



Bibliometrics research on radiomics of lung cancer

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Background: Lung cancer is currently the most commonly diagnosed malignant tumor worldwide. Exploring ways to improve the accuracy and timeliness of diagnosis has important clinical significance. Radiomics transforms images into high-dimensional data, and uses deep learning and artificial intelligence to improve the accuracy and efficiency of disease diagnosis. There is an increasing amount of research on radiomics in the diagnosis of lung cancer. This study analyzes the relevant literature in the Science Citation Index Expanded (SCI-E) database to understand the current research status and future development direction of lung cancer radiomics.

Methods: This study is based on the SCI-E database. The first search formula is topic = Lung cancer OR Lung neoplasms (#1), the second search formula is topic = Radiomics (#2), and the third search formula is #1 and #2, that is, literature that meets both the first and second search results. CiteSpace software was used to analyze lung cancer radiomics from the annual distribution of articles, countries, institutions, journals, and authors and keywords. HistCite software was used to visualize the citation chronology of the lung cancer radiomics literature, and Pajek software was used to analyze the main path of the citation chronology.

Results: There were a total of 749 publications, of which most were original articles (529, 70.63%) and reviews (109, 14.55%). The citation frequency is 21,676 times, the h-index is 66, and the average number of citations per publication is 28.94. The research mainly comes from the United States of America, China and other countries. The research institutions are mainly medical centers such as Moffitt Cancer Center, Maastricht University and Harvard Medical School. The authors are also mainly from these institutions. The literature was published in many related journals, mainly imaging and oncology journals. Keyword analysis shows that in recent years, research has focused on deep learning and artificial intelligence.

Conclusions: The field of lung cancer radiomics is developing rapidly, and the main focuses of research are deep learning and artificial intelligence.

Keywords: Lung cancer; radiomics; bibliometrics

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Introduction

Lung cancer is the cancer with the highest morbidity and mortality in China and worldwide (1). In China, the incidence and mortality of lung cancer have seen a clear

upward trend in recent years. According to the statistics of the National Cancer Center of China, the incidence and mortality of lung cancer in China ranked first among malignant tumors in 2014, with about 781,000 new cases and 626,000 deaths. The incident and mortality rates are

Table 1 Literature type

Literatures	Records	% of 749
Articles	529	70.63
Reviews	109	14.55
Meeting abstracts	93	12.42
Editorial materials	15	2.00
Early access	14	1.87
Proceeding papers	8	1.07
Corrections	3	0.40
Book chapters	2	0.27
Data paper	1	0.13

higher in males than in females, and higher in cities than in rural areas. There are also regional differences in the rate of morbidity and deaths, from high to low in the eastern, central and western regions (2). Most early-stage lung cancer has no obvious symptoms, and most patients are in the advanced stage when they show symptoms, resulting in a low overall 5-year survival rate for advanced-stage lung cancer (3). Thin-slice CT scanning has become an effective method for screening high-risk groups. In recent years, due to the popularization of health examinations and thin-slice CT examinations, the detection rate of early lung cancer has increased (4). After Lambin *et al.* first proposed the concept of radiomics in 2012, the technology has been widely used in clinical practice and research such as tumor diagnosis and prognosis (5-7). After nearly 10 years of development, the research of radiomics in the field of lung cancer has developed rapidly (8,9). This study is based on the Science Citation Index Expanded (SCI-E) database to evaluate lung cancer radiomics literature since 2012, and analyze the current status of related research and forecast the future development directions.

Methods

Data source

The literature was obtained from the SCI-E database in the Web of Science Core Collection (WOSCC).

Search strategy

The search was performed based on the SCI-expanded index. The first search formula is topic = Lung cancer OR

Lung neoplasms (#1), the second search formula is topic = Radiomics (#2), and the third search formula is #1 and #2, that is, literature that meets both the first and second search results. The search time range is from 1900 to March 18, 2021.

Analysis method

The full record of the search results and the cited references was exported in plain text format, and CiteSpace software was used to analyze the annual publication status, country and institution distribution, journal distribution, author distribution, and frequency of keywords used in publications of radiomics of lung cancer. HistCite software was used to visualize the citation chronology of lung cancer radiomics literature, and Pajek software was used to analyze the main path of the citation chronology. The bibliometric online analysis platform developed by the National Science Library of the Chinese Academy of Sciences was used to visualize analysis of historical keywords, number of articles in the past years, and national partnerships.

Statistical processing

This study mainly analyzes the distribution of lung cancer radiomics literature in different years, countries, institutions, authors. Therefore, statistical processing mainly uses absolute numbers and percentages (n, %) without comparison between groups.

Results

Literature search results

There are a total of 749 publications on lung cancer radiomics, including 529 original articles (70.63%), 109 reviews (14.55%), 93 meeting abstracts (12.4%), 15 editorial materials (2.00%), 14 articles of early access (1.87%), 8 proceeding papers (1.07%), 3 corrections, 2 books, and 1 data paper (*Table 1*). Although the search scope is from 1900, the first relevant document appeared in 2012 (*Table 2, Figure 1*). The citation frequency is 21,676 times, the h-index count is 66, and the average number of citations per item is 28.94 (*Figure 2*). There has been an almost exponential increase in the publication of related papers and the citation of references (*Figures 1,2*). The HistCite software was used to visualize the citation chronology of lung cancer radiomics literature, and the Pajek software was

Table 2 Literature distribution by year

Years	Records	% of 749
2021	27	3.60
2020	241	32.18
2019	173	23.10
2018	143	19.09
2017	89	11.88
2016	42	5.61
2015	21	2.80
2014	6	0.80
2013	5	0.67
2012	2	0.27

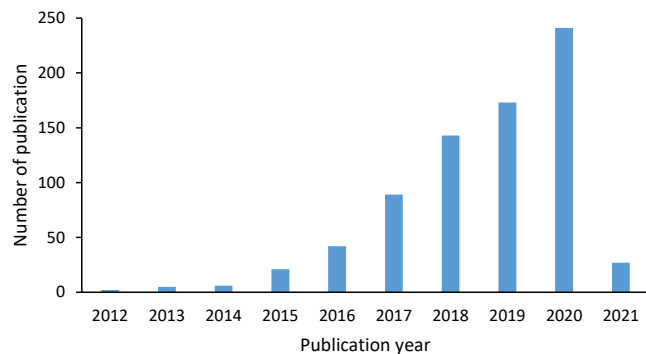


Figure 1 The number of publications increased by year.

