIS zentrum für virtual reality und visualisierung forschungs-gmbh, vienna, Austria. All these organizations lead to 2 documents each. Department of electrical engineering, pontifical catholic university of rio de janeiro, rio de janeiro, Brazil has highest number of citations of 27.

Figure 11: Co-authorship analysis in terms of Organizations

Source: http://scopus.com, (assessed on 9th Feb. 2021)

C) Co-authorship in terms of Country

Co-authorship can also be obtained in relation to the country. A total of 32 countries are there, in which this databases are present. After considering the threshold of minimum 2 documents in a country, 18 countries met the threshold.

Here, United States found to have the highest documents of 23, and the link strength of 25, and citations of 169 which are highest citations amongst all countries. As far as link strength is concerned, United Kingdom has the highest strength of 28.

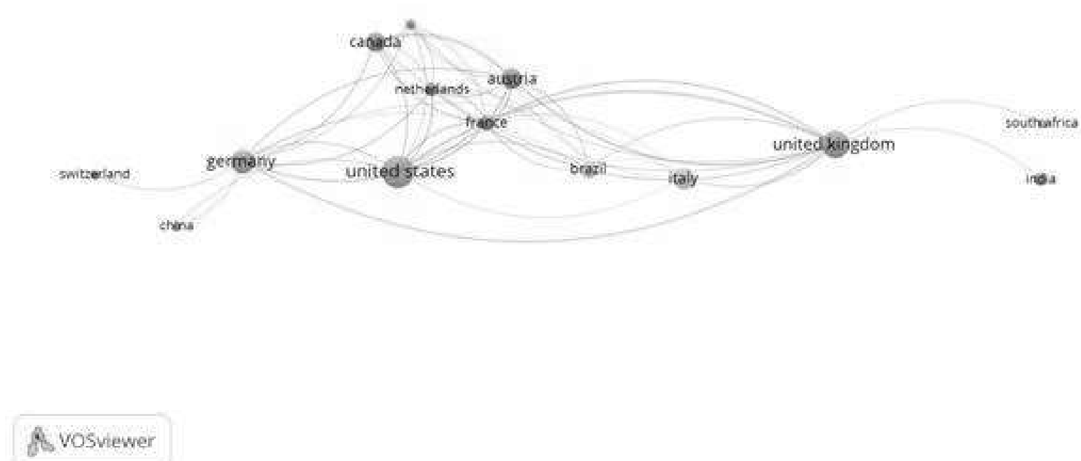


Figure 12: Co-authorship analysis in terms of Countries (Scale is with number of documents)

Source: http://scopus.com, (assessed on 9th Feb. 2021)

4.2.2. Network Analysis of Co-occurrences

A) Co-occurrence analysis in terms of all keywords

For the analysis of co-occurrences, different keywords are considered. Minimum number of occurrences in the keywords is considered to be 3. Out of 970 keywords, 92 keywords met the threshold. Explainable AI is the keyword with highest co-occurrence and has highest link strength of 249.

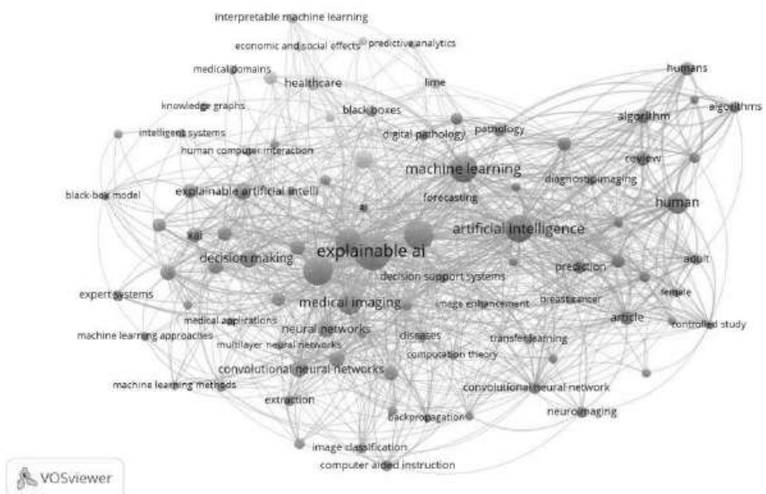


Figure 13: Co-occurrence Analysis in Terms of All Keywords

Source: http://scopus.com, (assessed on 9th Feb. 2021)

B) Co-occurrence analysis in terms of Author keywords

Co-occurrence of author keywords is analyzed with the minimum threshold of 3 per author. Out of 270 keywords by the authors, 17 keywords met the threshold. Author keywords "Explainable AI" is with highest co-occurrences followed by "Deep Learning" keyword.

