Journal of Scientometric Res. 2021; 10(3):318-327
http://www.jscires.org

Research Article

A Bibliometric Approach to Track Research Trends in Computer-Aided Early Detection of Cancer Using Biomedical Imaging Techniques

Mukta Kore[1,*], Deepali Nilesh Naik[1], Deptii Chaudhari[2]

[1]PES's Modern College of Engineering, Pune, Maharashtra, INDIA.
[2]Hope Foundation's International Institute of Information Technology, Pune, Maharashtra, INDIA.

ABSTRACT

The paper's primary goal is to conduct a comprehensive bibliometric analysis of scholarly publications related to computer-aided early detection of cancer using biomedical imaging techniques. Among many diseases, cancer is the second major cause of death in the world. Nevertheless, with advancements in cancer screening, the survival rate for many types of cancer is enhancing. If cancer is noticed in its early stage, it sets out the best chances for healing. Screening involves a physical examination, laboratory tests, imaging tests, and biopsy. According to research, imaging tests are the most accurate cancer diagnosis methods. This work seeks to acquire results from scholarly articles extracted from the Scopus database for the last two decades by analyzing growth in publications and sources, author's endowment, keyword analysis, article citation frequencies, etc. To exhibit the bibliometric study, open-source tools, namely BiblioShiny, VOSviewer, Word Cloud, are utilized. The analysis indicates, 78.52% of publications are of article and review type. Breast cancer, segmentation, melanoma, and deep learning are often used keywords in scholarly articles. Substantial work has been done in China, followed by Germany and the USA under the Computer Science area; also, it shows the elevation in several publications since 2019. Our study will furnish a broad range of perceptions for upcoming researchers by tracking the research study trends. This bibliometric analysis will be worthwhile for an apprentice to survey ongoing research under cancer detection using biomedical images.

Keywords: Bibliometric Analysis, Cancer Detection, Image Processing, Biomedical Image, Scopus.

Correspondence

Mukta Kore

PES's Modern College of Engineering, Pune 5, Maharashtra, INDIA.

Email id: mukta.jamage@moderncoe.edu.in

Received: 17-08-2021
Revised: 29-11-2021
Accepted: 14-12-2021
DOI: 10.5530/jscires.10.3.48

INTRODUCTION

Regardless of advancements in the medical diagnostic system, the detection and imagery of carcinoma are remaining impoverished. Uncontrolled cell growth leads to cancer. Once the transition starts, it rapidly influences nearby tissues in the human body, developing the uncontrolled group of cells known as tumors. Cancer diagnosis facts are in stages. The primary stage of cancer is named a tumor.[1] Biomedical imaging is a well-known technique in the diagnosis of any cancer. In the interest of lowering the mortality rate, early detection of cancer is essential. Computer-aided algorithms help in easy segmentation of anatomical structure to examine cancer images' regions of interest (ROI). Several researchers, radiologists, and medical professionals have made significant contributions in various ways to diagnose cancer to lower the mortality rate.

Cancer is a common disease, and various reasons cause cancer. In the account of all cancer, 5-10 % of cancer seems to be inherited from one of their parents. This inherited risk is because of a bit change in a gene which is also called a mutation. Cancer can also happen because of disorders that occurred during cell division. Even exposures to chemicals like tobacco, smoke, or radiation like the sun's UV rays are possibly the reasons for cancer.[2] Researchers recognize more than 100 kinds of cancers. Usually, the type of cancer is named for the organ or tissue where cancer develops. For example, 'Lung cancer' begins in lung cells, 'Brain tumor' initiates in cerebrum cells, 'Breast cancer' cells develop in bosoms, 'Leukemia cancer' starts in blood tissues, 'Ovarian cancer' is triggered in or on ovaries and so on.[3]

Review of Literature

According to[4] authors, segmentation is done to locate the region of interest by including or excluding the homogeneity for dental images. Local Contrast Modification (LSM), Local Binary Fitting (LBF), Pieces wise model (PC), and Local Image Fitting (LIF) techniques were used in the existing literature to show improvement in segmentation accuracy.

In the literature to diagnose breast cancer, primarily histopathological images were used by researchers. In case of inadequate training of histopathological images, it may communicate inaccurate results. To overcome the above-stated drawback, the use of deep learning approaches is more desirable. In the research,[5] authors preferred the activation feature of Support Vector Machine (SVM) to classify breast cancer images automatically. The authors also stated that using the Convolution Neural Network (CNN) with Linear Regression (LR) improves the result than using CNN and SVM.

In the experimental study,[6] the deep learning approach to classify Biopsy Microscopic Image Cancer Network (BMIC_Net) and results were displayed into eight divergent classified images. Besides, deep learning to extract features was conducted by segmentation on a training data set.[7] The Computer-Aided Design (CAD) system is regular for discern melanoma but still found challenging. With interest in improving image by eliminating variations, an Adaptive Median Filter (AMF) is used, followed by Principal Component Analysis (PCA) to lower data complexity.

After histopathological images, mammography is primarily used in the screening of breast cancer. According to the US national cancer institute, in mammography images, 10% to 30% of glands are missed inciting, which leads to diagnostic error. In the article,[7] the authors proposed optimized algorithms and deep learning approaches for preprocessing mammography to reduce noise by the median filter and derived the most optimal segmentation result using CNN. It also separates the background from RIO. In the study of,[8] researchers work on feature extraction and classification using SVM to differentiate benign and malignant tumors.[9] The authors acquired 96% Sensitivity, 93% Specificity, 85% PPV, 97% NPV, and 92% accuracy, which is better than any other existing techniques.

