Observational Study

Medicine OPEN

Research on the application of radiomics in breast cancer

A bibliometrics and visualization analysis

Zhe Yang, MM[a], Chenglong Liu, BM[a,*]

Abstract

Breast cancer is the most prevalent form of cancer worldwide. Therefore, improved disease detection has emerged as a focal point in clinical studies. At the forefront of innovation, radiomics has the capability to extract comprehensive insights from medical images, ultimately enhancing the accuracy of diagnostic procedures. There has been rapid growth in the field of radiomics research on breast cancer in the past few years. We explored pertinent research articles in the Web of Science Core Collection database to gain a thorough understanding of breast cancer radiomics. We used CiteSpace to conduct a bibliometric analysis of the annual distribution of different nations, institutions, journals, authors, keywords, and references in the field of breast cancer radiomics. GraphPad Prism software was used to examine and graph yearly and country-specific trends and the proportions of publications. The tools utilized for the visualization of science mapping included CiteSpace and VOSviewer. Of the 891 publications, most were original articles (731, 91.09%) and a few were reviews (160, 8.91%). Most academic research has been published in China and the United States. The study centers predominantly consisted of major academic institutions, such as Fudan University and the Chinese Academy of Sciences, with some of their members being prominent figures in the field. Pinker, Katja has published the largest number of research papers. The majority of these studies have been published in medical journals focusing on radiology and oncology in recent years. In the realm of cutting-edge medical research, the top two keywords, magnetic resonance imaging and machine learning stand at the forefront as current areas of intense focus. Breast cancer radiomics is advancing rapidly, presenting numerous opportunities and obstacles. Our study of the literature in this academic area aimed to pinpoint the primary themes addressed in the studies and anticipate prospective avenues for research.

Abbreviations: DCE = dynamic contrast-enhanced, DWI = diffusion-weighted imaging, MRI = magnetic Resonance Imaging, NAC = neoadjuvant chemotherapy, WOSCC = Web of Science Core Collection.

Keywords: bibliometrics, breast cancer, radiomics

1. Introduction

Breast cancer is frequently detected in women globally,[1] with significant morbidity and mortality rates, now ranking as the leading cancer type worldwide,[2] surpassing that of lung cancer. Although there has been a 40% decrease in the overall breast cancer death rate for women since 1988,[3] this illness continues to have a significant impact on women's well-being. Immediate action is necessary to prevent and treat breast cancer.[4] In recent years, there has been a noticeable increase in the number of breast cancer cases in China. In 2020, breast cancer was the fourth most prevalent malignant tumor in China, resulting in an estimated 420,000 new cases and 120,000 fatalities according to data from the National Cancer Center of China. In more advanced areas, the occurrence and death rates were slightly elevated. In many cases, breast cancer shows no symptoms in its early stages, which can result in a delayed diagnosis, allowing metastatic tumors to develop and leading to a lower 5-year survival rate. As imaging techniques continue to advance rapidly, such as magnetic resonance imaging (MRI) and multidetector row computed tomography, the ability to detect breast cancer in its early stages has significantly improved. However, these studies did not effectively assess the pathophysiological traits of cancer.

In 2012,[5] Lambin et al[6] were the first to propose the notion of radiomics, which is a noninvasive method that is widely

Informed consent statement: not applicable, because this study did not involve humans.

All authors have completed the ICMJE uniform disclosure form. The authors have no conflicts of interest to declare.

Data sharing is not applicable to this article as no datasets were generated or analyzed during the current study.

Statement of nonduplication: this manuscript is a unique submission and is not being considered for publication by any other source in any medium. Further, the manuscript has not been published, in part or in full, in any form.

This study did not involve human or animal subjects, and thus, no ethical approval was required.

[a] Department of Radiology, the Second Affiliated Hospital of Shandong First Medical University, Tai'an, Shandong, China.