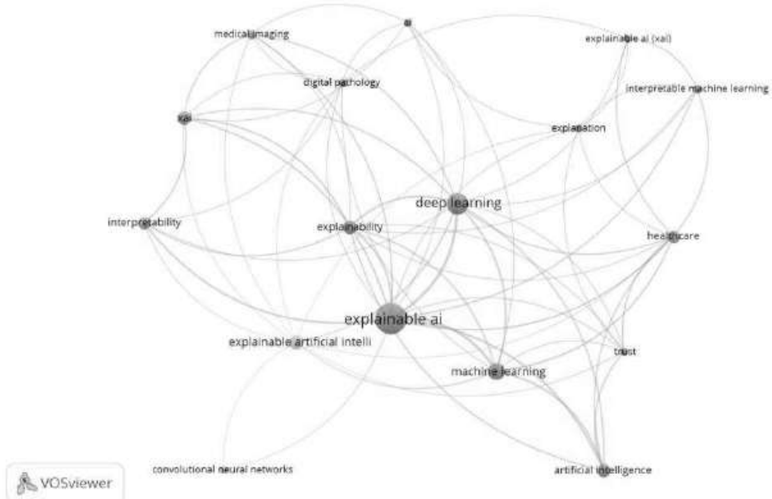


Figure 14: Co-occurrence Network Analysis (Author Keywords)

Source: http://scopus.com, (assessed on 9th Feb. 2021)

C) Co-occurrence in terms of Index Keywords

Co-concurrence is also considered by index keywords of 798, only 74 met the threshold with the threshold of 3 keywords. Diagnosis keywords has the highest co-occurrence value of 28 with higher link strength of 162, followed by the keyword "Deep Learning" with value of 25.

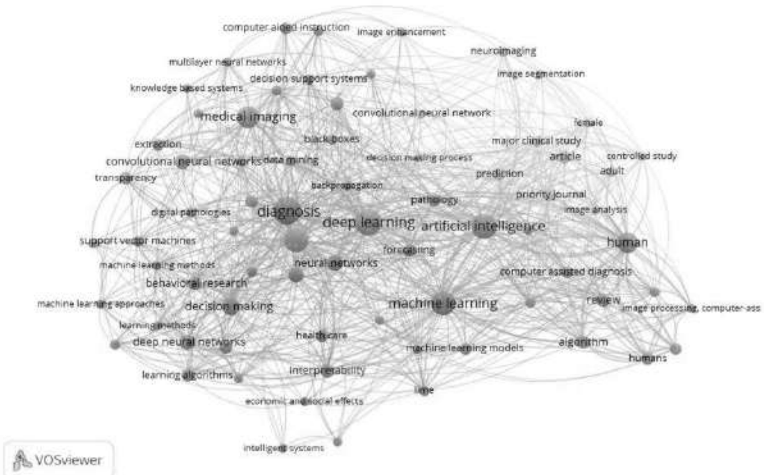


Figure 15: Co-occurrence of Index Keywords

Source: http://scopus.com, (assessed on 9th Feb. 2021)

4.2.3. Network Analysis of Citations

This analysis is done with the units of analysis including documents, sources, authors, country and organization.

A) Citation Analysis of Documents

Out of total of 91 documents, minimum 2 citations are considered as a threshold per document. So there are a total of 28 documents met the threshold. Goebel R. (2018) has the highest number of citations 61.