In lung cancer diagnosis using CT scan image, noise in image and nodules morphology has an alliance with cancer; thus, it causes difficulty detecting cancerous cells.[10] The authors proposed two techniques, such as CNN, DFD-Net, to diagnose lung cancer. [11] Authors claim that using ANN approaches provides entirely accurate results in lung cancer diagnosis.[12] The author proposed a Convolution Neural Network (CNN) and Multistage Convolutional Neural Network (MCNN) approach to classify CT images. Considering the structure of MCNN, the use of MCNN eliminates the need for the feature extraction step. Use of MCNN shows improved accuracy of diagnosis as 93.7%+0:3%.

In chest CT scan images, 3-D CT images proceed to 2-D slices using Hopfield Artificial Neural Network (HANN). The study[13] extracted features from chest tomography and segmented them by HANN Classifier. An automated Computer-Aided design (CAD) system was developed through HANN and used for early detection of lung cancer. Moreover, results were predicted as benign or malignant tumors.

Region of Interest (ROI) extraction, Image Enhancement (IE), and Feature Extraction (FE) are three mechanisms involved in mammography image processing. If image enhancement is not performed correctly leads to an error in ROI.[14] The authors suggested a Fuzzy-Rough Refined IP (FRIP) framework to indicate improved features extraction of images. Researchers[15] studies have shown expert-level performance in ophthalmology, dermatology, and radiology using CNN.

To solve the problem of false-positive findings in skin cancer detection, the researchers[16] proposed the Region-based CNN (R-CNN) technology to build an extensive data set comprising normal and benign images.[15] Authors put forward the algorithm with a combination of R-CNN and CNN, which can automatically locate suspected areas and predict the probability of a malignant lesion in an Asian population.

To diagnose ovarian cancer[12] authors proposed the Scale-Invariant Feature Transform (SIFT) algorithm for feature extraction. Genetic algorithm is one of the popular techniques used for the extraction of features. According to[17] authors, the fitness function of the Genetic Algorithm (GA) is optimized for Image Extraction (IE). Apart from this, the CNN technique is used to state the stages of ovarian cancer. The accuracy was achieved with a CNN classifier of 98.8% and SVM of 85.01% in the experiment.

With advances in medical science, the carcinoma subtype can be identified by using the deep residual network. This study will help the medical practitioner to estimate the future risk of developing carcinoma in patients. For this clinical assessment, lesions are referred to as standard references.

To classify breast cancer images into benign or malignant cancer, authors[18] proposed the MuDeRN (Multi-Category deep Residual Network) technique and categorized benign cancer into four subtypes. In the demonstration, the authors used a public data set (BreakHis) of 81 patients. Data is trained with ResN with 152 layers and images classified into benign and malignant. Authors recorded accuracy for classification as CCR 98.52%, 97.90%, 98.33%, and 97.66%. Again CCR in magnification factor as 95.40%, 94.90%, 95.70%, and 94.60.

With the help of feature extraction and feature reduction using RNN, it is effortless to predict breast cancer in its early stage.[19] The authors presented the Weiner filter in the preprocessing setting of Magnetic Resonance of Imaging (MRI) breast images followed by feature extraction with two-fold cross-validation.[12] To classify cancer images Radial

Basis Neural Network (RBNN) is used. The cuckoo search algorithm is an optimized algorithm by which radial function is calculated. Feature reduction is made by using a cuckoo search algorithm.[13] Authors claim 92% of classification accuracy by PNN algorithm with sensitivity and specificity of 95% and 89.7%, respectively. If the classification is found to be misleading, it is due to false nodule confusion in the natural network.

Need for Bibliometric Analysis

The bibliometric analysis techniques are very advantageous to the researchers to gain the selected research area's insights. The bibliometric studies also provide the quantification of the written research interactions in that particular field of research.[20] Many research scholars have undertaken a bibliometric analysis to evaluate the picked research domain's impact and review different scholars, countries, affiliations, and insight into worldwide research.

The bibliometric analysis can be performed on the statistical data of scholarly articles and other scientific publications extracted from the repository. The investigation can check current research development, prominent keywords used by authors, authors' contribution, source growth, and affiliation participation with statistical data assistance. Also, it assists in tracking the technological advancements in a selected research domain over a while.

This paper carried out a bibliometric survey of "computer-aided early detection of cancer using biomedical imaging techniques." This is the first bibliometric analysis paper proposed related to "computer-aided early detection of cancer using biomedical imaging techniques" to the best of the author's knowledge.

Primary Data collection

Researchers can acquire open access or paid publications through various databases or repositories, individual or institute subscriptions, and libraries in the data collection. Relevant scholarly articles related to "computer-aided early detection of cancer using biomedical imaging techniques" were collected using the SCOPUS database.

Methodology

Figure 1 shows the methodology used in the bibliometric analysis of scholarly articles related to "computer-aided early detection of cancer using biomedical imaging techniques." The finalization of significant keywords is the first step to retrieving relevant articles associated with a selected topic. When choosing essential keywords domain-specific keywords, the methodology used, techniques used in the existing research are the categories considered. After collecting all the significant keywords, the search query was designed to cluster the related keywords using boolean expressions and brackets. This search query was executed on the Scopus database, and in total, 298 documents were extracted. Bibliometric analysis was conducted on obtained statistical data and represented in tables, graphs, network diagrams, and other suitable diagrams.

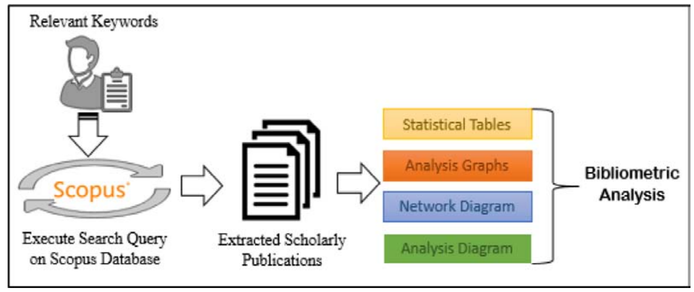

Figure 1: Methodology for Bibliometric Study.

