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Research article

# Worldwide research landscape of artificial intelligence in lung disease: A scientometric study

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ABSTRACT

*Purpose:* To perform a comprehensive bibliometric analysis of the application of artificial intelligence (AI) in lung disease to understand the current status and emerging trends of this field.
*Materials and methods:* AI-based lung disease research publications were selected from the Web of Science Core Collection. Citespace, VOS viewer and Excel were used to analyze and visualize co-authorship, co-citation, and co-occurrence analysis of authors, keywords, countries/regions, references and institutions in this field.
*Results:* Our study included a total of 5210 papers. The number of publications on AI in lung disease showed explosive growth since 2017. China and the United States lead in publication numbers. The most productive author were Li, Weimin and Qian Wei, with Shanghai Jiaotong University as the most productive institution. Radiology was the most co-cited journal. Lung cancer and COVID-19 emerged as the most studied diseases. Deep learning, convolutional neural network, lung cancer, radiomics will be the focus of future research.
*Conclusions:* AI-based diagnosis and treatment of lung disease has become a research hotspot in recent years, yielding significant results. Future work should focus on establishing multimodal AI models that incorporate clinical, imaging and laboratory information. Enhanced visualization of deep learning, AI-driven differential diagnosis model for lung disease and the creation of international large-scale lung disease databases should also be considered.

## 1. Introduction :

Respiratory diseases pose a significant health burden globally. Asthma, chronic obstructive pulmonary disease (COPD), acute lower respiratory tract infections, tuberculosis (TB) and lung cancer rank among the most common causes of severe illness and death worldwide [1]. Lung cancer, in particular, is associated with high morbidity and was the leading cause of cancer death in 2020, resulting in nearly 1.8 million fatalities [2,3]. Approximately 10 million people were newly infected with tuberculosis in 2017, and about 1.3 million people succumb to the disease annually [4]. Lower respiratory infections and COPD are also leading causes of morbidity and mortality in many countries and regions worldwide [5–7].

*Abbreviations:* AI, artificial intelligence; COPD, chronic obstructive pulmonary disease; TB, tuberculosis; WoSCC, Web of Science Core Collection; TLS, Total link Strength; BC value, betweenness centrality value; CPRL-4, completely portal robot lobectomy with 4 arms; SBRT, stereotactic body radiotherapy; CT, computed tomography; SVM, support vector machine.

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Prompt and accurate diagnosis and treatment are crucial for improving patient prognosis and treatment outcome. Traditional diagnosis and treatment process usually rely on the expertise of physicians, especially in underdeveloped and low-income nations where diseases like tuberculosis are more prevalent. This highlights the urgent need for objective, effective, and precise diagnosis and treatment methods. Artificial Intelligence (AI) offers a potential solution to address these challenges. Numerous researchers worldwide have conducted extensive studies, Examples include the use of AI for screening, diagnosis, and prognostic assessment of lung cancer [8,9], prognostic prediction of pulmonary fibrosis and interstitial lung disease [10,11], and identification of infectious diseases of the lung [12], yielding an abundance of accomplishment in the field.

As a result, it is essential to perform a comprehensive bibliometric analysis to understand the current status and trends of such research. Bibliometrics is a method that employs statistical quantitative analysis to evaluate large volume of published literature and its metadata within a specific field, aiming to assess research foundations, trend evolution and emerging hot spots [13]. Numerous bibliometric analyses have been conducted across various disciplines, including cardiovascular science [14], tumor pathology [15], pharmacy [16], obstetrics and gynecology [17], orthopedics [18], and radiology [19,20]. In a field related to the combination of radiographic imaging and AI, Kocak et al. conducted an analysis of AI and its subfields as well as radiomics in Radiology, Nuclear Medicine, and Medical Imaging [21]. In relation to lung disease, bibliometric investigations also have been carried out in various areas. Chassagnon et al. provided a review of AI applications in chest imaging [22], but did not systematically analyze possible future research directions. Kieu et al. only searched the literature related to deep learning [23], and did not deal with other AI techniques such as radiomics and support vector machines. Serindere et al. analyzed the 50 most cited articles on AI for lung cancer imaging [24], they only analyzed articles related to lung cancer. Li Ning et al. Chen Wang et al. respectively analyzed the research status of lung nodules and acute lung injury [25,26]. Su Jin Hong et al. on the other hand, used bibliometrics to count the 100 most cited chest imaging articles during 2000–2009, statistically analyzing their publication time, journal of publication, research institution, research topic, and techniques studied [27], in order to provide guidance to scholars working in this field. Unsurprisingly, most of the studies that have been conducted have been overviews of a particular lung disease or a particular AI technology, and there are currently few scholars who have conducted comprehensive scientometric analyses of the use of AI in thoracic diseases as a whole. This study attempts to comprehensively analyze the application of AI in all lung diseases over the past 20 years through bibliometrics, offer valuable insights into its current scholarly advancements and predict possible emerging trends.

## 2. Methods

### 2.1. Database

The Science Citation Index Expanded (SCI-Expanded 2003- present) of Clarivate Analytics'S Web of Science Core Collection (WoSCC) was employed to obtain the literature information. Articles and review articles from 2003 to 01-01 to 2022-12-31 was collected and the "plain text" format file with "Full Record and Cited References" was exported. All of the metadata of publications were downloaded on March 01, 2023.

### 2.2. Literature retrieval strategy

The details of our search rules are as follows:

#1: Topic=("artificial intelligence" OR "robotic*" OR "expert* system*" OR "intelligent learning" OR "feature* extraction" OR "feature* mining" OR "feature* learning" OR "machine learning" OR "feature* selection" OR "unsupervised clustering" OR "image* segmentation" OR "supervised learning" OR "semantic segmentation" OR "deep network*" OR "bayes* network" OR "deep learning" OR "neural network*" OR "neural learning" OR "neural nets model" OR "artificial neural network" OR "data mining" OR "graph mining" OR "data clustering" OR "big data" OR "knowledge graph")

#2: Title= (lung OR pulmonary).

#3: Author Keywords = (lung OR pulmonary).

The final retrieval formula was:(#1 AND #2) OR (#1 AND #3) AND Publication year = (2003-01-01 to 2022-12-31) AND Language = (English) AND Document types= (articles or reviews).

### 2.3. Data extraction and bibliometric analysis

The VOS viewer 1.6.18, CiteSpace V. 6.1.R6, Scimago Graphica, Excel and the online website were employed to perform statistical and visual analysis of the original information. The co-authorship analysis of countries/regions, authors, and institutions; the co-citation of journals, cited-references and the co-occurrence of author keywords were performed by the VOS viewer. The options and settings of VOS viewer are summarized in Supplementary Table 1. Compared with VOS viewer, Citespace concentrates on the connection between different fields, exploring current research hotspots and future research trends through knowledge changes. Parameters of Citespace were set as follows: time slice, January 2003 to December 2022, 1 year per slice; text processing, author, keywords, title, abstract; node type, from country/region, keyword, institution, author, co-cited author, co-cited journal, and co-cited literature; link range, within slices; link strength, cosine; pruning, pathfinding network method and pruning slices, integrated network; using the pathfinding network algorithm. During the analysis, modules (Q-value) and profiles (S-value) were used to assess network structure and network homogeneity. S-values greater than 0.7 indicate high clustering confidence, while Q-values greater than 0.3 indicate significant clustering structure [28]. The logarithmic likelihood ratio algorithm was used to extract noun phrases [29].

Citespace was adopted to achieve co-citation analysis of authors, journals and references. The visualization of dual-map overlay of journals and citation burst of references and keywords were also accomplished by Citespace.

## 3. Results

Based on our search criteria, a total of 5210 publications were identified. As shown in Fig. 1, the number of publications remained minimal prior to 2010, followed by a gradual increase over the next few years. However, a remarkable surge in publication volume occurred after 2017. Culminating in a record high of 1310 publications in 2022.