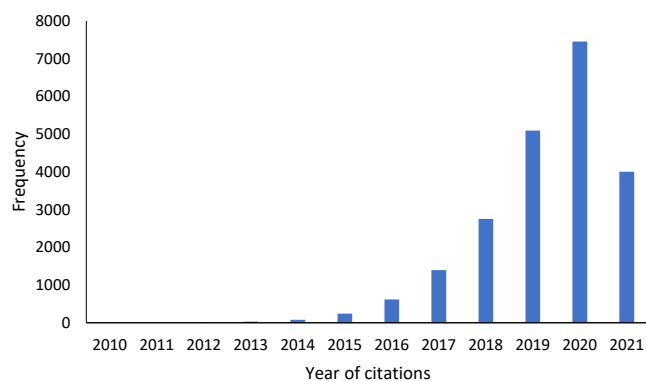


Figure 2 The frequency of citations increased significantly by year.

used to analyze the main path of the citation chronology. The 30 documents with the highest frequency of citations are selected to make the citation chronology, as shown in

Figure 3. We exported the citation relationship matrix of the current citation chronicle in HistCite, and imported the matrix file into Pajek for main path analysis. An in-depth analysis found that these 14 documents (Figure 4) represent the development stage of lung cancer radiomics and related research, from the initial image analysis to the clinical significance to the recent standardization, which basically reflects the development process of related fields (Table 3).

Distribution of countries and institutions

The country visualization map (Figures 5,6) and the list (Table 4) show the top 5 countries with the number of publications: the United States, China, the Netherlands, Italy, and France. The top five centrally ranked countries are the United States, China, France, Canada, and Germany. In the visualization view, the number of network nodes (N=70), and the number of connections (E=187) were both small, indicating that although a large number of countries have participated in the research of lung cancer radiomics, it is still dominated by a few countries (Table 5). The visualization of papers published in different countries over the years (Figure 7) shows that the number of papers published by major countries and the overall number are on the rise. Institutional visualization map (Figure 8) and list (Tables 6,7) show similar results. Related studies are mainly concentrated in medical centers such as Moffitt Cancer Center, Maastricht University, and Harvard Medical School, resulting in cooperation mainly between authors from these institutions (Figure 9).

Authors distribution

The top-ranked authors in terms of distribution have published a lot of work, and their papers are often published in the more authoritative journals. Further analysis reveals that these authors come from major institutions. Philippe Lambin and Ralph T. H. Leijenaar are from Maastricht Univ, while Hugo J. W. L. Aerts, Raymond H. Mak, and Chintan Parmar are all from Harvard Medical School. Robert J. Gillies, Matthew B. Schabath, and Yoganand Balagurunathan are all from Moffitt Cancer Center, and these authors often cooperate in important articles. Therefore, we can see in the centrality index that these authors have high centrality rankings (Tables 8,9). Similarly, due to the quality of their work, these authors are also cited more than other authors (Tables 10,11, Figure 10).