Table 1: Significant Keywords.

Identified Keywords	Cancer image, CT scan image, ultrasonography image, stage detection, screening, cyst, tumor, malignant tumor, early cancer diagnosis, image processing, neural network, genetic algorithm
Search Query	(("cancer image" or "CT scan image" or "ultrasonography image") and ("Stage detection" or "screening") and ("Cyst" or "Tumor" or "malignant tumor" or "early cancer diagnosis") and ("image processing") and ("neural network" or "genetic algorithm"))

Important Keywords

The expert's opinion is considered while defining the essential keywords in the bibliometric analysis of "computer-aided early detection of cancer using biomedical imaging techniques." Table 1 shows the division of essential keywords into two identified keywords and search queries.

Initial search results

After executing the search query on Scopus, we fetched 298 documents. Language-wise allocation of extracted scholarly articles is represented in Table 2. The majority of publications are available in English, and 1 or 2 papers are available in Chinese, German, French, and Persian.

Table 3 shows the division of extracted scholarly articles by source type. All the research articles related to "computer-aided early detection of cancer using biomedical imaging techniques" are categories into six groups as articles (180), review (54), conference paper (45), book chapter (15), book (3), and short survey (1). The majority of research work has been published in articles that are 60.40%, followed by a review of 18.12%.

The year-wise growth in "computer-aided early detection of cancer using biomedical imaging techniques" publications

Table 2: Language wise Division of Extracted Scholarly Articles.

Sr. No.	Article Language	No. of Articles
1	English	292
2	Chinese	2
3	German	2
4	French	1
5	Persian	1
Total:		**298**

Source: http://www.scopus.com (accessed on 7th December 2020)

Table 3: Publication Type wise Division of Extracted Scholarly Articles.

Sr. No.	Document Type	No. of Documents	Percentage
1.	Article	180	60.40 %
2.	Review	54	18.12 %
3.	Conference Paper	45	15.10 %
4.	Book Chapter	15	5.03 %
5.	Book	3	1 %
6.	Short Survey	1	0.33 %
Total :		**298**	**100 %**

Source: http://www.scopus.com (accessed on 7th December 2020)

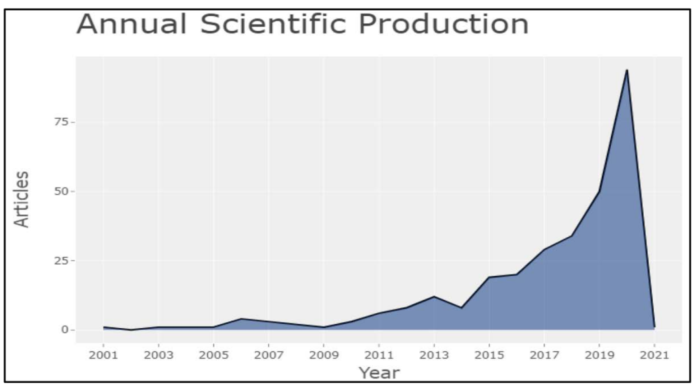

Figure 2: Annual Expansion in Scientific Production.

is presented in Table 4 and Figure 2. The first document was published in 2001 and continues to date. Figure 2 demonstrated that the highest number of scholarly articles are published in 2020, followed by 2019. Figure 2 exhibit the annual scientific production for 20 years that is from 2001 to 2021. This publication's growth analysis demonstrates the need for "computer-aided early detection of cancer using biomedical imaging techniques" research.

Bibliometric Analysis

With bibliometric analysis, we identify the uniqueness of relevant keywords, research trends, most contributing authors, sources, affiliations, citations, document analysis, geographical region, etc. We pointed out the growth of sources per year by

Table 4: Annual Expansion in Documents.

Year of Publication	Count	Year of Publication	Count
2021	1	2011	6
2020	94	2010	3
2019	50	2009	1
2018	34	2008	2
2017	29	2007	3
2016	20	2006	4
2015	19	2005	1
2014	8	2004	1
2013	12	2003	1
2012	8	2001	1
Total:			298

Source: http://www.scopus.com (accessed on 7th December 2020)

Table 5: Top 10 Keywords used by Authors.

Keyword	Occurrence
Breast Cancer	50
Segmentation	42
Deep Learning	33
Classification	29
Lung Cancer	28
Feature Extraction	18
Machine Learning	17
Mammography	14
Melanoma	14
Skin Cancer	12

Source: http://www.scopus.com (accessed on 7th December 2020)

analyzing source data. Furthermore, we analyze the author's records to identify the author's production over time. Three Field Analysis bears witness the correlation between author, source and keywords, country, affiliation, and author. The network analysis demonstrates the interrelationship between co-authorship and countries.

This detailed bibliometric analysis presents an overview of both quantitative and qualitative research trends. This analysis is conducted with the help of bibliometric tools such as VOSviewer, Biblioshiny, and cite space.

Keyword Analysis

The main aim of the selection of relevant keywords is to find relevant publications from extensive databases. The choice of proper keywords by researchers indicates the direction of research. The accurate combination of relevant keywords means knowledge about the topic. With the help of keyword analysis, we can get comprehension about recent research topic trends. Table 5 shows the top 10 keywords used by

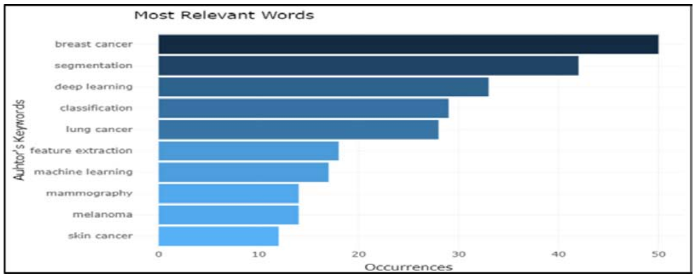

Figure 3: Most Relevant Keywords used by Authors.