### 3.1. Co-authorship: countries/regions

A total of 108 countries/regions contributed to this field. As shown in Fig. 2A-B, China led in publication volume with 1958 publications, followed by the United States (n = 1399) and India (n = 398). The top three countries in terms of total citations were the United States (40,656), China (26,932) and Netherlands (7,219). The highest average citations were observed for the Netherlands. Total link Strength (TLS) represents the extent of collaboration between countries. As illustrated in Fig. 2C, the United States (TLS = 1072), China (TLS = 629) and the United Kingdom (TLS = 503) held the top positions. Countries in North America, Europe, Oceania demonstrated a higher level of inter-state cooperation. Western developed countries generally engaged in this field earlier, while eastern countries have become active in this field in recent years.

### 3.2. Co-authorship: institutions

The top 10 most productive institutions and top 10 institutions with most citations are presented in Table 1. The co-authorship between institutions is showed in Fig. 3A-B. Among the top 10 institutions with the highest total number of citations, seven were located in the United States. As expected, the connection strength was strongest within the same country, suggesting that inter-institutional collaboration was more prevalent among institutes from the same country/region.

### 3.3. Authors and co-cited authors

A total of 26,047 authors contributed to the studies included in our analysis. In Table 2, we highlight the 10 most productive authors and the 10 most frequently cited authors. Li, Weimin and Qian Wei from the United States and China, respectively, led the list with 24 publications each. Although Van Ginneken Bram from Germany had only 21 publications, his work amassed 1746 citations. In terms of co-cited authors, six of the top 10 most cited authors were based in the United States. Samuel G. Armato from the University of Chicago received the highest total citations with 829, followed by Rebecca L Siegel and Kaiming He. Betweenness centrality value (BC value) is a measure of the importance of nodes in a network and is guided by tree hole theory, in Citespace, nodes with a BC value greater than 0.1 are considered critical nodes. Authors in our study with BC value no less than 0.1 are as follows: Samuel G. Armato (BC value = 0.34) maintained the top position, followed by Kaiming He (BC value = 0.20) and Denise R. Aberle (BC value = 0.19), William D. Travis (BC value = 0.11), Wang Shuo (BC value = 0.11).

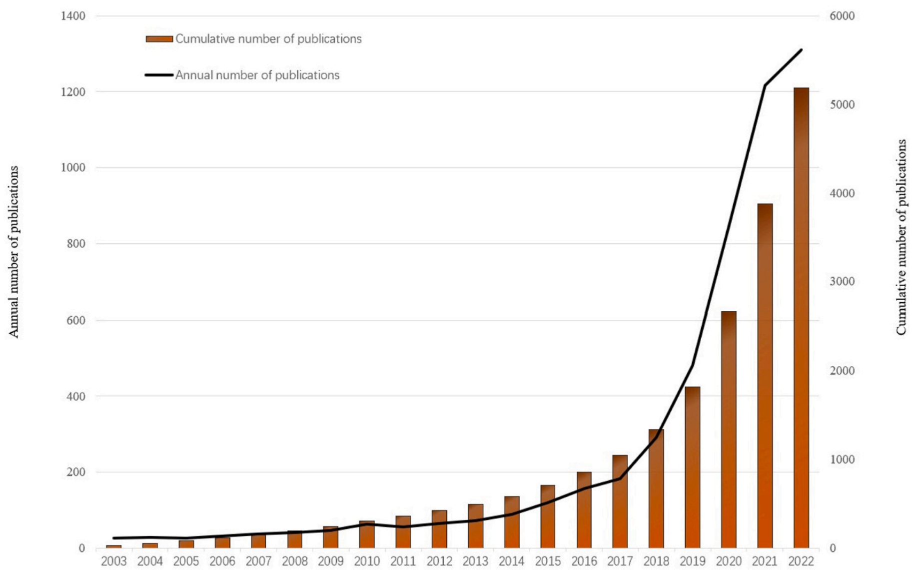



**Fig. 1.** Number of publications.

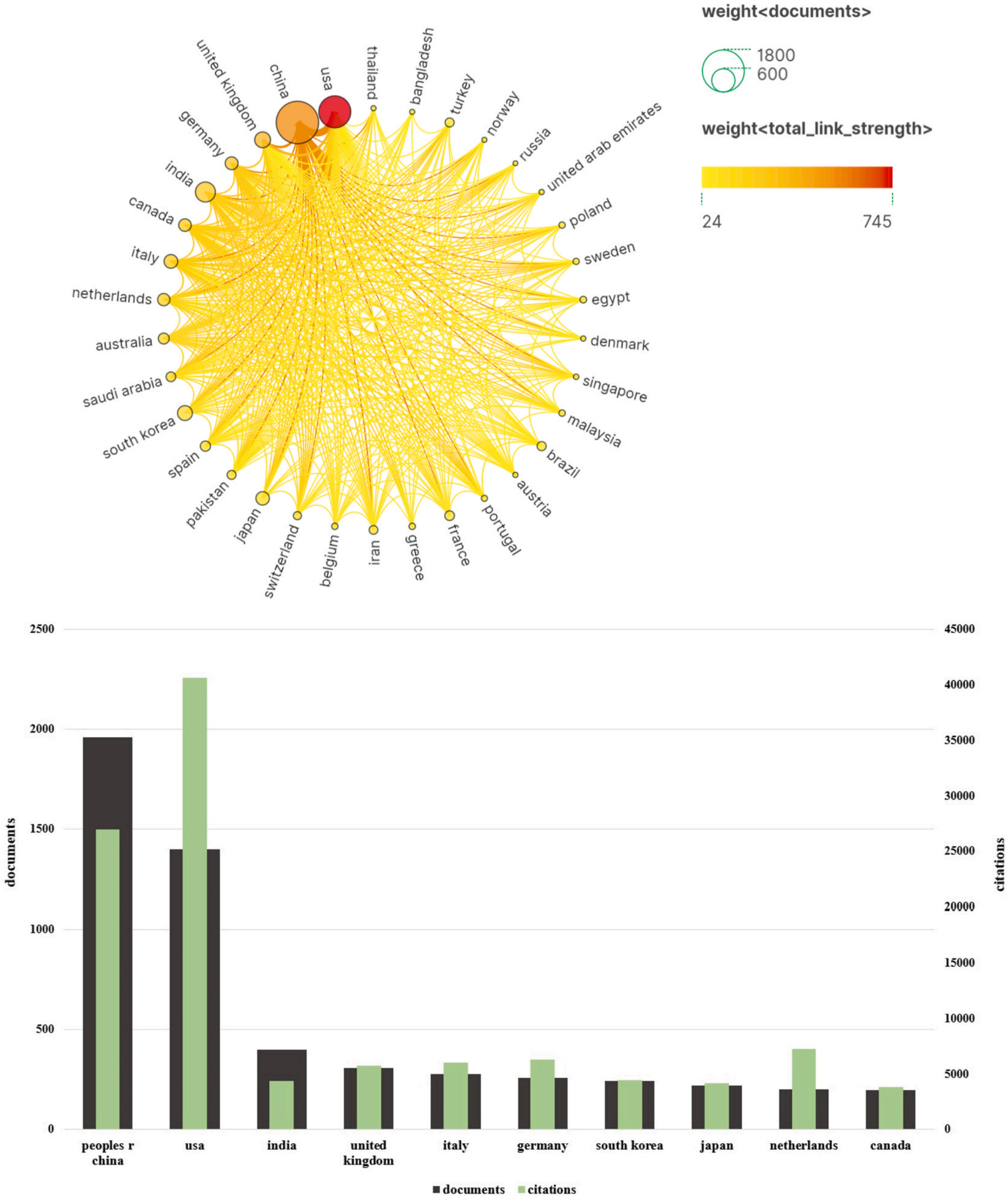



**Fig. 2.** A : Visualization of cooperative relationships between countries/regions. Circles represent the number of publications, lines represent cooperative relationships. B : Top 10 countries/regions in terms of the number of publications and total citations. C : The overlay visualization of co-authorship between countries/regions with more than 20 publications. The nodes represent countries/regions, the size and color represent the number of publications and the year respectively, the thickness of lines represent the strength of relationship. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