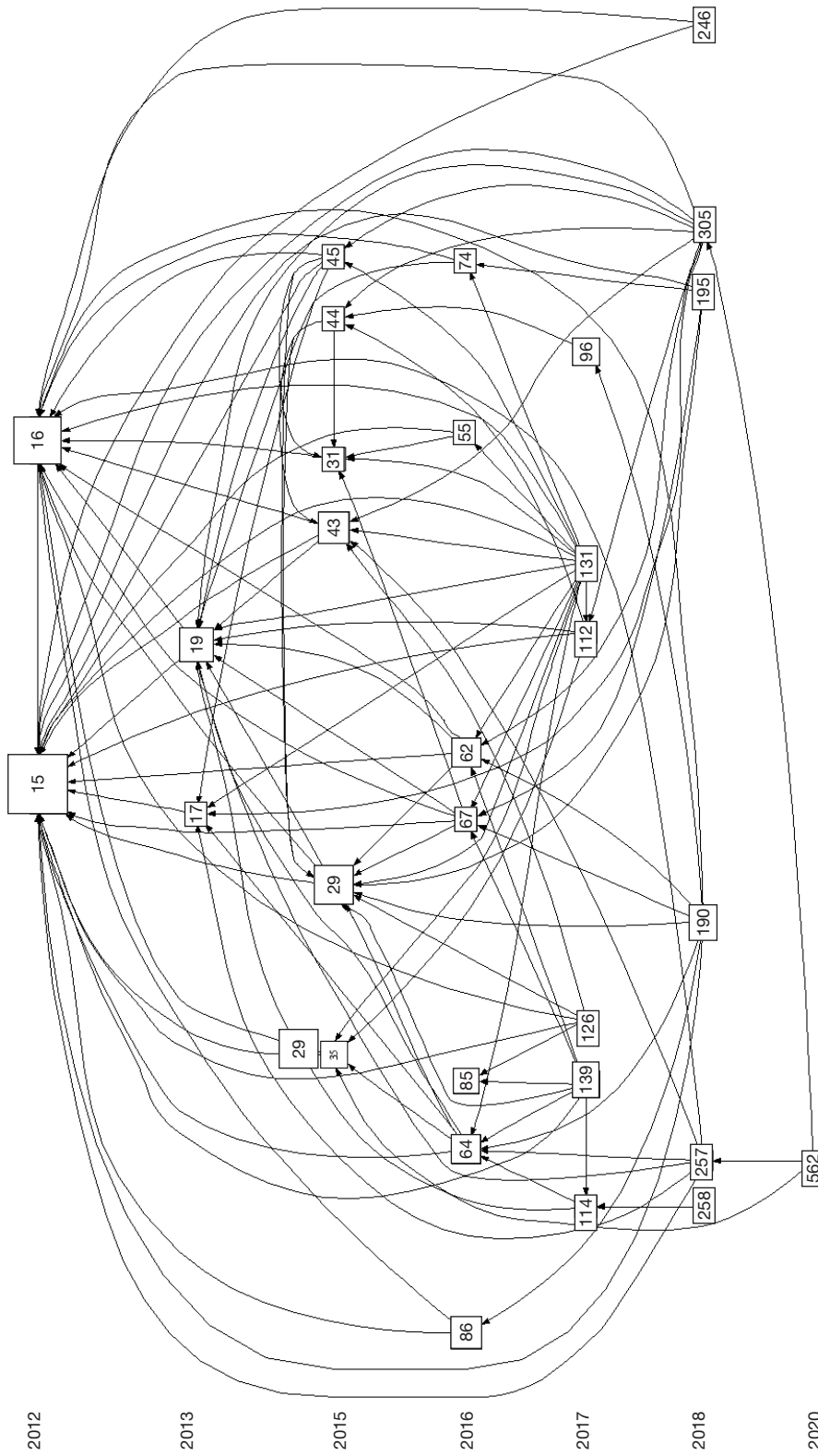


Figure 3 Chronological chart of the top 30 most frequent citations. The number of nodes in the graph is 30, and the number of connections is 109 (the 30 articles have 109 mutual references). The maximum number of citations is 280, and the minimum is 26. The size of the box in the figure above represents the frequency of citations. The arrow line represents the citation relationship between the document nodes, and the documents pointed to by the arrows are the cited documents. A document collection was created based on the 749 documents. The number in the box is the serial number of the document in the document collection.

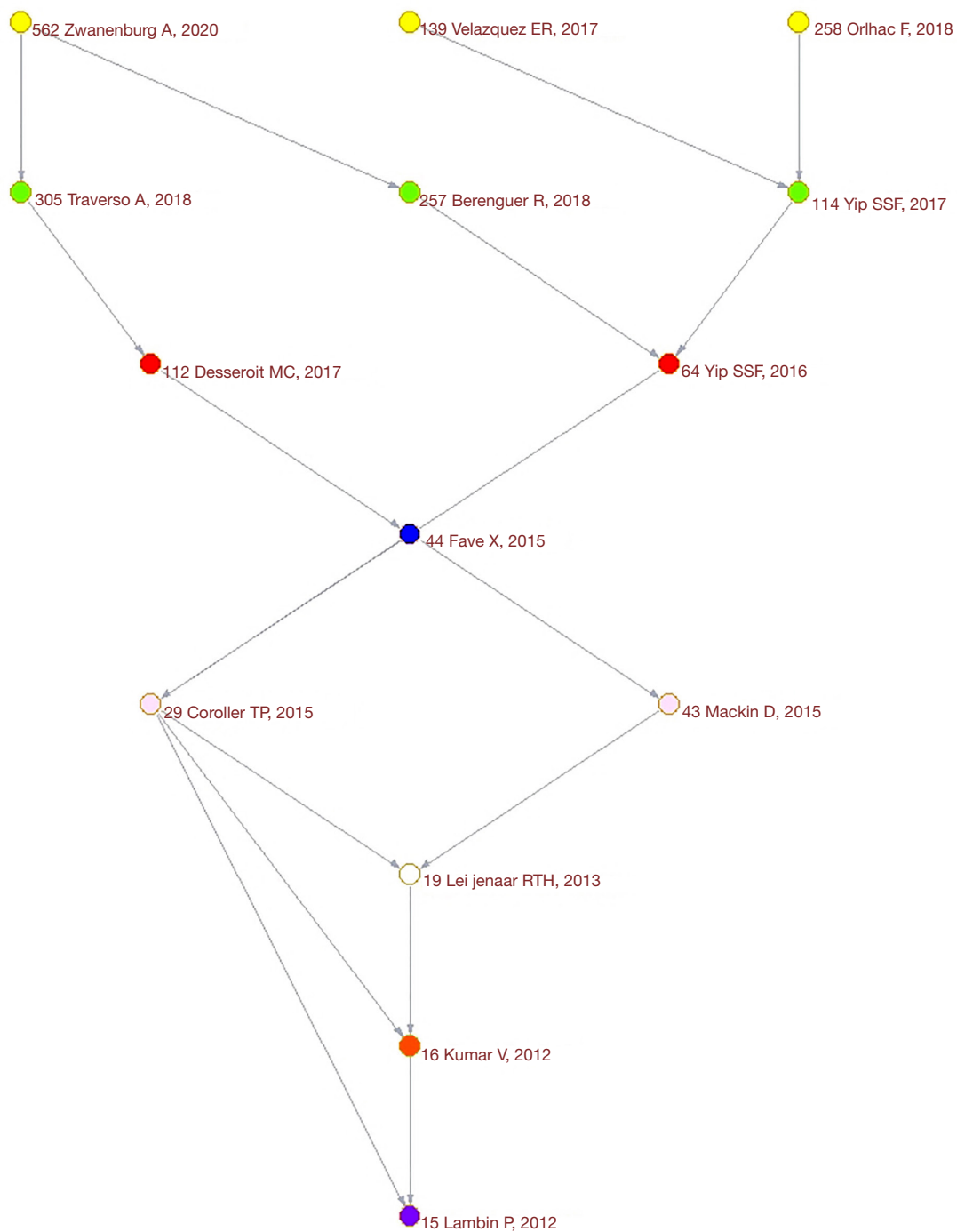
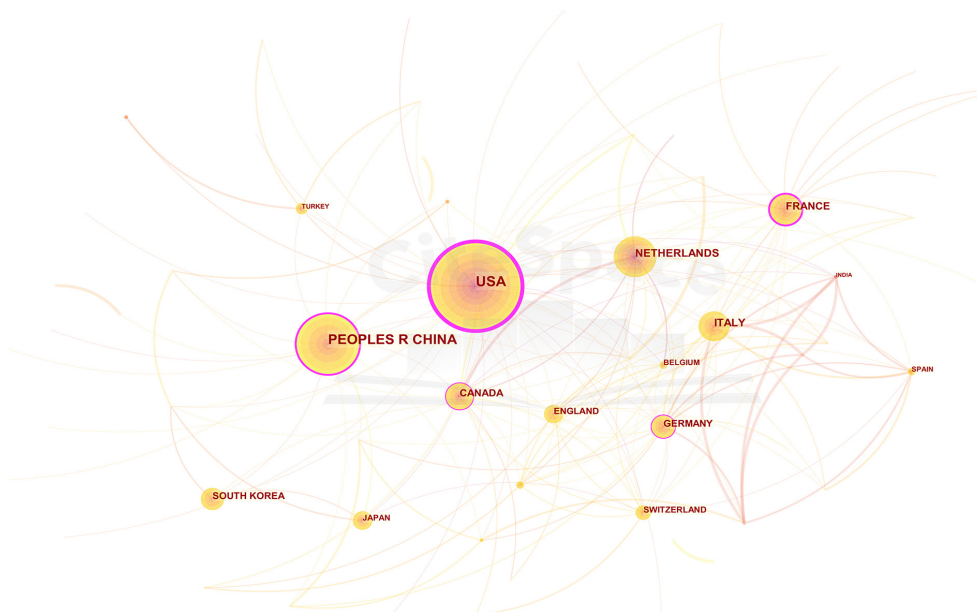