Figure 4: TreeMap of Most Relevant Keywords used by Authors.

authors in the existing literature about "computer-aided early detection of cancer using biomedical imaging techniques." Also, the graphical analysis of the most relevant keywords is demonstrated in Figure 3. The authors' most relevant keywords are shown in Figure 4, which gives an even more precise view.

Affiliation Analysis

Table 6 and Figure 5 show universities' participation, according to affiliations stated in the scholarly articles. Northeastern University and Tianjin University have significant contributions in studying "computer-aided early detection of cancer using biomedical imaging techniques". From 2001 to 2020, a total of 24 articles were published by Northeastern University. Figure 6 demonstrated the association between countries, affiliation, and authors with the aid of three field analysis designs using Biblioshiny. Concerning three field analyses of the country, affiliation, and author, it is observed that significant work has been done by collaborations in China, followed by Germany and the USA.

Documents Citation Analysis

Citation analysis of retrieved scholarly articles is given in Table 7 under the topic "computer-aided early detection of cancer using biomedical imaging techniques" from 2016 to 2020. Out an out, 5014 citations are recorded for 298 publications.

Citation analysis implies the impact and popularity of the articles and authors. Table 8 gives the details like DOI, total citation, and total citation per year of top-cited documents. Table 8 and Figure 7 presents the analysis of the top 10

Table 6: Top 10 Relevant Affiliations.

Affiliations	No of Publications
Northeastern University	24
Tianjin University	14
University of Malaya	12
Shanghai Jiao Tong University	11
University of Calgary	10
University of Rome Tor Vergata	10
Deutsches Krebsforschungszentrum (dkfz)	9
School of Medical Science and Technology	9
University of Sydney	9
Comsats Institute of Information Technology	8

Source: http://www.scopus.com (accessed on 7th December 2020)

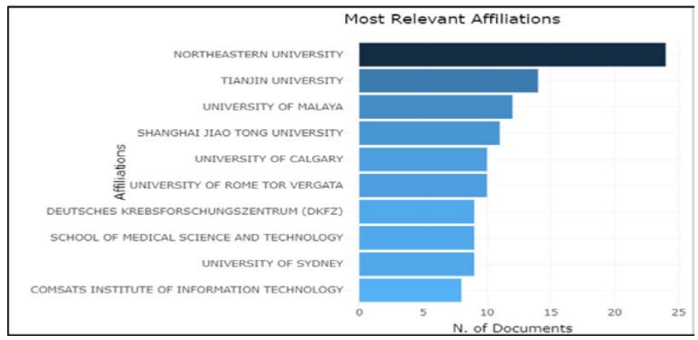

Figure 5: Top 10 Most Relevant Affiliations.

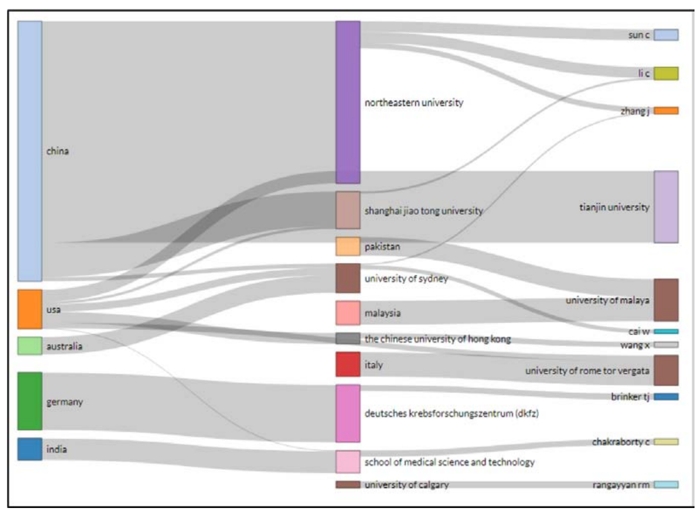

Figure 6: Three Field Analysis of Country, Affiliation, and Author.

Table 7: Overview of Citation from Retrieved Documents.

Year	<2016	2016	2017	2018	2019	2020	>2020	Total
Citation	1132	279	445	657	1016	1412	73	5014

Source: http://www.scopus.com (accessed on 7th December 2020)

Table 8: Ten Most Cited Publications.

Paper	DOI	Total Citations	TC per Year
Ganster H, 2001, Ieee Trans Med Imaging	10.1109/42.918473	430	21.5
Rangayyan Rm, 2004, Biomedical Image Analysis		235	13.8235
Korotkov K, 2012, Artif Intell Med	10.1016/j. artmed.2012.08.002	216	24
Xing F, 2016, Ieee Rev Biomed Eng	10.1109/ RBME.2016.2515127	189	37.8
Balagurunathan Y, 2014, Transl Oncol	10.1593/tlo.13844	174	24.857
Ganesan K, 2013, Ieee Rev Biomed Eng	10.1109/ RBME.2012.2232289	165	20.625
Xing F, 2016, Ieee Trans Med Imaging	10.1109/ TMI.2015.2481436	149	29.8
Masood A, 2013, Int J Biomed Imaging	10.1155/2013/323268	138	17.25
Choy G, 2018, Radiology	10.1148/ radiol.2018171820	135	45
Koschan A, 2007, Digit Color Image Proces	10.1002/9780470230367	122	8.71 43

Source: http://www.scopus.com (accessed on 7th December 2020)

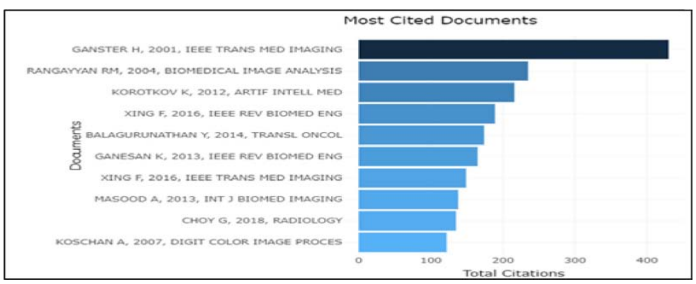

Figure 7: Top 10 Most Cited Documents.

most cited papers. This analysis reveals that the "Automated melanoma recognition" article published in IEEE Transactions on Medical Imaging possesses the highest number of citations.