### *3.4. Co-cited journals*

Table 3 presents the top 10 co-cited journals. *Radiology* boasted the most citation, while *IEEE Transactions on Medical Imaging* and *Medical Physics* each garnered over 3000 citations. These three journals also had the highest TLS. In our count, there were 5 journals with BC value greater than 0.1, *Radiology* ranked first (BC value = 0.36), followed by *Medical Physics* (BC value = 0.14), *Scientific Reports-UK* (BC value = 0.13), *New England Journal of Medicine* (BC value = 0.11), *IEEE Access* (BC value = 0.1). Fig. 4 depicts a double-overlay map of journals related to AI research on lung disease. The map on the left showed the citing literature, mainly distributed across 1) Mathematics, Systems, Mathematical; 2) Molecular, Biology, Immunology; 3) Medicine, Medical, Clinical. The map on the

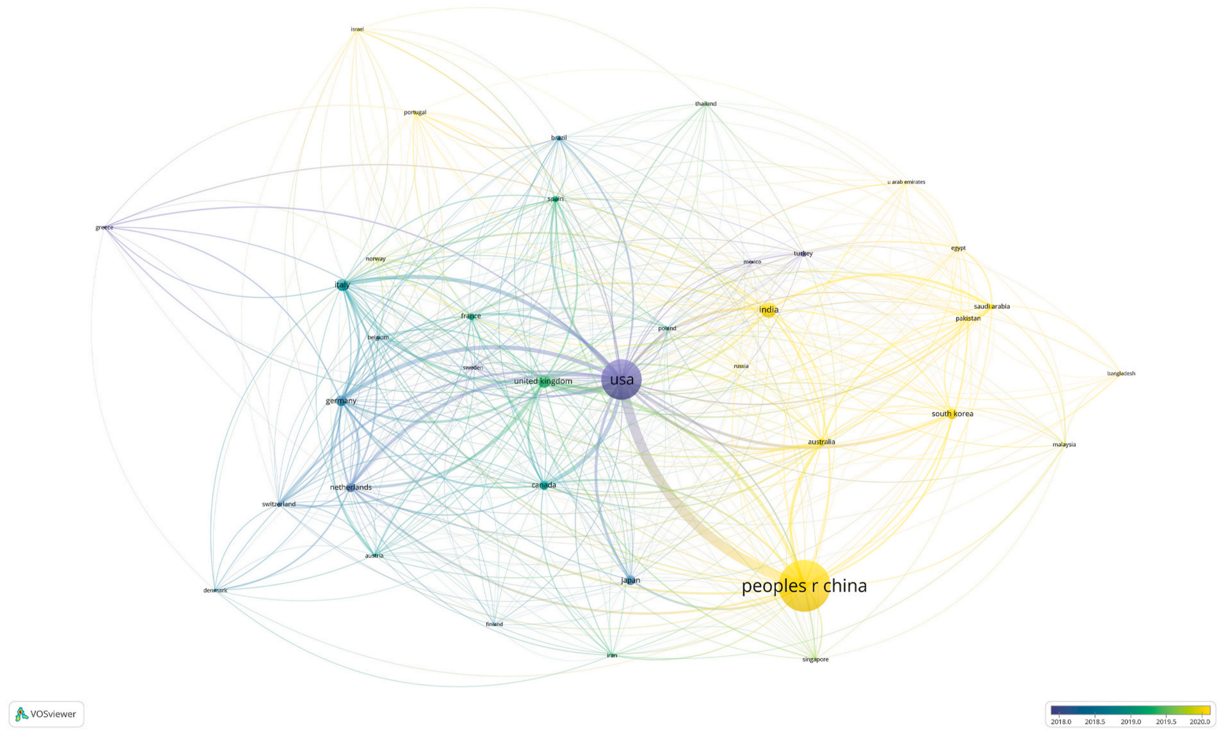



**Fig. 2.** (*continued*).

**Table 1**
The top 10 most productive institutions and top 10 institutions with most citations.

| Rank | Institution | Publications | Institution | Citations |
|---|---|---|---|---|
| 1 | Shanghai Jiaotong University | 126 | Harvard University | 3608 |
| 2 | Fudan University | 109 | Stanford University | 2863 |
| 3 | Harvard University | 94 | University of Michigan | 2500 |
| 4 | Chinese Academy of Sciences | 89 | Radboud University Nijmegen | 2461 |
| 5 | Chinese Academy of Medical Sciences | 78 | Mayo Clinic | 2410 |
| 6 | Zhejiang University | 76 | University of Chicago | 2399 |
| 7 | Sun Yat-Sen University | 70 | Chinese Academy of Sciences | 2395 |
| 8 | Tongji University | 69 | University of Washington | 1943 |
| 9 | Northeastern University | 64 | Mem Sloan Kettering Cancer Center | 1803 |
| 10 | Sichuan University | 62 | Shanghai Jiaotong University | 1706 |

right highlighted the cited literature, predominately located in the 4) Molecular, Biology, Genetics; 5) Health, Nursing, Medicine, indicates these are the foundational building blocks.

### 3.5. Co-citation references

Table 4 listed the 10 most frequently cited references from the retrieved publication corpus, with the paper by Samuel G Armato et al., in 2011 [30] receiving the most citations (citations = 401), this study established a large, multi-center CT image database of lung nodules. In the second place was an article by the National Lung Screening Trial Research Team [31] in 2011, they demonstrated that low-dose CT screening could reduce lung cancer mortality. The fifth study, by Freddie Bray et al. [3], provided statistics on the incidence and mortality of 36 cancers across 185 countries. The tenth article was an introduction to radiomics by Robert J. Gillies et al. [32]. The remaining six articles all related to computer algorithm development. Table 5 displays publications (n = 11) with a BC value greater than 0.1, among which seven were related to AI in lung nodule detection and classification. Fig. 5A and B shows the co-citation cluster diagram and its timeline visualization created by Citespace. We displayed the six largest clusters to understand the development trends. Clusters 0, 1, 2 revealed that COVID-19, lung cancer, and radiomics have been recent research hotspots and continue to be highly relevant. In the largest cluster 0, numerous burst references with a BC value greater than 0.1 appeared, all related to lung nodule detection and characteristic analysis, laying a solid foundation for subsequent COVID-19 AI research [33–36]. The publication with the highest citation count was from Kaiming He et al. [37]in cluster 5; they presented a residual learning framework to facilitate the