Figure 4 Main path diagram. Each node in the figure represents a document, and the annotation on the right side of the node is the serial number, author, and publication year of the document in the document collection. It can be seen from the figure that the reference relationship is back and forth along the arrow direction. The main path shown in the figure spans 9 years from 2012 to 2020. It is divided into 8 stages according to colors, and a total of 14 documents.

Table 3 The 14 documents involved in the main path (sorted by year)

No.	Articles	Citation	Reference
1	Lambin P, Rios-Velazquez E, Leijenaar R, <i>et al.</i> Radiomics: extracting more information from medical images using advanced feature analysis	280	(5)
2	Kumar V, Gu Y, Basu S, <i>et al.</i> Radiomics: the process and the challenges	178	(10)
3	Leijenaar RT, Carvalho S, Velazquez ER, <i>et al.</i> Stability of FDG-PET radiomics features: an integrated analysis of test-retest and inter-observer variability	94	(11)
4	Coroller TP, Grossmann P, Hou Y, <i>et al.</i> CT-based radiomic signature predicts distant metastasis in lung adenocarcinoma	122	(12)
5	Mackin D, Fave X, Zhang L, <i>et al.</i> Measuring computed tomography scanner variability of radiomics features	80	(13)
6	Fave X, Mackin D, Yang J, <i>et al.</i> Can radiomics features be reproducibly measured from CBCT images for patients with non-small cell lung cancer?	42	(14)
7	Yip SS, Aerts HJ. Applications and limitations of radiomics	62	(15)
8	Desseroit MC, Tixier F, Weber WA, <i>et al.</i> Reliability of PET/CT shape and heterogeneity features in functional and morphologic components of non-small cell lung cancer tumors: a repeatability analysis in a prospective multicenter cohort	37	(16)
9	Yip SS, Kim J, Coroller TP, <i>et al.</i> Associations between somatic mutations and metabolic imaging phenotypes in non-small cell lung cancer	38	(17)
10	Rios Velazquez E, Parmar C, Liu Y, <i>et al.</i> Somatic mutations drive distinct imaging phenotypes in lung cancer	59	(18)
11	Berenguer R, Pastor-Juan MDR, Canales-Vazquez J, <i>et al.</i> Radiomics of CT features may be nonreproducible and redundant: influence of CT acquisition parameters	34	(19)
12	Orlhac F, Boughdad S, Philippe C, <i>et al.</i> A postreconstruction harmonization method for multicenter radiomic studies in PET	27	(20)
13	Traverso A, Wee L, Dekker A, <i>et al.</i> Repeatability and reproducibility of radiomic features: a systematic review	27	(21)
14	Zwanenburg A, Vallieres M, Abdalah MA, <i>et al.</i> The image biomarker standardization initiative: standardized quantitative radiomics for high-throughput image-based phenotyping	31	(22)

**Figure 5** National visualization map.

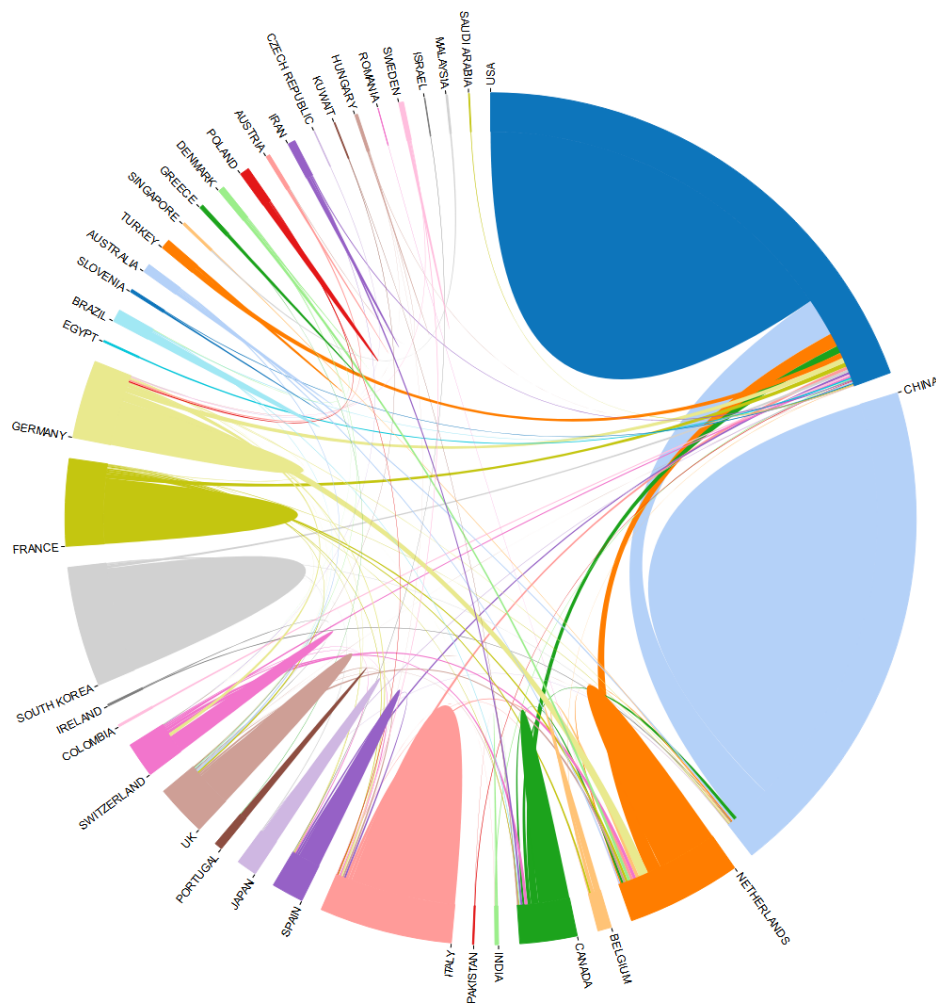


Figure 6 Visual diagram of cooperation between countries. The amount of cooperation in related research between China and the United States is relatively large, and there are many countries that cooperate with American researchers.