Source Analysis

Table 9 and Figure 8 provide the information about the scholarly articles published by a source per year in "computer-aided early detection of cancer using biomedical imaging techniques". The analysis of scholarly articles' sources aligns with the year-wise growth of publications in the source. Figure 9 is a self-event to show the development of multimedia tools and applications sources followed by IEEE access in selected research areas.

Table 9: Top 10 Sources.

Sources	Articles
Multimedia Tools and Applications	10
IEEE Access	9
Expert Systems with Applications	7
International Journal of Imaging Systems and Technology	7
Applied Sciences (Switzerland)	6
Computer Methods and Programs In Biomedicine	6
Dermoscopy Image Analysis	6
Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes In Bioinformatics)	6
Medical Image Analysis	6
Biomedical Engineering - Applications Basis and Communications	4

Source: http://www.scopus.com (accessed on 7th December 2020)

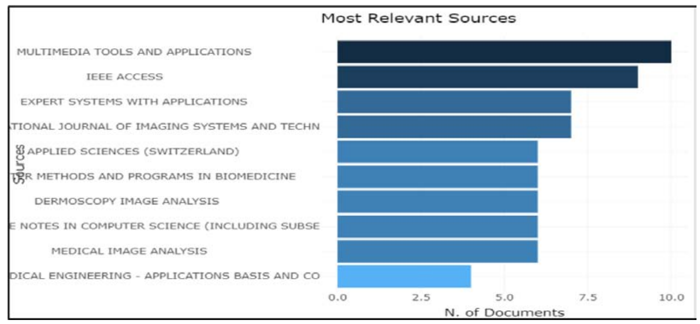

Figure 8: Top 10 Most Relevant Sources.

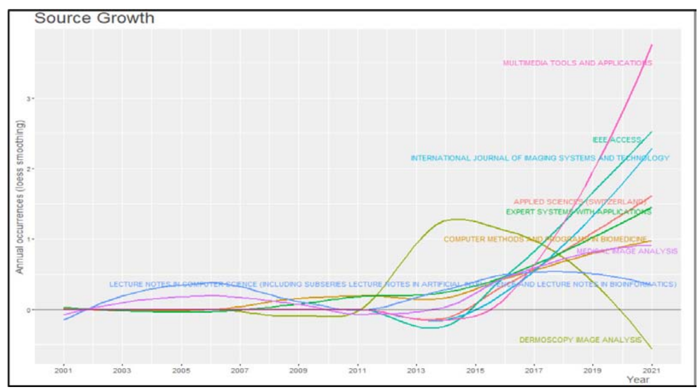

Figure 9: Source Growth per Year.

Author Analysis

The author analysis points out the endowment of authors in the field of research. Table 10 shows the list of most prolific authors and articles fractionalized contributed to the study of "computer-aided early detection of cancer using biomedical imaging techniques". Figure 10 present the correspondence of the top 10 productive authors with several published articles. Figure 11 portrays the production over the time of the top ten authors. A frequency measure parameter for the number of documents is considered to show the productivity of the authors.

Table 10: Most prolific Authors.

Authors	Articles	Articles Fractionalized
Wang X	5	0.85
Cai W	4	1.03
Chakraborty C	4	1.20
Li C	4	0.54
Rangayyan Rm	4	2.00
Tahmoush D	4	3.00
Wang Y	4	0.73
Banik S	3	1.00
Brinker Tj	3	0.38
Chatterjee S	3	0.66

Source: http://www.scopus.com (accessed on 7th December 2020)

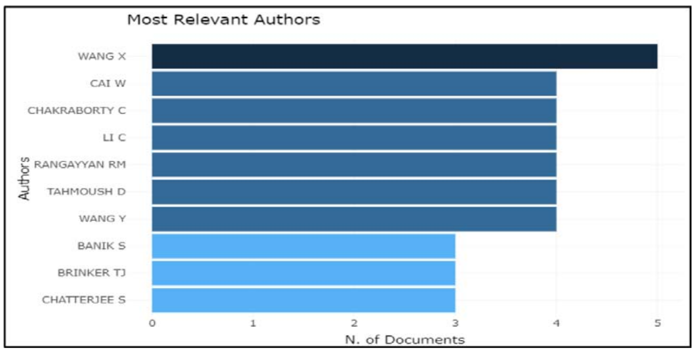

Figure 10: Most Prolific Authors.

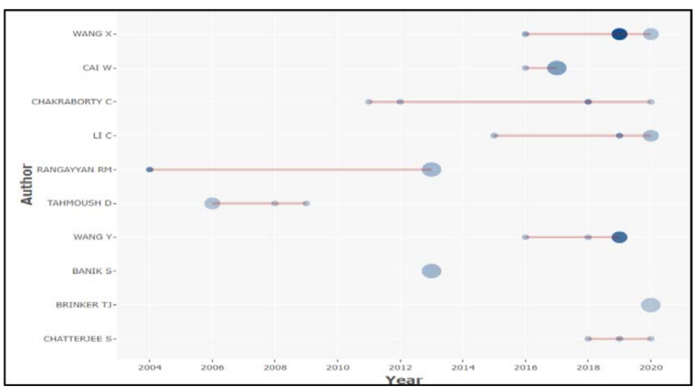

Figure 11: Top 10 Authors Production over the Time.