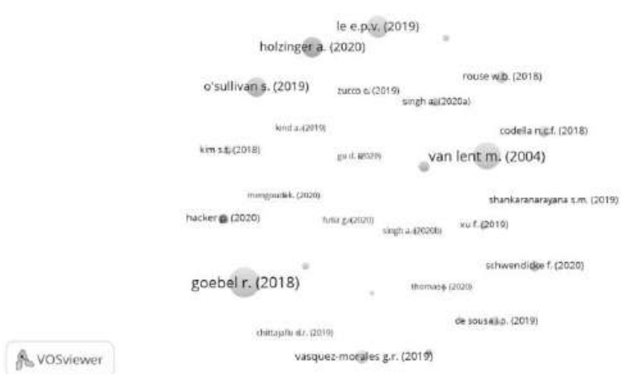


Figure 16: Network Analysis of Citations (In terms of Documents)

Source: http://scopus.com, (assessed on 9th Feb. 2021)

B) Citation Analysis of Sources

Citation analysis of sources is obtained by considering the threshold of 2 citations per source. Out of the 56sources only 13 met the threshold. Lecture Notes in Computer Science has got maximum number of documents of 21 with the citations of 82.

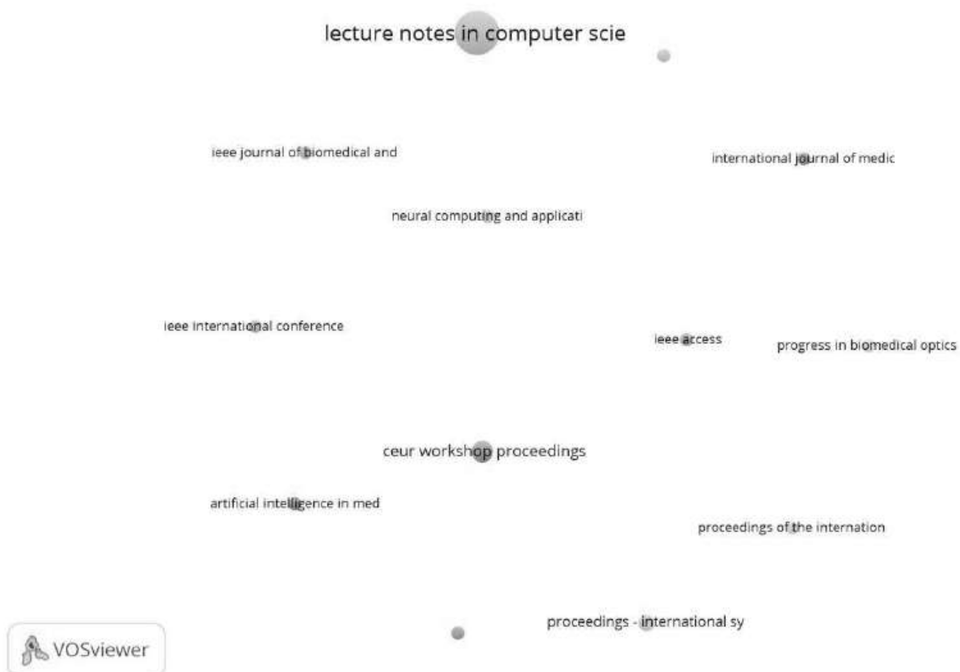


Figure 17: Network Analysis of citation by sources Source: http://scopus.com, (assessed on 9th Feb. 2021)

C) Citation analysis by Authors

Threshold considered here is 2 citations per author. A total of 333 authors met the threshold amongst the total of 24 authors. Holzinger A. has maximum citations of 116 with highest number of documents of 7.