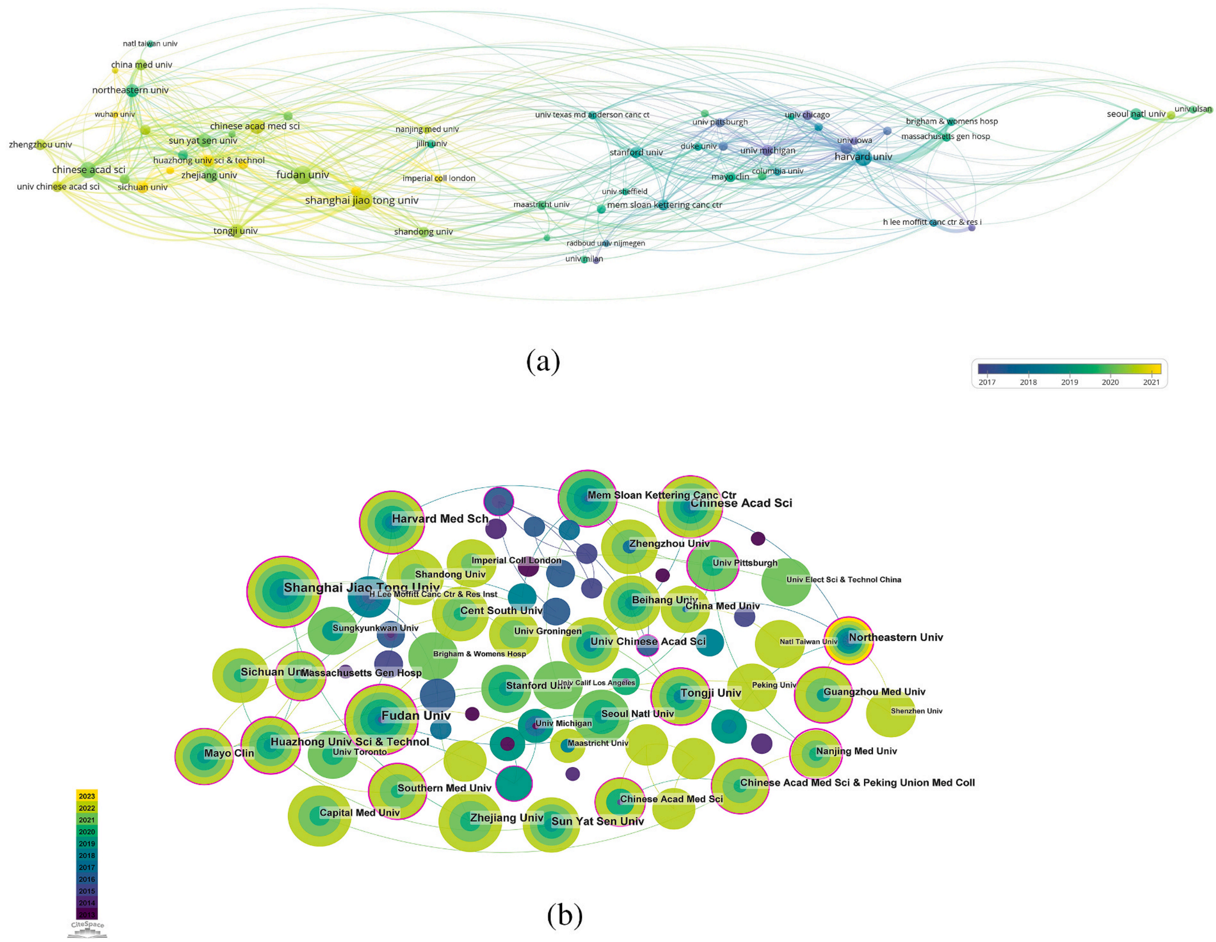



**Fig. 3.** **(A)**The overlay visualization map of institutions with more than 25 publications. **(B)** The co-authorship between institutions. The nodes represent academic institutions, the size and color of the nodes represent the number of publications and the average publication year respectively. The lines represent the strength of cooperative relationship between institutions, and the depth of color indicates the average publication time of institutions. The purple outer circle indicates that the node's BC value is greater than 0.1. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

**Table 2**
The 10 most productive authors and top 10 co-cited authors.

| Rank | Author | Country | Publications | Citation | Co-cited Author | Country | Citations | Total link strength |
|---|---|---|---|---|---|---|---|---|
| 1 | Li, Weimin | China | 24 | 220 | Samuel G. Armato | USA | 829 | 8409 |
| 2 | Qian, Wei | USA | 24 | 690 | Rebecca L Siegel | USA | 503 | 3451 |
| 3 | Seo, Joon Beom | South Korea | 23 | 475 | Kaiming He | USA | 496 | 4445 |
| 4 | Veronesi, Giulia | Italy | 23 | 883 | Olaf Ronneberger | Germany | 463 | 3682 |
| 5 | Wang, Jing | USA | 23 | 261 | Setio, Arnaud Arindra Adiyoso | Netherlands | 458 | 5904 |
| 6 | Goo, Jin Mo | South Korea | 21 | 722 | Denise R. Aberle | USA | 443 | 3655 |
| 7 | Van Ginneken, Bram | Germany | 21 | 1746 | Yann LeCun | USA | 375 | 3509 |
| 8 | LambinPhilippe | Netherlands | 20 | 770 | Suzuki, Kenji | USA | 371 | 3363 |
| 9 | Qi, Shouliang | China | 20 | 313 | Alex Krizhevsky | Canada | 352 | 3603 |
| 10 | Wang, Wei | China | 19 | 357 | Philippe Lambin | Netherlands | 342 | 2417 |

training of substantially deeper networks than those previously used. According to the timeline visualization, topics such as lung cancer and radiomics will continue to be the focus of attention in the future. Fig. 5C summarizes the top 25 references with the strongest citation bursts. The first burst in citations detected was from a publication by Robert J Cerfolio et al., in 2011 [38], which found that completely portal robot lobectomy with 4 arms (CPRL-4) had a better prognosis and was more convenient than rib- and nerve-sparing thoracotomy.

**Table 3**
Top 10 co-cited journals.

| Rank | Journal | Citations | Total link strength | JCR ( 2021 ) |
|---|---|---|---|---|
| 1 | Radiology | 5124 | 153006 | Q1 |
| 2 | Ieee Transactions on Medical Imaging | 3941 | 103835 | Q1 |
| 3 | Medical Physics | 3817 | 106181 | Q2 |
| 4 | New England Journal of Medicine | 2866 | 83852 | Q1 |
| 5 | Annals of Thoracic Surgery | 2738 | 54678 | Q1 |
| 6 | Chest | 2643 | 67585 | Q1 |
| 7 | Lecture Notes in Computer Science | 2477 | 68702 | / |
| 8 | Plos One | 2475 | 67278 | Q2 |
| 9 | American Journal of Respiratory and Critical Care | 2449 | 67199 | Q1 |
| 10 | Scientific Reports-Uk | 2401 | 72644 | Q2 |

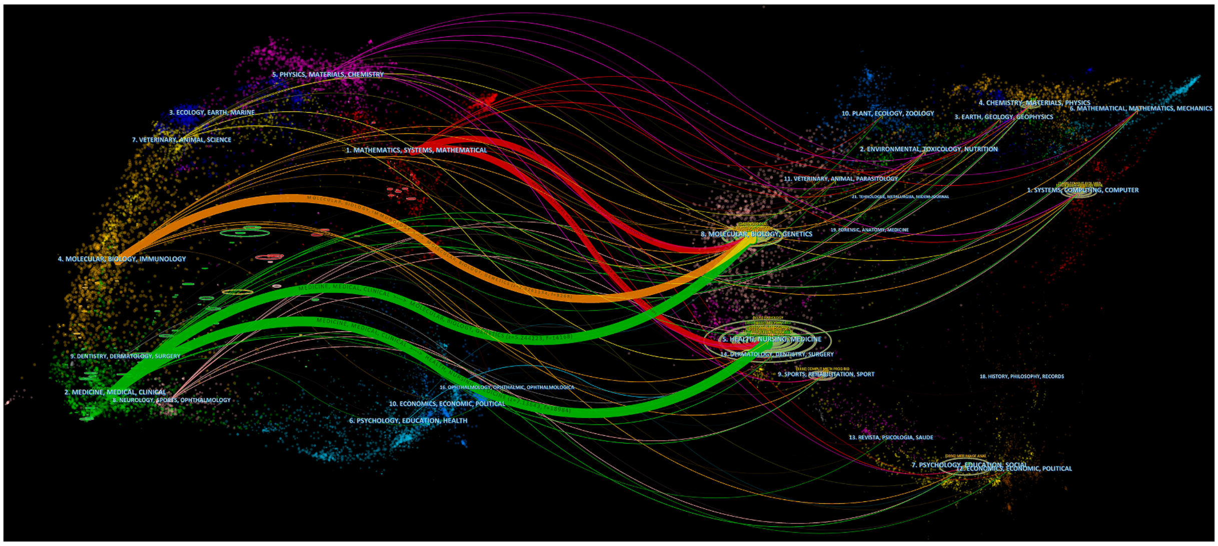



**Fig. 4.** Dual-map overlay of journals on AI studies related to lung disease. The width of the lines is proportional to the frequency of citations, the horizontal and vertical axis lengths of the ellipse are proportional to the number of authors and the number of papers, respectively.

### 3.6. *Keywords*

After consolidating synonyms and removing meaningless words, Fig. 6A summarizes the top 10 author keywords with the highest frequency. Lung cancer, pulmonary nodule, COVID-19 and non-small cell lung cancer were the most frequently studied diseases/signs. Chest CT was the most important research imaging method, as it has been listed as a vital recommended screening and diagnosis method for numerous chest diseases, such as lung nodules, lung cancer and COVID-19 [2,39,40]. Deep learning, machine learning and convolutional neural network were the most frequently used artificial intelligence algorithms.