Geographical region analysis

A total of thirty-nine countries have contributed to the research of "computer-aided early detection of cancer using biomedical imaging techniques". The leading publications are from India, followed by China. India endowed 259 scholarly articles separately and in partnership along with different countries. Figure 12 depicts the number of scholarly articles published by select countries. Geographical region analysis presents the division of worldwide spacecraft of research outputs.

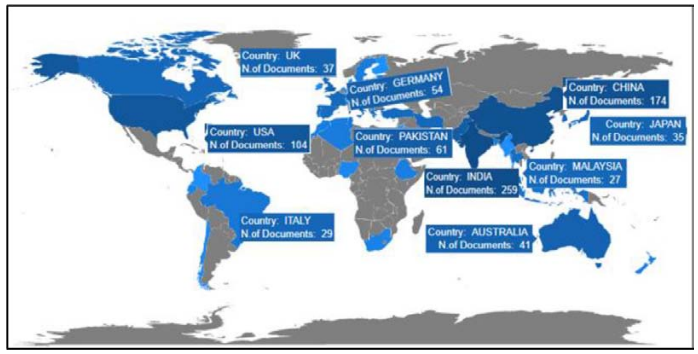

Figure 12: Geographical Region Analysis.

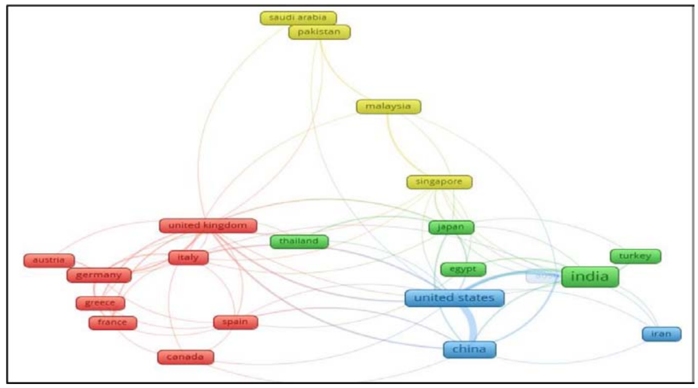

Figure 13: Network Analysis of Co-authorship and Countries.

Network Analysis

The correlation between the several statistical elements is demonstrated graphically for retrieved scholarly articles with network diagrams. All the network diagrams from the present sections are configured using the 'VOSviwer' tool, open-source software used to analyze and visualize scientific literature by designing network diagrams.

Figure 13 shows the network analysis of co-authorship and countries in researching "computer-aided early detection of cancer using biomedical imaging techniques." To design this network diagram totals 59 countries are considered. A complete counting method is used with a minimum of five documents. There are twenty-two meet thresholds present.

Figure 14 present the connections between the keywords used by authors in their articles. To make the layout of the stated network diagram Fruchterman Reingold algorithm is used

Document Analysis

The document analysis is carried out to identify the latest development in the research area of "computer-aided early detection of cancer using biomedical imaging techniques." Trend topics of abstracts are as shown in figure 15. We considered word minimum frequency, number of words per year, and word label size as comparison parameters to configure the abstract trend topics.

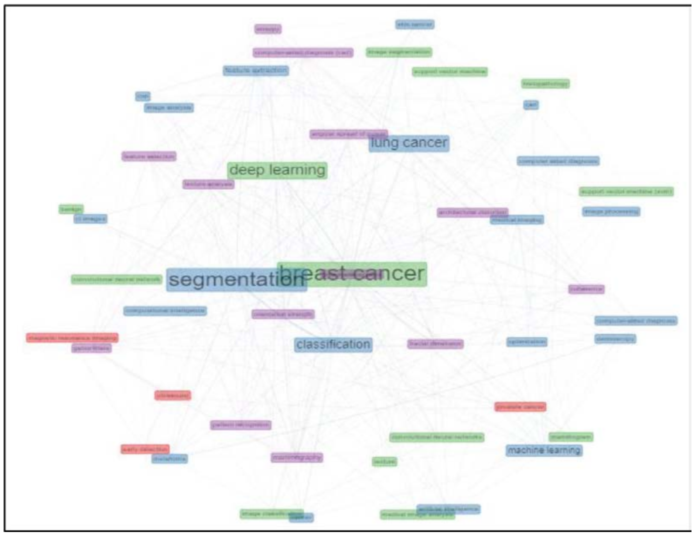

Figure 14: Network Analysis of Authors Keywords.

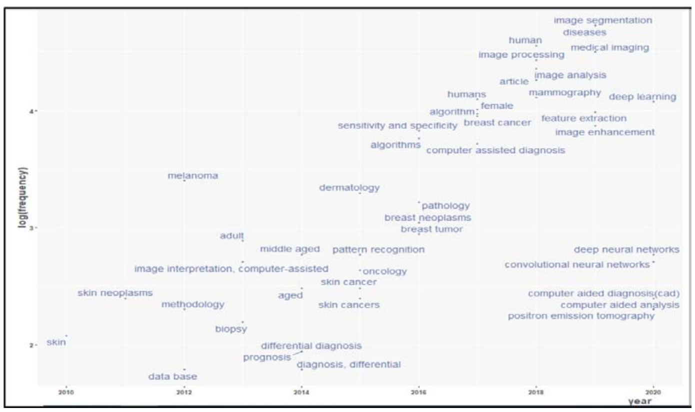

Figure 15: Trend Topics of abstracts.