Table 4 Top 10 countries in terms of posting volume

Rank	Countries	Frequency
1	USA	296
2	China	236
3	Netherlands	66
4	Italy	63
5	France	59
6	Canada	42
7	Germany	40
8	South Korea	40
9	England	31
10	Switzerland	26

Table 5 Top 10 countries for centrality

Rank	Countries	Centrality
1	USA	0.73
2	China	0.28
3	France	0.26
4	Canada	0.13
5	Germany	0.12
6	Netherlands	0.10
7	Italy	0.09
8	England	0.06
9	Singapore	0.05
10	Switzerland	0.03

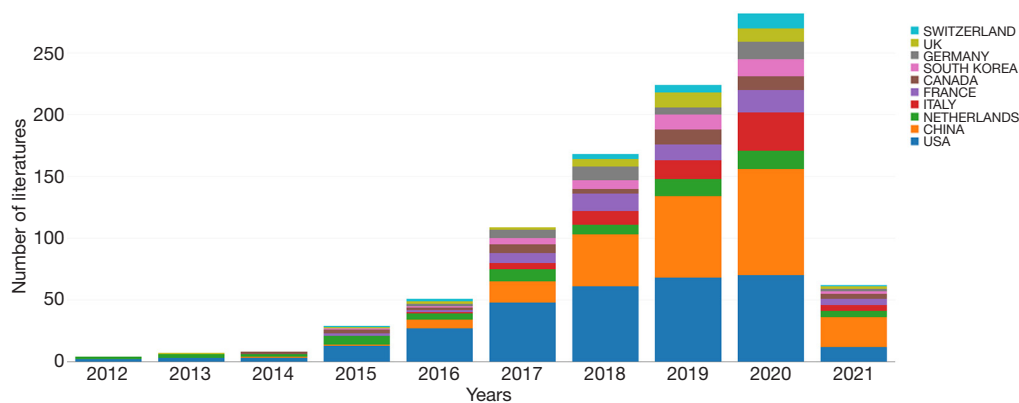


Figure 7 Changes in the number of articles in different countries over the years. The X-axis is the year, and the Y-axis is the number of publications.

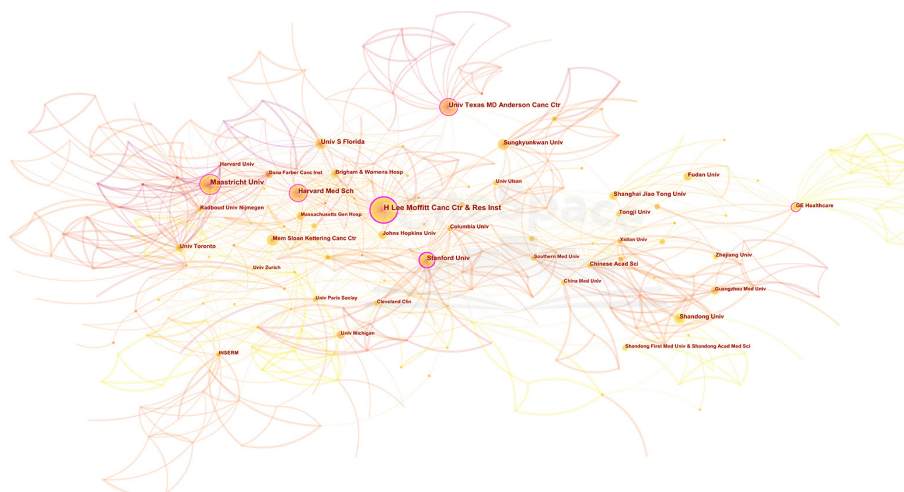


Figure 8 Institutional visualization map.

Table 6 Top 10 institutions in terms of numbers of publications

Rank	Institutions	Frequency
1	H. Lee Moffitt Canc Ctr & Res Inst	43
2	Maastricht Univ	40
3	Harvard Med Sch	29
4	Univ Texas MD Anderson Canc Ctr	28
5	Stanford Univ	26
6	Univ S. Florida	25
7	Shanghai Jiao Tong Univ	21
8	Sungkyunkwan Univ	19
9	Shandong Univ	19
10	Fudan Univ	17

Table 7 Top 10 institutions by centrality

Rank	Institutions	Centrality
1	Stanford Univ	0.36
2	H. Lee Moffitt Canc Ctr & Res Inst	0.21
3	Maastricht Univ	0.12
4	Harvard Med Sch	0.12
5	GE Healthcare	0.11
6	Univ Texas MD Anderson Canc Ctr	0.10
7	Univ Groningen	0.10
8	Univ Toronto	0.09
9	Shanghai Jiao Tong Univ	0.08
10	Chinese Acad Sci	0.08

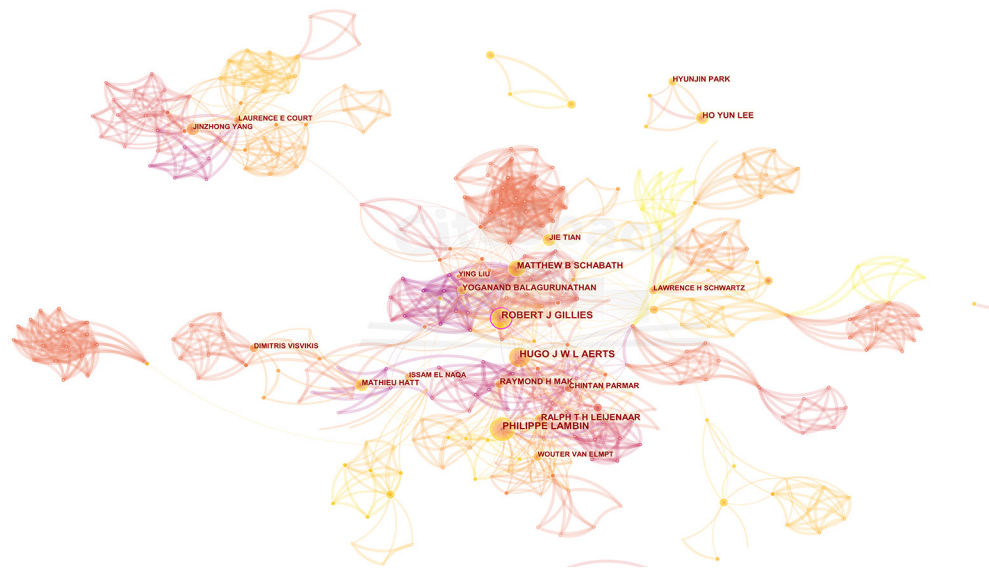


Figure 9 Visualization map of co-authors.