As seen in the author keywords overlay visualization (Fig. 6B), neural network and computed tomography (CT) were the earliest hot keywords, with an average year of appearance in 2017, while deep learning and COVID-19 emerged as new hot topics, with an average year of appearance in 2021. Fig. 6C is a network visualization of keywords, displaying the strength of association between them and dividing the visualization into five clusters. The two largest clusters are as follows: deep learning algorithms used in the segmentation and feature extraction of chest images (mainly CT), lung cancer detection and identification research, especially for non-small cell lung cancer.

## 4. Discussion

We used scientific bibliometric method to analyze articles related to the application of AI in lung disease over the past 20 years, and systematically analyzed authors, institutions, countries/regions, author keywords, references, etc. We sorted out the countries/regions, authors, and institutions that have made important contributions to this field, and summarized current research status as well as research directions that may become hotspots in the future.

The number of papers published from 2017 to 2022 accounts for 83.47 % of the total number of papers published in these 20 years. On one hand, this growth can be attributed to the development of numerous new deep learning networks, such as AlexNet, CNN, ResNet, RNN, variants derived from such networks excel in lesion detection, classification, and segmentation, which have further

**Table 4**
Top 10 most cited references.

| Title | Author | Journals | Year | Citations | Countries | Total link strength |
|---|---|---|---|---|---|---|
| The Lung Image Database Consortium, (LIDC) and Image Database Resource Initiative (IDRI): A Completed Reference Database of Lung Nodules on CT Scans | Samuel G Armato 3rd et al. | Medical Physics | 2011 | 401 | USA | 3677 |
| Reduced Lung-Cancer Mortality with Low-Dose Computed Tomographic Screening | National Lung Screening Trial Research Team et al. | New England Journal Of Medicine | 2011 | 387 | USA | 2535 |
| U-Net: Convolutional Networks for Biomedical Image Segmentation | Olaf Ronneberger et al. | Medical Image Computing And Computer-Assisted Intervention – MICCAI 2015 | 2015 | 357 | Germany | 2462 |
| Deep Residual Learning for Image Recognition | Kaiming He et al. | 2016 IEEE Conference On Computer Vision And Pattern Recognition (CVPR) | 2016 | 347 | USA | 2591 |
| Global cancer statistics 2018: GLOBOCAN estimates of incidence and mortality worldwide for 36 cancers in 185 countries | Freddie Bray et al. | CA-A Cancer Journal For Clinicians | 2018 | 325 | France | 1523 |
| Very Deep Convolutional Networks for Large-Scale Image Recognition | Karen Simonyan et al. | Computer Vision And Pattern Recognition | 2014 | 254 | UK | 2188 |
| Decoding tumour phenotype by noninvasive imaging using a quantitative radiomics approach | Hugo J. W. L. Aerts et al. | Nature Communications | 2014 | 239 | Netherlands | 1667 |
| ImageNet Classification with Deep Convolutional Neural Networks | Alex Krizhevsky et al. | Communications Of The ACM | 2012 | 225 | USA | 1937 |
| Pulmonary Nodule Detection in CT Images: False Positive Reduction Using Multi-View Convolutional Networks | Arnaud Arindra Adiyoso Setio et al. | IEEE Transactions On Medical Imaging | 2016 | 222 | Netherlands | 2426 |
| Radiomics: Images Are More than Pictures, They Are Data | Robert J Gillies et al. | Radiology | 2016 | 212 | USA | 1351 |

**Table 5**
Publications with centrality > 0.1

| Centrality | Title | Author | Journals | Year | Countries |
|---|---|---|---|---|---|
| 0.37 | The Lung Image Database Consortium, (LIDC) and Image Database Resource Initiative (IDRI): A Completed Reference Database of Lung Nodules on CT Scans | Samuel G Armato 3rd et al. | Medical Physics | 2011 | USA |
| 0.32 | Reduced Lung-Cancer Mortality with Low-Dose Computed Tomographic Screening | National Lung Screening Trial Research Team et al. | New England Journal Of Medicine | 2011 | USA |
| 0.25 | Texture Feature Analysis for Computer-Aided Diagnosis on Pulmonary Nodules | Fangfang Han et al. | Journal Of Digital Imaging | 2015 | USA |
| 0.22 | Comparing two classes of end-to-end machine-learning models in lung nodule detection and classification: MTANNs vs. CNNs | Nima Tajbakhsh et al. | Pattern Recognition | 2017 | USA |
| 0.18 | Development and Validation of a Deep Learning Algorithm for Detection of Diabetic Retinopathy in Retinal Fundus Photographs | Varun Gulshan et al. | JAMA | 2016 | USA |
| 0.17 | Lung nodule segmentation and recognition using SVM classifier and active contour modeling: a complete intelligent system | Mohsen Keshani et al. | Computers in Biology and Medicine | 2013 | Iran |
| 0.15 | Pulmonary Nodule Detection in CT Images: False Positive Reduction Using Multi-View Convolutional Networks | Arnaud Arindra Adiyoso Setio et al. | Ieee Transactions On Medical Imaging | 2016 | Netherlands |
| 0.14 | End-to-end lung cancer screening with three-dimensional deep learning on low-dose chest computed tomography | Diego Ardila et al. | Nature Medicine | 2019 | USA |
| 0.13 | Radiomics: Images Are More than Pictures, They Are Data | Robert J Gillies et al. | Radiology | 2016 | USA |
| 0.12 | Deep Residual Learning for Image Recognition | Kaiming He et al. | 2016 IEEE CVPR | 2016 | USA |
| 0.12 | Knowledge-based Collaborative Deep Learning for Benign-Malignant Lung Nodule Classification on Chest CT | Yutong Xie et al. | IEEE Transactions on Medical Imaging | 2019 | China |

improved the accuracy and efficiency of chest image recognition and classification [41,42]. On the other hand, the COVID-19 pandemic that emerged at the end of 2019 has played a role, as chest image, especially CT, became one of the crucial means for diagnosing COVID-19. This has attracted numerous institutions and scholars to participate in chest AI research.

From the perspective of countries/regions and institutions, developing countries such as China and India exhibit high publication yield but have not yet achieved substantial influence. One reason for this is that the United States was an early participant in this field, whereas developing countries joined later, with most of their accomplishments emerging in recent years. Although the number of citations is a frequently-used method to evaluate a publication's impact [43], it is a time-dependent indicator since papers usually do not receive citations until one or two years after publication, and citations reach a maximum approximately three to ten years later [44]. As a result, recently published papers might not have had enough time to accumulate citations [45]. Therefore, although the