Along with abstracts trend topics, we have also evaluated the index keywords available in the scholarly articles. The density visualization of index keywords is demonstrated in figure 16, which is generated in VOSviewer. In Figure 16, two hundred and three items are distributed in five clusters with 9815 links, whereas the link's total strength is 1668. The fractional counting method is applied for calculations.

Conceptual Structure of Author's Keywords

To reveal the documents' conceptual structure, we present the thematic map and thematic evolution of author keywords, as shown in Figure 17 and Figure 18, respectively. To represent the thematic evolution of author keywords, we incorporated 250 keywords in the analysis. Minimum cluster frequency is assigned as 1 to 5, and inclusion index weighted by word occurrence is one of the parameters used in scrutiny. In the diagrammatic representation year, 2015 is taken into account as a cutting point.

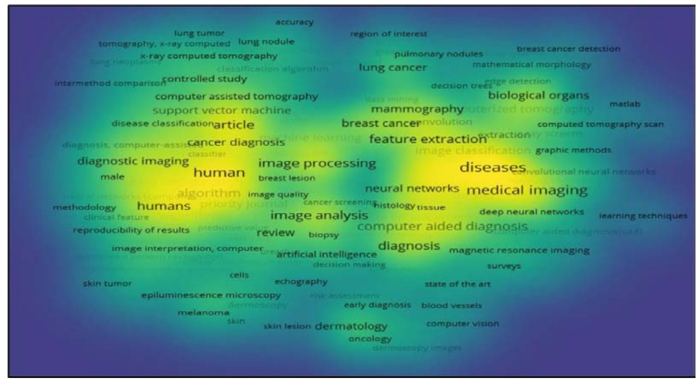

Figure 16: Density Visualization of Index Keywords.

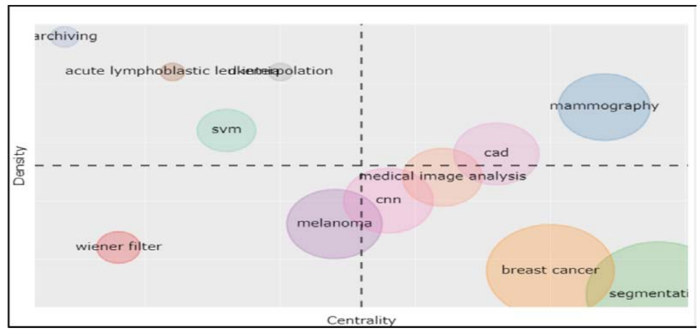

Figure 17: Thematic Map of Authors Keywords.

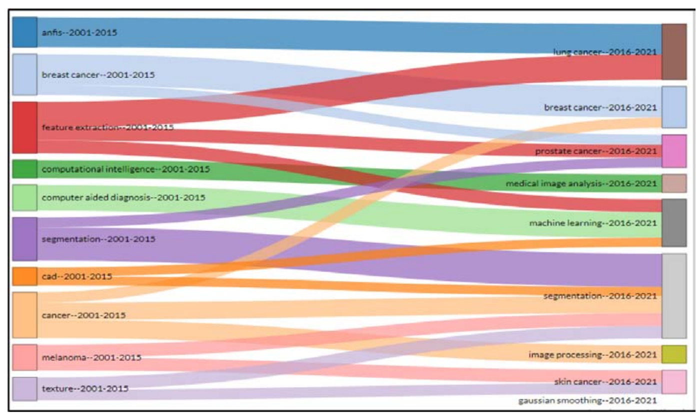

Figure 18: Thematic Evolution of Authors Keywords.

Critical Analysis of The Study

Worldwide research has been done under the topic of "computer-aided early detection of cancer using biomedical imaging techniques." In addition to that, this research work is growing uninterruptedly considering the count of publications portray in Figure 2. The bibliometric survey promotes the rapid, innovative, creative idea. It sheds light on the essentiality of research work in the early detection of cancer to motivate emerging researchers and medical practitioners.

Significant research has been done in computer-aided early cancer diagnosis using biomedical imaging techniques in the recent past (Table 4) and found peak growth in 2020. Considering the list of essential keywords, we can reveal that much work has been done to diagnose cancer cell growth using cancer image data captured by ultrasonography, mammography, tomography, or CT scan to distinguish between malignant or benign tumors.

Various biomedical imaging techniques have been designed using support vector machine, classification, segmentation using genetic algorithm, artificial intelligence, deep learning, CNN, CAD, and Machine Learning algorithms (Figure 14) for different cancer images. However, the frequency of early detection of carcinoma keywords is comparatively low. For a medical practitioner, it is appropriated to detect any melanoma in its early stage preemptively. This study implies the substantial research gap concentrating on early detection research utilizing clinical tests or simple segmentation. The geographical analysis (Figure 12) implies that most research efforts in findings melanoma are concentrated in china followed by the USA and Australia.

With the advances in biomedical imaging, researchers and medical professionals can predict benign and malignant tumors in their early stages. In computer-aided early detection of cancer using biomedical imaging techniques, no bibliometric survey article exists in 298 scholarly publications. This signifies a great deal of scope of work for researchers in the selected research area.

CONCLUSION

The bibliometric survey on computer-aided early cancer detection using biomedical imaging techniques indicates that leading publications are article types followed by review articles. The study ascertained that progress of contribution gradually increased, and maximum research was published in English. Many publications are from affiliations present in China, followed by Germany and then the USA. Segmentation is the prominent keyword used in the literature, proving the amount of work done in preprocessing biomedical cancer images, especially breast and lung cancer. The year-over-year growth of scholarly articles is evidence of the need for research in selected areas.