Table 8 Top 10 authors by number of publications

Rank	Authors	Records
1	Lambin P	32
2	Aerts HJWL	31
3	Gillies RJ	29
4	Schabath MB	22
5	Leijenaar RTH	19
6	Balagurunathan Y	17
7	Mak RH	16
8	Lee HY	15
9	Parmar C	14
10	Tian J	14

Table 9 Authors with the highest centrality

Rank	Authors	Centrality
1	Gillies RJ	0.12
2	Mackin D	0.08
3	Zhang GG	0.08
4	Tian J	0.05
5	Leijenaar RTH	0.05
6	Latifi K	0.04
7	Schabath MB	0.04
8	Lambin P	0.04
9	Napel S	0.04
10	Moros EG	0.03

Journals

This study includes 749 radiomics articles that were published in 184 journals, of which 18 journals have more than 10 articles (Table 12). These journals have published 402 publications, accounting for 53.67% of the total literature (Table 8). The citation frequency and centrality ranking of these journals show that the top 10 journals are mainly imaging and oncology journals (Tables 13,14). The results also show that journals such as *Medical Physics*, *Frontiers in Oncology*, and *European Radiology* have great influence on lung cancer radiomics.

Keywords

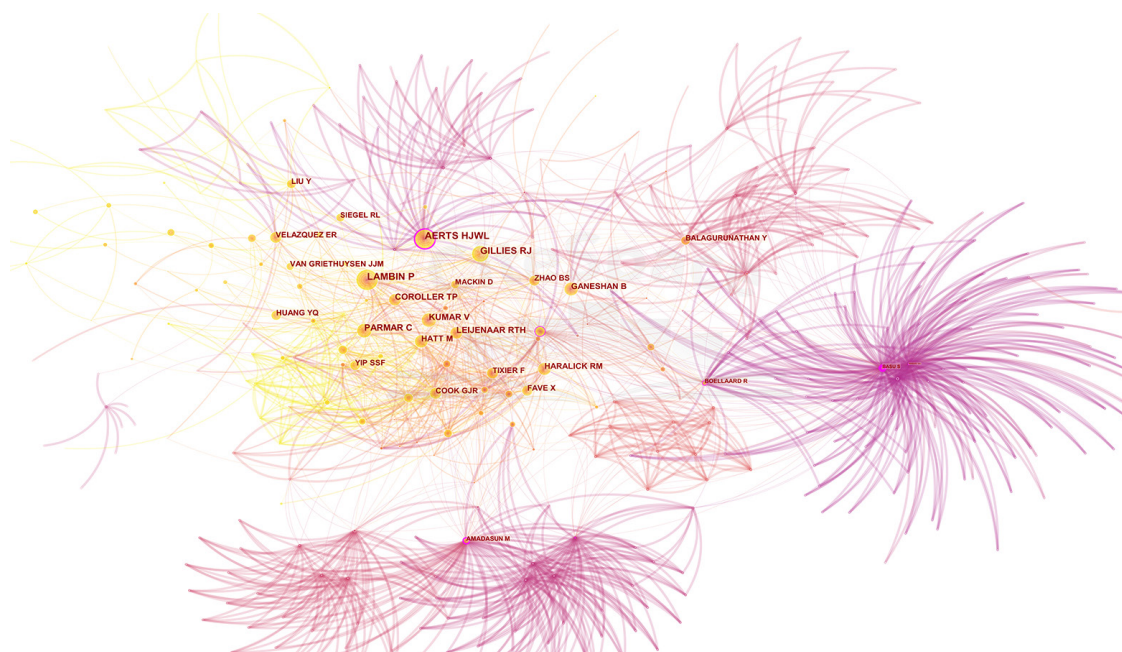
CiteSpace V was used to construct a keyword co-occurrence map (Figure 11: N=355, E=1,877, Tables 15,16), which shows that radiomics, lung cancer, survival, characteristics, and CT are keywords in the literature. Further, using CiteSpace for burst detection for high-frequency keywords (Figure 12) shows that the focus of research is gradually shifting from imaging feature analysis to deep learning and artificial intelligence. Therefore, the current and future research hotspots are not about extracting image features from the image itself in the past, but turning to how to use

Table 10 Top 10 authors cited in total

Rank	Authors	Frequency
1	Lambin P	354
2	Aerts HJWL	347
3	Gillies RJ	277
4	Parmar C	207
5	Kumar V	179
6	Coroller TP	160
7	Leijenaar RTH	153
8	Ganeshan B	142
9	Haralick RM	139
10	Hatt M	128

Table 11 Top 10 authors of centrality of co-citation

Rank	Authors	Centrality
1	Basu S	0.64
2	Amadasun M	0.30
3	Aerts HJWL	0.22
4	Gevaert O	0.12
5	Armato SG	0.12
6	Boellaard R	0.10
7	Alic L	0.10
8	Coroller TP	0.09
9	Cook GJR	0.08
10	Balagurunathan Y	0.08

**Figure 10** Visualized map of authors co-cited.

artificial intelligence to more accurately judge lesions. In other words, it is necessary to further integrate radiomics with clinical practice and prognosis analysis, and use the accumulated big data to make more accurate diagnostic and prognostic judgments, and even provide reasonable treatment plans. The keyword visualization view over time shows that the frequency of use of the main keywords is increasing year by year, which is consistent with the increase in the number of related publications (*Figure 13*).