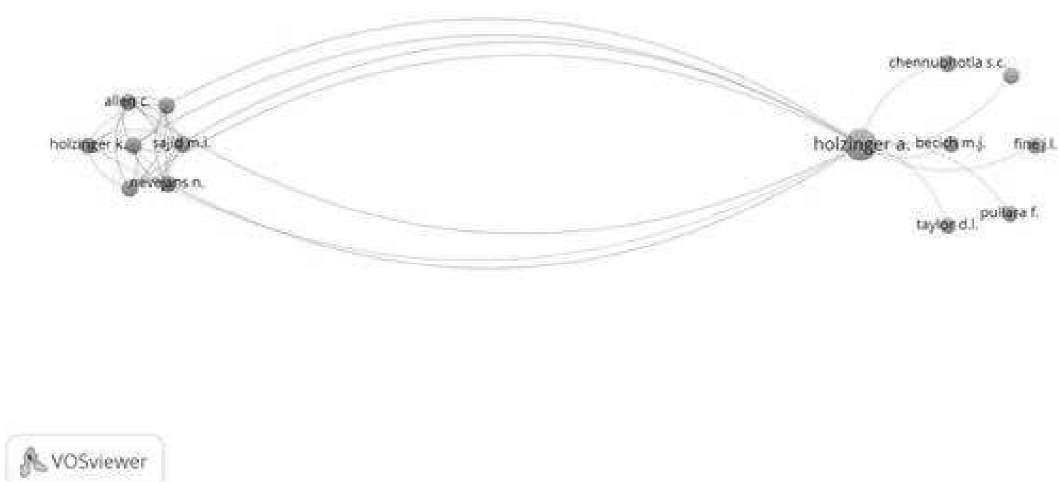


Figure 18: citation analysis by Authors, Source: http://scopus.com, (assessed on 9th Feb. 2021)

D) Citation analysis by organization

Considering minimum documents of 2 per organization as threshold, 4 organizations met the threshold out of 228 organizations. Department Of Pathology, Faculdade De Medicina, Universidade De São Paulo, São Paulo, Brazil has Maximum citations of 27.

Figure 19: Citations by Organizations, Source: http://scopus.com, (assessed on 9th Feb. 2021)

E) Citation analysis by country

Total of 32 countries have the databases of the explainable AI work. Out of which 11 met the citation criteria considering a threshold of minimum 2 citations per country and 3 documents per country.

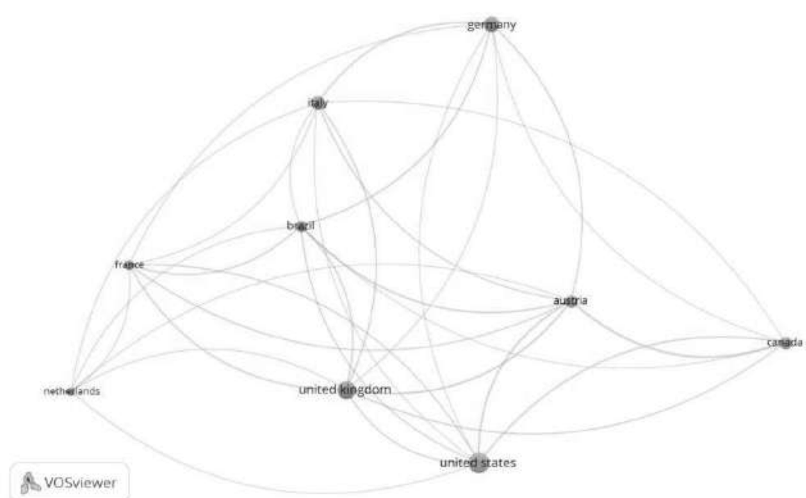


Figure 20: Citation analysis of country, Source: http://scopus.com, (assessed on 9th Feb. 2021)