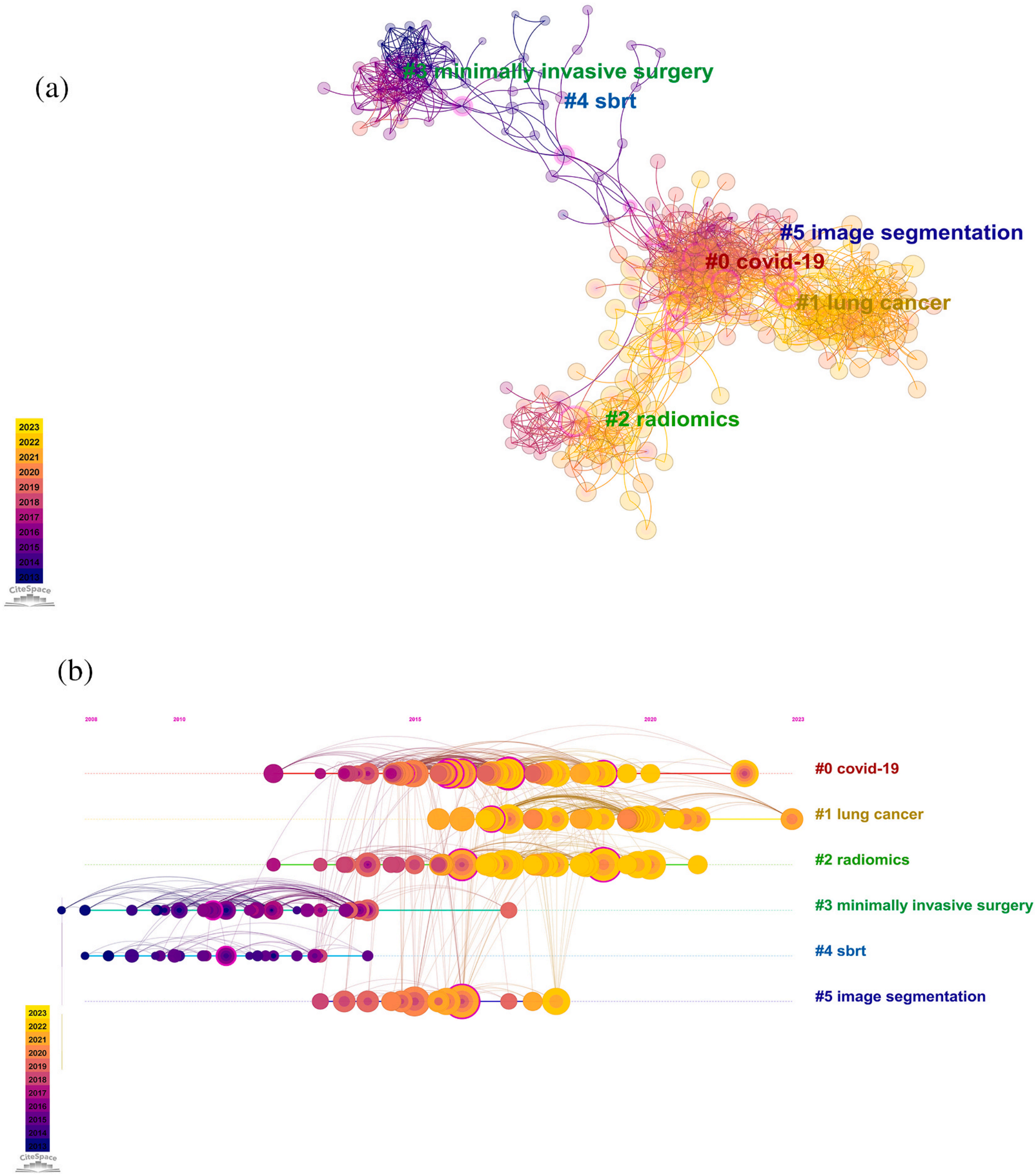
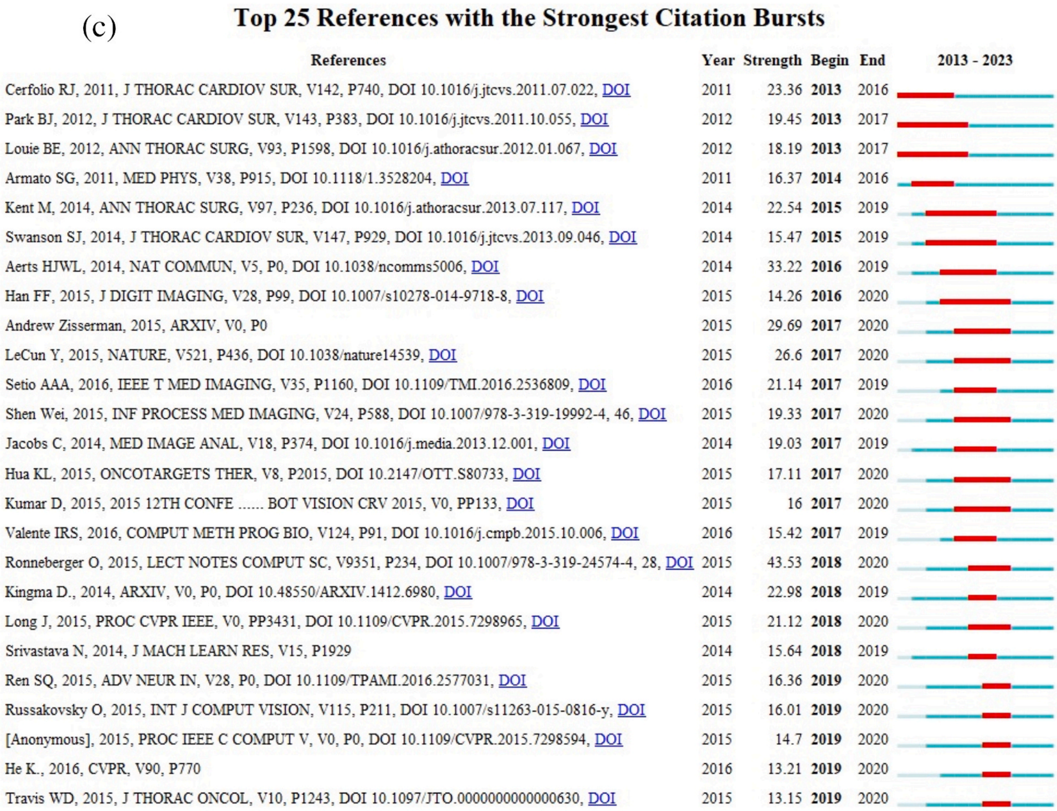



**Fig. 5. (A)(B)** The co-citation map and its timeline visualization drawn by Citespace. The nodes represent the references, the size and color represent the citation times and years, and the lines represent the citation relationship. The purple circle in （**A**）represents the reference with BC value no less than 0.1, and the red circle in **(B)** represents the reference that emerges suddenly. **(C)** Visualization map of top 25 references with the strongest citation bursts. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

accomplishments of developing countries may not have garnered significant international influence thus far, they hold potential for the future. In terms of cooperation, the United States engages in the most frequent cooperation with other countries (TLS = 1072), followed by China and the United Kingdom. Institutions and authors with the highest BC value are almost all from developed countries led by the U.S. Although developing countries such as China have a large number of publications, they lack influential institutions and authors, and there is still room for development.

Co-citation analysis of references is a crucial aspect of bibliometrics. AI research related to pulmonary nodule dominates the field. This prevalence can be easily explained, in essence, the detection of pulmonary nodules is the detection of early-stage lung cancer [46–48]. Lung cancer has consistently been associated with high morbidity and mortality rates worldwide. AI, being objective, can reduce the likelihood of misdiagnosis caused by human factors and enhances work efficiency. Simultaneously, underdeveloped regions can also benefit from its integrated high-end resources. The most recent burst detected was in 2019–2020, all of which were related to