The biomedical imaging technique gives insight into the anatomical structure and assists medical practitioners in analyzing the organs internally. Often, capturing a meaningful image becomes a tedious job because anatomical structuring, such as few organs, lies beneath the skin layer or other organs, leading to error inaccurate diagnosis. From this analysis, it is observed that computer-aided technology boosts cancer diagnosis in its earliest stage. Our verdicts also reveal that in preprocessing of imaging segmentation gives accurate insights into the region of interest. In the existing literature, practitioners preferring to use biomedical image testing out of four techniques of screening cancer. Screening of abdominal organs is arduous due to noise in captured images, even though significant research has to be done in this area.

Nowadays, intelligence-based learning is a topic of study and research for automating the screening of cancer images. Upcoming researchers can focus their work on early detection of cancer to lower the mortality rate using intelligence-based medical image learning. The researchers can propose a system that can detect cancer in an early stage with the desired accuracy.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest.

REFERENCES

1. Saranyaraj D, Manikandan M, Maheswari S. A deep convolutional neural network for the early detection of breast carcinoma with respect to hyper-parameter tuning. Multimedia Tools and Applications. 2020;79(15-16):11013-38.
2. Rahman A, Anam AI, Yeasin M. Robust modeling of epistemic mental states. Multimedia Tools and Applications. 2020;79(47-48):35785-809. doi: 10.1007/s11042-020-09145-5.
3. Melekoodappattu JG, Subbian PS. A hybridized ELM for automatic micro calcification detection in mammogram images based on multi-scale features. Journal of medical systems. 2019;43(7):183. doi: 10.1007/s10916-019-1316-3, PMID 31093789.
4. Alarifi A, Alwadain A. Computer-aided cancer classification system using a hybrid level-set image segmentation. Measurement. 2019;148. doi: 10.1016/j.measurement.2019.106864.
5. Gupta K, Chawla N. Analysis of histopathological images for prediction of breast cancer using traditional classifiers with pre-trained CNN. Procedia Computer Science. 2020;167:878-89. doi: 10.1016/j.procs.2020.03.427.
6. Murtaza G, Shuib L, Mujtaba G, Raza G. Breast cancer multi-classification through deep neural network and hierarchical classification approach. Multimedia Tools and Applications. 2020;79(21-22):15481-511. doi: 10.1007/s11042-019-7525-4.
7. Sha Z, Hu L, Rouyendegh BD. Deep learning and optimization algorithms for automatic breast cancer detection. International Journal of Imaging Systems and Technology. 2020;30(2):495-506. doi: 10.1002/ima.22400.
8. Jiménez-gaona Y, Rodríguez-álvarez MJ, Lakshminarayanan V. Deep-learning-based computer-aided systems for breast cancer imaging: A critical review. Appl Sci. 2020;10(22):1-29. doi: 10.3390/app10228298.
9. Debelee TG, Schwenker F, Ibenthal A, Yohannes D. Survey of deep learning in breast cancer image analysis. Evolving Systems. 2020;11(1):143-63. doi: 10.1007/s12530-019-09297-2.
10. Sori WJ, Feng J, Godana AW, Liu S, Gelmecha DJ. DFD-Net: Lung cancer detection from denoised CT scan image using deep learning. Frontiers of Computer Science. 2021;15(2). doi: 10.1007/s11704-020-9050-z.
11. Yektaei H, Manthouri M. Diagnosis of Lung Cancer using Multiscale Convolutional Neural Network. Biomedical Engineering - Applications, Basis and Communications. 2020;32(5). doi: 10.4015/S1016237220500301.
12. Institute of Electrical and Electronics Engineers. PPG Institute of Technology. Proceedings of the 2nd international conference on Communication and Electronics Systems (ICCES 2017). Vols. 19-20(Oct); 2017.
13. Sammouda R. Segmentation and analysis of CT chest images for early lung cancer detection. In: Proceedings Global Summit on Computer and Information Technology, GSCIT 2016. Vol. 2017. Institute of Electrical and Electronics Engineers Inc; 2016. p. 120-6.
14. Qu Y, Fu Q, Shang C, Deng A, Zwiggelaar R, George M, *et al*. Fuzzy-rough assisted refinement of image processing procedure for mammographic risk assessment. Applied Soft Computing. 2020;91. doi: 10.1016/j.asoc.2020.106230.
15. Han SS, Moon IJ, Lim W, Suh IS, Lee SY, Na JI, *et al*. Keratinocytic skin cancer detection on the face using region-based convolutional neural network. JAMA dermatology. 2020;156(1):29-37. doi: 10.1001/jamadermatol.2019.3807, PMID 31799995.

16. Magalhaes C, Mendes J, Vardasca R. The role of AI classifiers in skin cancer images. Skin Research and Technology. 2019;25(5):750-7. doi: 10.1111/srt.12713, PMID 31106913.
17. Wang X, Chen H, Ran AR, Luo L, Chan PP, Tham CC, *et al*. Towards multi-center glaucoma OCT image screening with semi-supervised joint structure and function multi-task learning. Medical Image Analysis. 2020;63:101695. doi: 10.1016/j.media.2020.101695, PMID 32442866.
18. Gandomkar Z, Brennan PC, Mello-Thoms C. MuDeRN: Multi-category classification of breast histopathological image using deep residual networks. Artificial intelligence in medicine. 2018;88:14-24. doi: 10.1016/j.artmed.2018.04.005, PMID 29705552.
19. Rajathi GM. Optimized Radial Basis Neural Network for Classification of Breast Cancer Images. Current medical Imaging. 2021;17(1):97-108. doi: 10.2174/1573405616666200516172118. PMID 32416697.
20. Bhanage DA, Pawar AV. Bibliometric survey of IT Infrastructure Management to Avoid Failure Conditions. Information Discovery and Delivery. 2021;49(1):45-56. doi: 10.1108/IDD-06-2020-0060.