4.2.4. Network Analysis of Bibliographic Coupling

A) **Bibliographic Coupling of Documents**

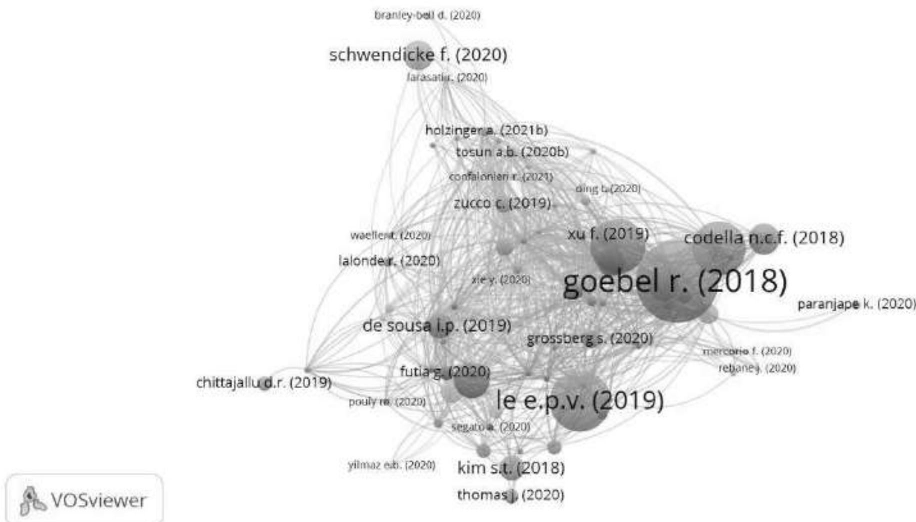


Figure 21: Bibliographic coupling of documents, Source: http://scopus.com, (assessed on 9th Feb. 2021)

B) **Bibliographic coupling of Sources**

A total of 56 sources considered for bibliographic coupling with the threshold of minimum of 1. Lecture Notes in Computer Science has highest link strength of 432.

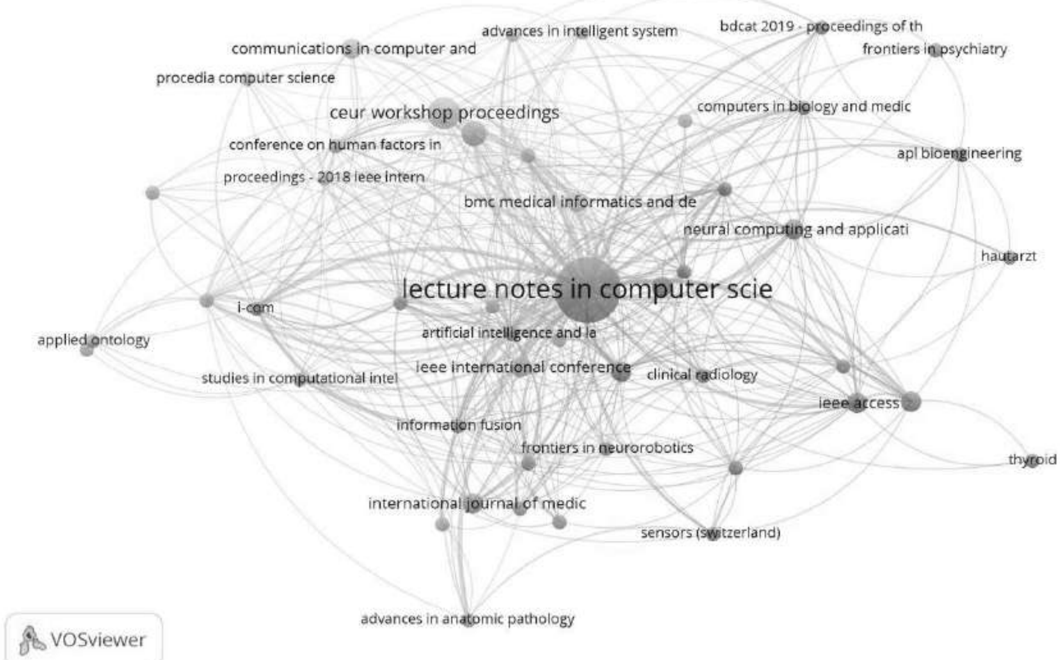


Figure 22: Bibliographic coupling of Sources, Source: http://scopus.com, (assessed on 9th Feb. 2021)

C) **Bibliographic coupling of Authors**

Considering, 2 documents per author as a minimum threshold value. Out of total 333 authors, 24 authors met the threshold criteria.