Discussion

This study analyzed the research literature related to lung cancer since the first introduction of radiomics in 2012, and found that radiomics research in the field of lung cancer has developed rapidly. The number of related publications and the citation frequency have increased almost exponentially, especially in recent years. The recent traction of computer deep learning and artificial intelligence has seen the focus

Table 12 Top 18 journals by volume

Rank	Journals	Records	% of 749
1	<i>Medical Physics</i>	50	6.68
2	<i>Frontiers in Oncology</i>	39	5.21
3	<i>European Radiology</i>	31	4.14
4	<i>Scientific Reports</i>	30	4.01
5	<i>European Journal of Nuclear Medicine and Molecular Imaging</i>	28	3.74
6	<i>International Journal of Radiation Oncology, Biology, Physics</i>	28	3.74
7	<i>Physics in Medicine and Biology</i>	28	3.74
8	<i>Journal of Thoracic Oncology</i>	25	3.34
9	<i>Radiotherapy and Oncology</i>	21	2.80
10	<i>PLoS One</i>	20	2.67
11	<i>Journal of Nuclear Medicine</i>	18	2.40
12	<i>Translational Lung Cancer Research</i>	15	2.00
13	<i>European Journal of Radiology</i>	14	1.87
14	<i>Cancers</i>	12	1.60
15	<i>Lung Cancer</i>	12	1.60
16	<i>Radiology</i>	11	1.47
17	<i>Journal of Thoracic Disease</i>	10	1.34
18	<i>Physica Medica: European Journal of Medical Physics</i>	10	1.34

Table 13 Top 10 journals by citation frequency

Rank	Journals	Frequency
1	<i>Radiology</i>	537
2	<i>Sci Rep-UK</i>	407
3	<i>PLoS One</i>	390
4	<i>Nat Commun</i>	353
5	<i>Med Phys</i>	343
6	<i>Eur Radiol</i>	340
7	<i>Radiother Oncol</i>	335
8	<i>Eur J Cancer</i>	331
9	<i>J Nucl Med</i>	282
10	<i>Int J Radiat Oncol</i>	277

Table 14 Top 10 journals by centrality

Rank	Journals	Centrality
1	<i>Algorithms</i>	0.22
2	<i>Algorithms Cluster D</i>	0.22
3	<i>AaaI Spring S Series</i>	0.22
4	<i>Acad Radiol</i>	0.19
5	<i>Am J Roentgenol</i>	0.14
6	<i>Clin Cancer Res</i>	0.12
7	<i>Lung Cancer</i>	0.11
8	<i>Acta Oncol</i>	0.11
9	<i>CA Cancer J Clin</i>	0.11
10	<i>Brit J Cancer</i>	0.10

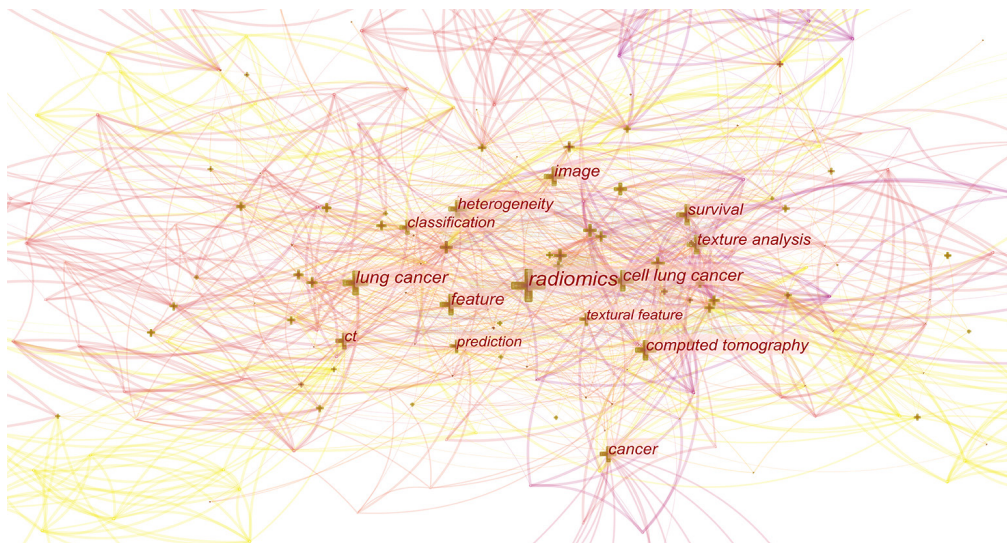


Figure 11 Keyword co-occurrence map generated by CiteSpace V software.

Table 15 Top 10 keywords by frequency

Rank	Keywords	Frequency
1	Radiomics	445
2	Lung cancer	178
3	Feature	152
4	Cell lung cancer	139
5	Image	136
6	Texture analysis	116
7	Computed tomography	110
8	Survival	107
9	Cancer	104
10	CT	101

Table 16 Top 10 keywords by centrality

Rank	Keywords	Centrality
1	Chemotherapy	0.18
2	Radiomics	0.17
3	Carcinoma	0.13
4	Cancer	0.12
5	CT	0.12
6	NSCLC	0.12
7	Immunotherapy	0.10
8	Texture analysis	0.09
9	Heterogeneity	0.09
10	Diagnosis	0.09

Top 24 Keywords with the Strongest Citation Bursts

Keywords	Year	Strength	Begin	End	2012-2021
image feature	2012	2.88	2012	2017	
tumor	2012	2.59	2012	2014	
radiotherapy	2012	2.44	2013	2015	
lung	2012	4.28	2014	2018	
stage	2012	2.85	2014	2016	
quantitative imaging	2012	4.74	2015	2018	
parameter	2012	3.54	2015	2017	
quantification	2012	3.09	2015	2017	
prognostic factor	2012	2.65	2015	2017	
esophageal cancer	2012	2.63	2015	2018	
f 18 fdg pet	2012	8.92	2016	2018	
tumorheterogeneity	2012	4.76	2016	2018	
test retest	2012	4.49	2016	2018	
fdg pet radiomics	2012	3.99	2016	2017	
tumor heterogeneity	2012	3.66	2016	2017	
texture feature	2012	3.76	2017	2018	
fdg pet/ct	2012	3.38	2017	2018	
pet/ct	2012	3.01	2017	2018	
intratumor heterogeneity	2012	3.01	2017	2018	
reconstruction	2012	2.63	2017	2018	
prostate cancer	2012	3.09	2018	2019	
stage i	2012	3.2	2019	2021	
deep learning	2012	3.11	2019	2021	
artificial intelligence	2012	2.95	2019	2021	