(c) Top 25 References with the Strongest Citation Bursts

| References | Year | Strength | Begin | End | 2013 - 2023 |
|---|---|---|---|---|---|
| Cerfolio RJ, 2011, J THORAC CARDIOV SUR, V142, P740, DOI 10.1016/j.jtcvs.2011.07.022, DOI | 2011 | 23.36 | **2013** | 2016 | |
| Park BJ, 2012, J THORAC CARDIOV SUR, V143, P383, DOI 10.1016/j.jtcvs.2011.10.055, DOI | 2012 | 19.45 | **2013** | 2017 | |
| Louie BE, 2012, ANN THORAC SURG, V93, P1598, DOI 10.1016/j.athoracsur.2012.01.067, DOI | 2012 | 18.19 | **2013** | 2017 | |
| Armato SG, 2011, MED PHYS, V38, P915, DOI 10.1118/1.3528204, DOI | 2011 | 16.37 | **2014** | 2016 | |
| Kent M, 2014, ANN THORAC SURG, V97, P236, DOI 10.1016/j.athoracsur.2013.07.117, DOI | 2014 | 22.54 | **2015** | 2019 | |
| Swanson SJ, 2014, J THORAC CARDIOV SUR, V147, P929, DOI 10.1016/j.jtcvs.2013.09.046, DOI | 2014 | 15.47 | **2015** | 2019 | |
| Aerts HJWL, 2014, NAT COMMUN, V5, P0, DOI 10.1038/ncomms5006, DOI | 2014 | 33.22 | **2016** | 2019 | |
| Han FF, 2015, J DIGIT IMAGING, V28, P99, DOI 10.1007/s10278-014-9718-8, DOI | 2015 | 14.26 | **2016** | 2020 | |
| Andrew Zisserman, 2015, ARXIV, V0, P0 | 2015 | 29.69 | **2017** | 2020 | |
| LeCun Y, 2015, NATURE, V521, P436, DOI 10.1038/nature14539, DOI | 2015 | 26.6 | **2017** | 2020 | |
| Setio AAA, 2016, IEEE T MED IMAGING, V35, P1160, DOI 10.1109/TMI.2016.2536809, DOI | 2016 | 21.14 | **2017** | 2019 | |
| Shen Wei, 2015, INF PROCESS MED IMAGING, V24, P588, DOI 10.1007/978-3-319-19992-4, 46, DOI | 2015 | 19.33 | **2017** | 2020 | |
| Jacobs C, 2014, MED IMAGE ANAL, V18, P374, DOI 10.1016/j.media.2013.12.001, DOI | 2014 | 19.03 | **2017** | 2019 | |
| Hua KL, 2015, ONCOTARGETS THER, V8, P2015, DOI 10.2147/OTT.S80733, DOI | 2015 | 17.11 | **2017** | 2020 | |
| Kumar D, 2015, 2015 12TH CONFE ...... BOT VISION CRV 2015, V0, PP133, DOI | 2015 | 16 | **2017** | 2020 | |
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| Ronneberger O, 2015, LECT NOTES COMPUT SC, V9351, P234, DOI 10.1007/978-3-319-24574-4, 28, DOI | 2015 | 43.53 | **2018** | 2020 | |
| Kingma D., 2014, ARXIV, V0, P0, DOI 10.48550/ARXIV.1412.6980, DOI | 2014 | 22.98 | **2018** | 2019 | |
| Long J, 2015, PROC CVPR IEEE, V0, PP3431, DOI 10.1109/CVPR.2015.7298965, DOI | 2015 | 21.12 | **2018** | 2020 | |
| Srivastava N, 2014, J MACH LEARN RES, V15, P1929 | 2014 | 15.64 | **2018** | 2019 | |
| Ren SQ, 2015, ADV NEUR IN, V28, P0, DOI 10.1109/TPAMI.2016.2577031, DOI | 2015 | 16.36 | **2019** | 2020 | |
| Russakovsky O, 2015, INT J COMPUT VISION, V115, P211, DOI 10.1007/s11263-015-0816-y, DOI | 2015 | 16.01 | **2019** | 2020 | |
| [Anonymous], 2015, PROC IEEE C COMPUT V, V0, P0, DOI 10.1109/CVPR.2015.7298594, DOI | 2015 | 14.7 | **2019** | 2020 | |
| He K., 2016, CVPR, V90, P770 | 2016 | 13.21 | **2019** | 2020 | |
| Travis WD, 2015, J THORAC ONCOL, V10, P1243, DOI 10.1097/JTO.0000000000000630, DOI | 2015 | 13.15 | **2019** | 2020 | |

**Fig. 5.** (*continued*).

the development of more mature convolutional neural networks. Researchers are focusing on the development of deeper networks, which, despite the increase in computational effort, perform significantly better in tasks such as image target detection and classification for fast and highly accurate diagnostics [49–51]. Another important task for researchers is to gradually transition the initial supervised learning networks to semi-supervised and unsupervised learning, and then to self-supervised learning, which has become a big hit in recent years. Supervised learning, which was the first and most mature deep learning technique applied to medical image analysis, requires manual annotation of the image data and then handing it over to the model for training, which implies a huge amount of workload, and another challenge is that such a model is much less expressive when it is applied to an external dataset for validation, which limits the generalization of the model [52]. We note that in the last two years researchers have attempted to apply self-supervised learning to medical images. Self-supervised learning was first applied to the field of natural language processing, where it first creates large pre-trained language models [53], and then creates generalist models fine-tuned for different downstream tasks to achieve the goal, which greatly reduces the amount of data that needs to be labeled, and performs well on new tasks. Therefore, researchers have attempted to apply this technique to the field of computer vision and have achieved excellent results [54,55], which also provides an important technical solution to the problem of scarce medical image data [56]. Although this technique performs well in training medical images, there are still difficulties in translating it into useable medical models. The main difficulty lies in the fact that the doctor's main claim is to detect abnormal regions of the image, but the random masking operation often utilized by self-supervised learning methods may also alter a medical image's semantic meaning by removing image regions with diseases or abnormalities. Therefore, the development of new techniques to ensure that the representation of image regions with similar semantic features remains unchanged during self-supervised learning, as well as the development of unique image augmentation strategies for this feature of medical images will be a worthwhile research direction for researchers in the coming period [57,58]. Another point worth noting is that despite the large number of high-quality models that have been developed, the vast majority of studies remain in the laboratory stage. The black box characteristic of deep learning [59], or its uninterpretable nature, have limited its clinical application. Consequently, there has also been a growing interest in visualization research to make deep learning interpretable, which could propel deep learning forward significantly. This is also consistent with our findings that "visualization" appears as one of the popular keywords in the keywords overlay visualization (Fig. 6B). It can be predicted that visualization research in deep learning will become a future trend.

According to author keywords analysis, lung cancer appeared most frequently in the author keywords co-occurrence analysis ( occurrence = 951 ), which was the most studied chest disease, the high incidence and mortality of lung cancer make the early diagnosis and prognosis of lung cancer crucial. The application of AI in lung cancer has evolved from the detection of disease to the

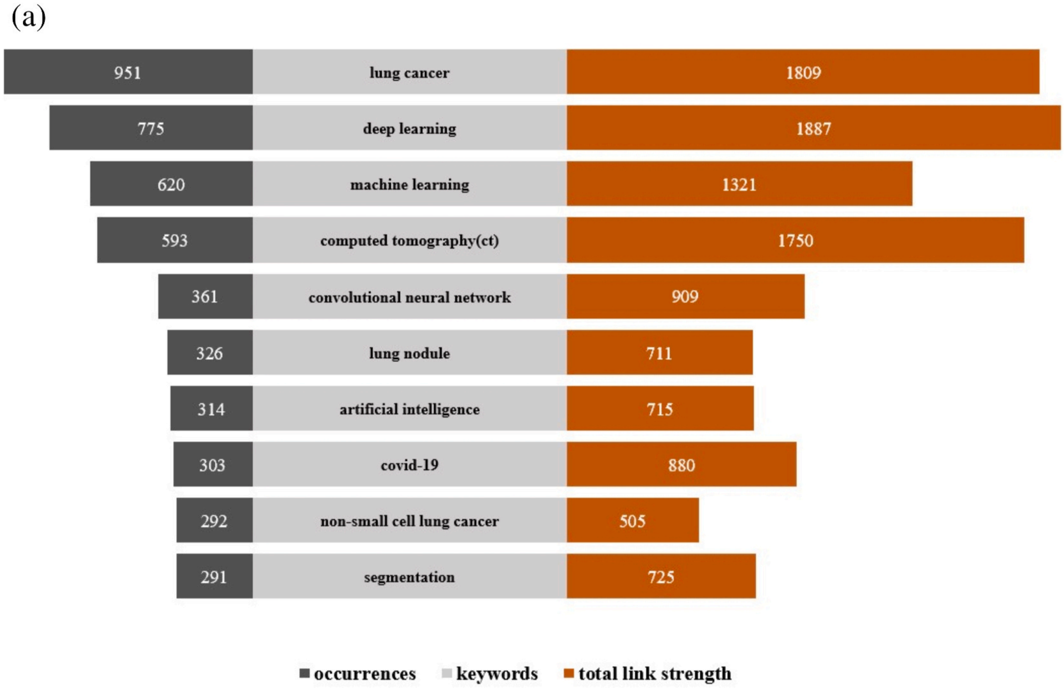


**Fig. 6.** **(A)** The top 10 keywords. **(B)**The co-occurrence overlay visualization of author keywords. **(C)** The co-occurrence network visualization of author keywords. The nodes represent keywords, the size represents the frequency of occurrence, the color represents average year of occurrence**(B)** and the cluster**(C)** respectively, and the thickness of the lines represents the strength of the relationship. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