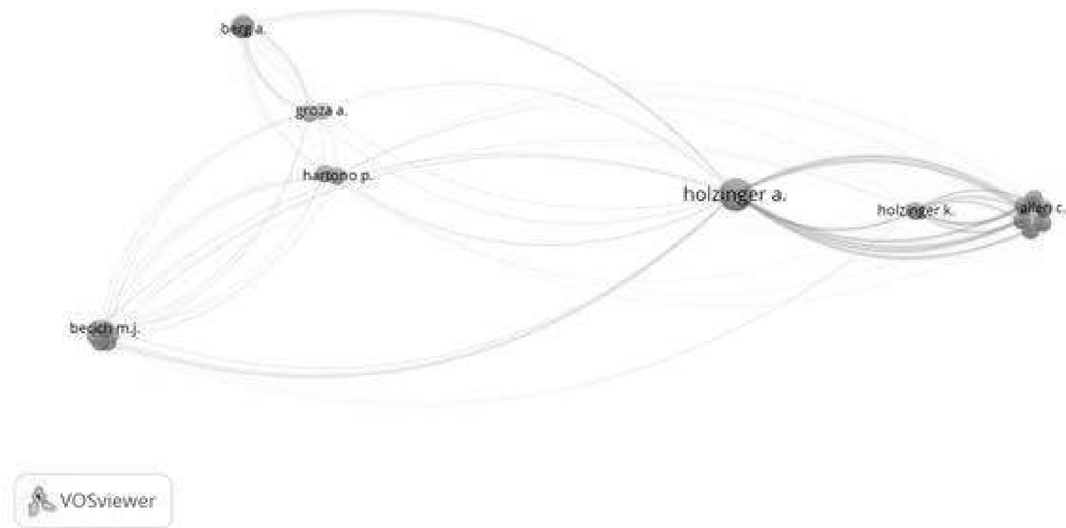


Figure 23: Bibliographic coupling of Authors, Source: http://scopus.com, (assessed on 9th Feb. 2021)

D) **Bibliographic coupling of Organizations :**

Out of 228 organizations, the bibliographic coupling is as shown below.

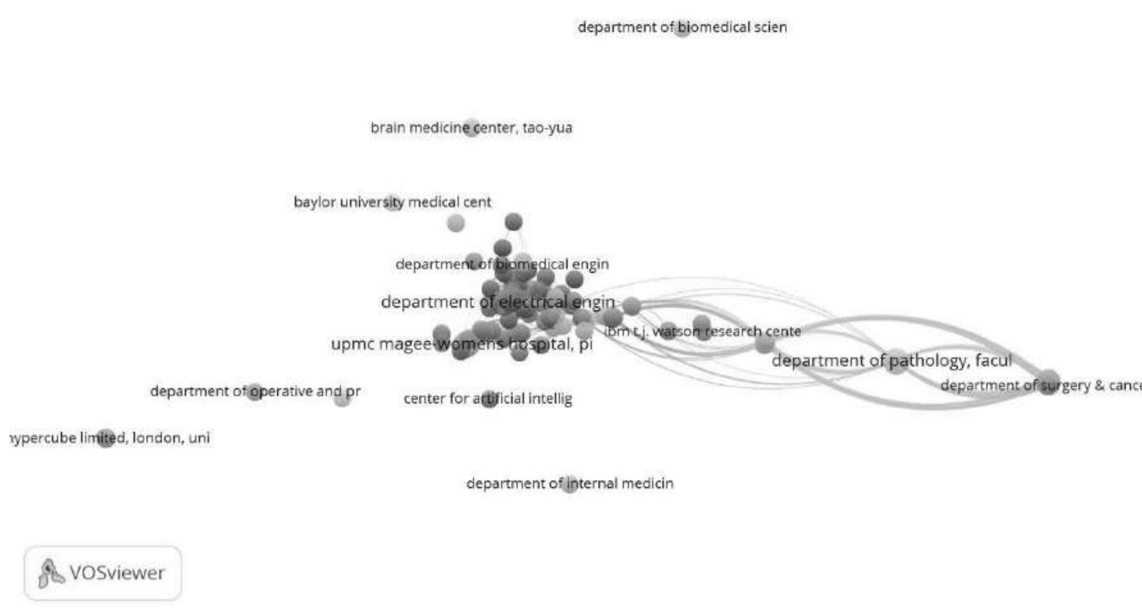


Figure 24: Bibliographic coupling of Organizations, Source: http://scopus.com, (assessed on 9th Feb. 2021)

E) **Bibliographic coupling of Countries :**

A total of 32 countries have the database of the mentioned work on explainable AI. Considered the threshold of minimum of 2 documents per country, a total of 18 countries found the bibliographic coupling relations.