Figure 12 CiteSpace performs burst detection on keywords. The results show the top 24 keywords with the strongest citation bursts.

of research has gradually shift from the initial image feature data extraction, classification, and mining to the current deep learning based on big data. On this basis, artificial intelligence applied to practical work has greatly improved the accuracy and efficiency of diagnosis. In terms of the distribution of research, the data shows that lung cancer

radiomics research is mainly concentrated in the United States, China, the Netherlands and other countries. Some of these countries (such as the United States and the Netherlands) have done a lot of pioneering work based on theoretical and technological leadership. Some countries (such as China) generate abundant clinical data based on a

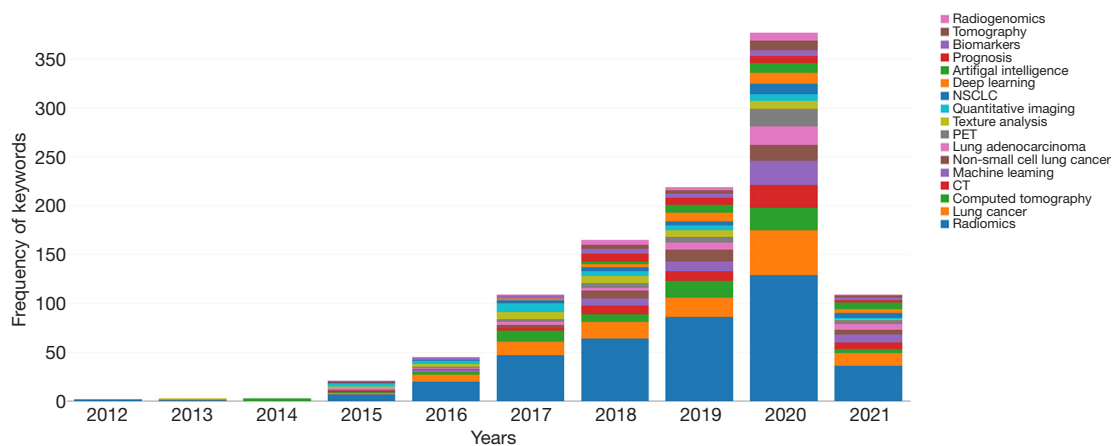


Figure 13 Changes in the number of keywords over the years. The X-axis is the year, and the Y-axis is the frequency.

large number of cases, combined with advanced computer technology, and contribute important practical application results. Therefore, the current related research is relatively concentrated in the aforementioned countries and research institutions, but the cooperative research in this field is relatively extensive, and many authors have participated in international cooperation.

Radiomics refers to the use of computer technology to screen and analyze image features extracted from regions of interest such as CT, magnetic resonance imaging, and PET through quantitative methods, to quantitatively describe the biological characteristics and heterogeneity of tumors. This high-throughput quantitative analysis method avoids the bias caused by the subjectivity of imaging physicians (23,24). Radiomics usually includes five processes including standardized image acquisition and reconstruction, lesion image segmentation, feature extraction and selection, prediction model construction and verification, and model classification and prediction (25). Currently, in clinical work, doctors' image analysis is mainly limited to the preliminary analysis of tumor morphology and geometric characteristics, including roughly measuring the size of the lesion, and a simple description of CT values, PET-CT, and MRI signal levels. Radiomics is based on conventional imaging diagnosis, in-depth mining of image data, and looking for systemic imaging diagnosis technology that reflects the objective characteristics of the disease. In recent years, it has also been combined with the pathophysiological changes at the tissue, cell, and gene level to develop radiomics that can better reflect the biological characteristics of tumors (26-28).

Due to the popularity of thin-slice CT scans, a large number of lung nodules have been discovered. Distinguishing

between benign and malignant nodules is a huge challenge for radiologists and clinicians. Since applying radiomics in the diagnosis of lung cancer, significant progress has been made in the identification of lung masses (29,30). Based on the previous research, Alahmari *et al.* found that combining delta radiomics features with conventional radiomics features can further improve the ability to identify lung tumors, that is to say that the dynamic changes of radiomic characteristics can better distinguish between benign and malignant lung tumors, but the authors did not conduct follow-up studies on the prognostic images yielded by this method (31). Dynamic changes mean that a certain period of observation is required, and time is an important cost for cancer patients. Sun *et al.* performed radiomics analysis on lung adenocarcinoma with simple ground-glass nodules and found that radiomic-based nomograms combined with RAD scores, edge morphology, acupuncture signs, and tumor size can be used to evaluate whether simple ground-glass nodules are biomarkers of aggressiveness. Similar studies are abundant (32,33). Differentiating between benign and malignant tumors determines the course of treatment, and the specific treatment plan requires more individualized information, especially the pathological type and genotype of the tumor tissue. The results of radiomics combined with histopathology and gene phenotype showed that the appearance and imaging features of tumors are closely related to pathological changes, and changes in gene, protein, and molecular expression, that is, imaging features are closely related to lung tumor histology (34-36). In addition to differential diagnosis and pathological gene prediction, radiomics can also predict the prognosis of lung cancer patients. Hosny *et al.* conducted a retrospective radiomics

study on patients with non-small cell lung cancer (NSCLC), and the results showed that based on standard CT images from NSCLC patients, deep learning networks can be used to stratify the risk of death in these patients (37). It is evident that radiomics as a diagnostic evaluation technique has been applied to all aspects of lung cancer. The quantitative analysis of relevant literature shows that radiomics has good prospects in the field of lung cancer. But at present, it is relatively limited to a few countries and research institutions. The potential regional differences in these results and differences in environmental factors need to be further analyzed based on big data, combined with artificial intelligence and deep learning. However, such a huge amount of work is difficult to complete by humans, thus radiomics will have greater value in the future.

Limitations

Due to the large number of documents retrieved, we only conducted in-depth analysis of the top-ranked institutions, authors, and journals, and were unable to analyze specific documents one by one, and did not sufficiently explore the associations between research details, especially in the lack of further analysis of important documents. Future research should focus on the related work of some important investigators and research institutions based on the results of this research.

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Footnote

Conflicts of Interest: All authors have completed the ICMJE uniform disclosure form (available at <https://dx.doi.org/10.21037/tcr-21-1277>). The authors have no conflicts of interest to declare.

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