prediction of tumor histology and gene mutation, prediction of response to radiotherapy/chemotherapy, prognostic assessment, and distant metastasis assessment using deep learning and radiomics [60,61], such research is often rigorously screened images to extract features to build a model under specific imaging conditions, in fact, it is difficult for such a model to on behalf of the clinical routine [62], for it is often able to perform excellently in a single task, but less expressive when it is extended to the validation of external datasets, the model's robustness and reproducibility are the important challenges that need to be urgently solved. We note that another keyword with a high frequency of occurrence is CT (occurrence = 593), and in the diagnosis of chest diseases, AI is excellent in detecting abnormalities in Chest-X-ray images [63], but CT can be performed to diagnose a broader spectrum of diseases, with the most widespread use in lung cancer, pneumonia, and tuberculosis. In addition to these, it performs well in the detection, quantitative analysis and classification of COPD, interstitial lung disease, and pulmonary fibrosis, overall the performance of AI models in diffuse lung disease is lower than that of the first three categories of disease [64,65], we hypothesize that this is due to the lack of specificity in the image presentation of diffuse lung diseases, the overlap between different types of image presentations, and the lack of large image databases such as those for lung cancer, lung nodules, and pneumonia. Additionally, it is much more difficult to annotate the images of diffuse lung diseases, so the establishment of large databases of these diseases is also a future task for scholars. On the other hand, in the cluster analysis of keywords (Fig. 6C) we found that there were fewer connections between different diseases, most research efforts concentrate on detecting single disease and their differentiation from healthy controls, while multi-class disease models remain absent. We analyzed that this is also related to the imbalance of existing databases for various types of diseases [66], and the results will be biased by too large a difference in the amount of data between the studied diseases. Therefore, the creation of large public databases of all types of chest diseases, the publicizing of private databases, or the strengthening of collaborations to utilize existing databases would be worthwhile initiatives for future researchers. In the clustering and co-occurrence analysis of keywords, we found that the terms "prospective study" and "longitudinal study" did not appear in our high frequency vocabulary, indicating that most of the studies conducted are still retrospective cross-sectional studies. An interesting experiment found that in comparison with radiologists, AI models were more effective than doctors in analyzing individual images, when longitudinal comparisons were made with previous images of patients to predict disease progression, the models' effectiveness was comparable to that of doctors [67], which clearly shows that there is still a lot of potential for longitudinal AI models to be used in predicting disease prognosis. Finally, we note that few clinical indicators appear in the keyword clustering network, which remains a weak part of the current study. Manual diagnosis typically incorporates clinical manifestations and laboratory tests for discrimination and assessment. Although AI can detect features that may be challenging for humans to identify through high-throughput feature extraction, relying solely on imaging features for disease recognition is virtually impossible. Consequently, future research should focus on developing multi-modal fusion models that integrate clinical manifestations, imaging features, and laboratory tests for AI-based differential diagnosis.

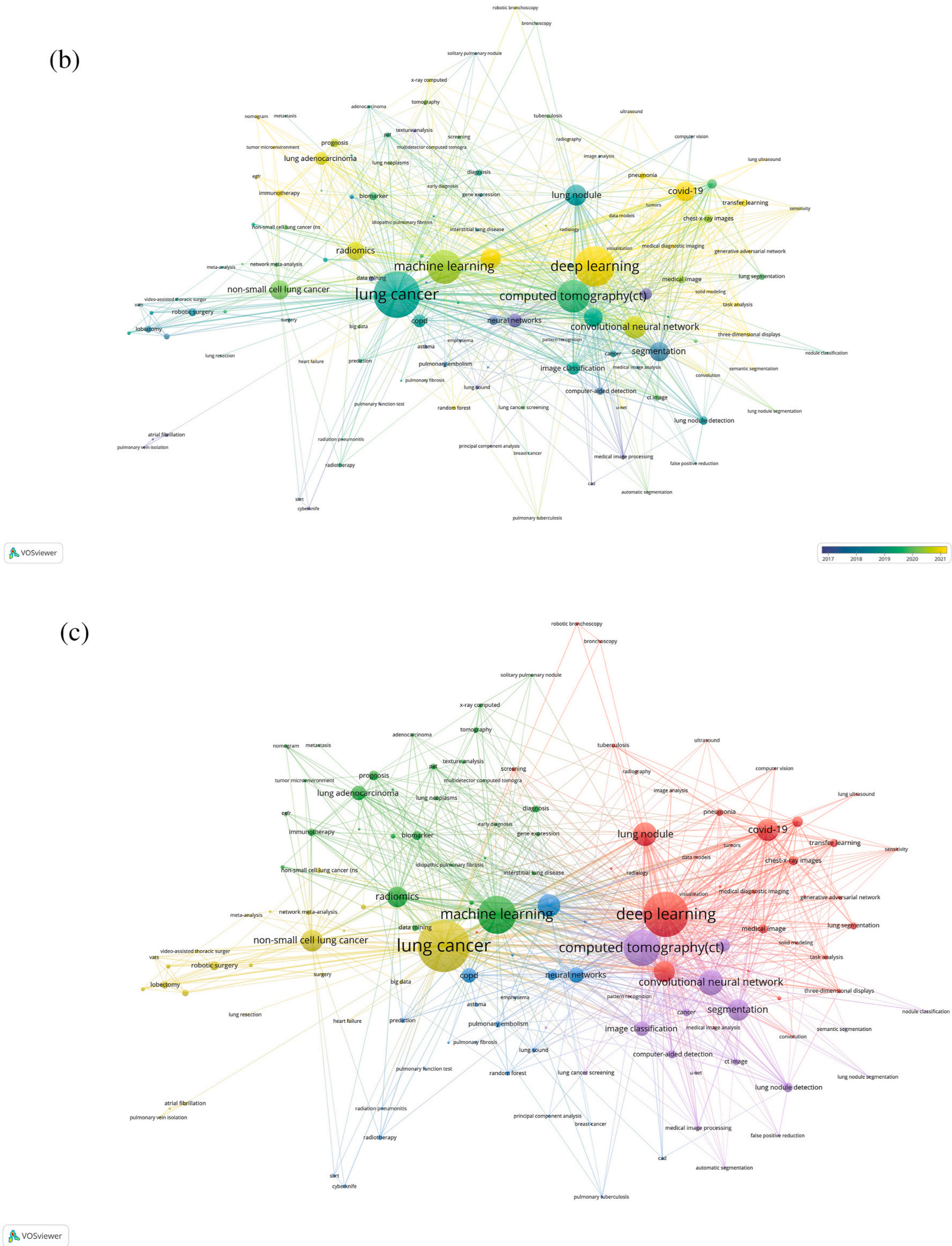


**Fig. 6.** (*continued*).

## 5. Limitations

This study presents several limitations that warrant consideration. First, we exclusively utilized the WoSCC database for data acquisition, potentially omitting relevant literature indexed in alternative databases. Second, the bibliometric software employed in this study is unable to discern between authors with identical names. Although efforts were made to minimize this issue during the statistical process, some data may still be affected by this limitation. Nevertheless, the overall impact on the comprehensive statistical results is expected to be minimal.

## 6. Conclusions

In conclusion, our comprehensive examination of the application of AI to lung disease management over the past two decades shows that this field is flourishing. The United States and other developed countries continue to spearhead advancements in this area, while China and other developing countries are also making significant strides. However, the primary factors hindering widespread clinical implementation are the limited interpretability of AI algorithms, scarcity of large-scale prospective studies and longitudinal studies, it is also necessary to build large public databases of various lung diseases and multi-modal fusion models. Addressing these challenges will be the focal point of future research endeavors.

## Ethics declarations

Review and/or approval by an ethics committee was not needed for this study because there is no participant/patient involved, the informed consent was not required for the same reason.

## Data availability statement

The data associated with our study didn't been deposited into a publicly available repository since the method of obtaining the data has been presented in the article.

## CRediT authorship contribution statement

**Meng Zeng:** Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **XianQi Wang:** Writing – original draft, Visualization, Software, Methodology, Formal analysis, Conceptualization. **Wei Chen:** Writing – review & editing, Supervision, Software, Methodology, Investigation, Funding acquisition, Data curation, Conceptualization.

## Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Wei Chen reports financial support was provided by The Foundation of Chongqing Science and Health Joint Medical Science and Technology Innovation Program (2023ZDXM008).

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## Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.heliyon.2024.e31129.

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