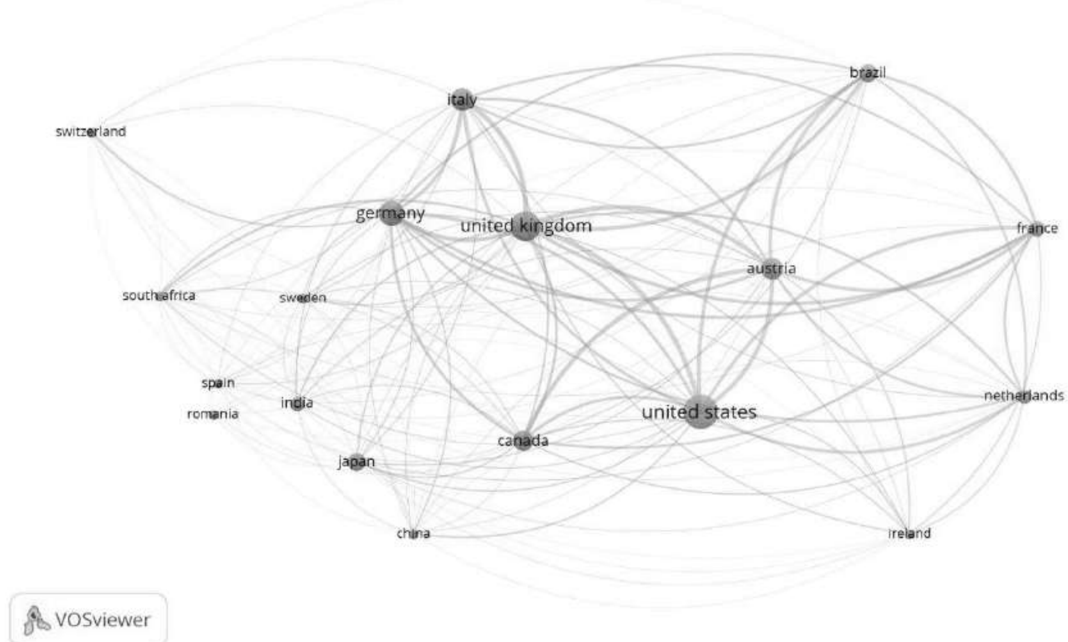


Figure 25: Bibliographic coupling of Countries, Source: http://scopus.com, (assessed on 9th Feb. 2021)

F) Co-citation of Cited References

In this database there are a total of 3690 cited references. By keeping the threshold of minimum of 2 citations per cited references, a total of 49 met the threshold.

Figure 26: Bibliographic coupling of Countries, Source: http://scopus.com, (assessed on 9th Feb. 2021)

G) Co-citation of Cited Sources:

There are a total of 2313 sources, out of which 21 met the minimum threshold of 10 citations per source.

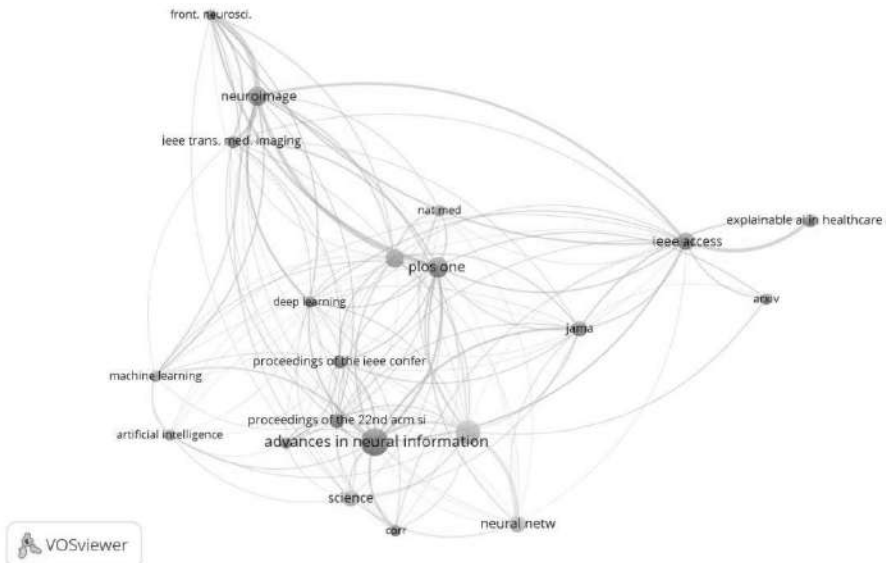


Figure 27: Bibliographic coupling of Co-citation of Cited Sources, Source: http://scopus.com, (assessed on 9th Feb. 2021

H) Co-citation of Cited Authors:

There is a total number of 7348 author associated with the database. To obtain the co-citation of cited authors a minimum threshold of 10 is considered for analysis. The outcome of the analysis shows that 103 authors met the threshold value.

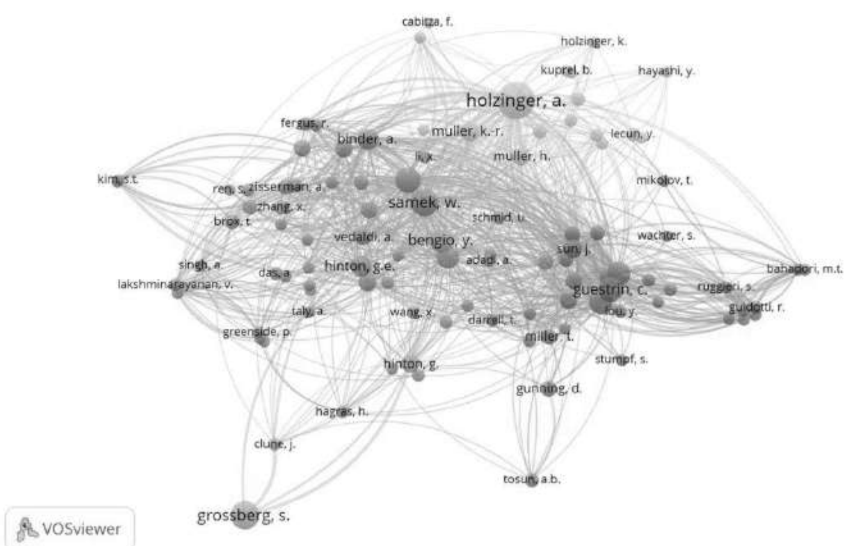


Figure 27: Bibliographic coupling of Co-citation of Cited Authors, Source: http://scopus.com, (assessed on 9th Feb. 2021)

5. CONCLUSION

Bibliometric survey on Explainable AI in Medical Field is carried out by considering the worldwide popular database- Scopus. The database is considered from the year 2004 onwards. The keyword search is used with AND and OR operator for searching of the database. A total of 91 documents are obtained as the outcome of the search.

The different parameters are considered for analysis of this database. It is seen that English language has most of the documents 90 followed by German with only one document. The Keyword search outcome indicates that maximum publications are with the keyword "*Explainable AI.*" Maximum documents are published in the year 2020 followed by the year 2019. The subject area Computer Science and Engineering is the one which covered almost 37.1% of the documents. As far as, the type of document is considered, article of journal are 27 and conference papers are of 45 in numbers. The analysis of countries proved, United states as the highest number of documents followed by United Kingdom within the period.

The highest sponsoring authority in this area is "National Institute of Health."

Holziger A is the author having the highest documents of 6 in this database.

The network analysis is also performed by using the VOSViewer 1.65 version software. The different analysis types are performed. These include co-authorship analysis co-occurrence analysis citation analysis and bibliographic coupling are done with the same database. All these different network analysis indicates a quite significant information about different mentioned above. It could also be seen that the major work in this field related to medical imaging is done in 2019 and 2020. In upcoming years a very vast and major work is expected in this area.

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