** Correspondence: Chenglong Liu, Department of Radiology, the Second Affiliated Hospital of Shandong First Medical University, Tai'an city, Shandong province, China (e-mail: liuchenglong12301@163.com).*

How to cite this article: Yang Z, Liu C. Research on the application of radiomics in breast cancer: A bibliometrics and visualization analysis. Medicine 2024;103:35(e39463).

Received: 26 March 2024 / Received in final form: 24 April 2024 / Accepted: 6 August 2024

http://dx.doi.org/10.1097/MD.0000000000039463

applied to the diagnosis, treatment, and prognosis prediction[7–11] of diseases, especially tumors. Over the past decade, radiomics has received significant attention. Radiomics uses related computer software to extract[12–15] and further analyze image features[11,16–19] of regions of interest after imaging checks, including plain and enhanced CT, MRI, and positron emission tomography. It can quantitatively reflect the biological and pathological characteristics of tumors and their microenvironment.[20] The efficacy of this technique remains unbiased and impervious to the subjective influence of the medical professionals.

Radiomics is a complex process comprising five crucial steps: (1) obtaining high-quality and standardized imaging data, (2) manual or automatic recognition of the region of interest, (3) region of interest segmentation and 3D reconstruction, (4) feature extraction and quantification, and (5) establishment of clinical prediction models. Currently, conventional image evaluation continues to be predominantly limited to analyzing imaging features, such as tumor morphology and density, which are solely quantified through CT values. Similar to other computer-aided diagnosis techniques,[21,22] radiomics, an innovative technology, has revolutionized disease diagnosis by enabling the differentiation between benign and malignant tumors, predicting tumor classification, and determining tumor prognosis,[17] surpassing the limitations of conventional imaging techniques. Autonomic technologies have rapidly advanced in recent years, enabling the integration of radiomics with other omics for a more precise depiction of tumor pathophysiology down to the cellular and genetic levels.[23] The field of breast cancer radiomics has witnessed a surge in research activity, resulting in numerous publications addressing every facet of this domain. However, studies on the trend of breast cancer radiomics are still rare.

Our study aimed to conduct a bibliometric analysis based on the Web of Science Core Collection (WOSCC) database to analyze the breast cancer radiomics literature since 2015, identify the focus of relevant studies, and predict upcoming trends.

2. Materials and Methods

2.1. Database and search method

Data collection was sourced exclusively from the WOSCC database. The search formula is ((((((((TS = (breast cancer)) OR TS = (breast tumor)) OR TS = (Mammary Cancer)) OR TS = (Malignant Neoplasm of Breast)) OR TS = (Cancer of Breast)) OR TS = (Carcinoma, Human Mammary)) OR TS = (Human Mammary Neoplasm)) OR TS = (Breast Carcinoma)) AND TS = (radiomics). The search time ranged from January 1, 2015, to December 10, 2023.

2.2. Inclusion and exclusion criteria

The inclusion criteria were as follows: (1) publications related to breast cancer radiomics, (2) articles and reviews written in English, and (3) publications published between January 1, 2015 and December 10, 2023. The exclusion criteria were as follows: (1) the topic was not related to breast cancer radiomics and (2) the types of publications were conference abstracts, news, book chapters, corrections, and briefings, et al.

2.3. Analysis tools

We used GraphPad Prism v8.0.2 to analyze and plot annual and national publication trends and proportions. In addition, CtieSpace (6.2.4R (64 bit) Advanced Edition) and VOSviewer (1.6.18 Edition) were used to analyze the data and visualize science mapping.

VOSviewer was created by Waltman et al[24] in 2009 as a free software based on JAVA for analyzing large amounts of literature data and displaying them in a map format.

To visualize research achievements in certain fields by drawing literature co-citation network diagrams, Professor Chen created the CiteSpace software,[25] which attempted to use an experimental framework to study new concepts and evaluate existing technologies. This enables users to better understand the knowledge domain, research frontiers, and trends, and to predict their future research progress.

2.4. Statistical analysis

After analyzing the distribution of different publishing years, nations, institutions, journals, and authors, we recorded their numbers and proportions.

3. Results

3.1. Overall trend

The results showed that from January 1, 2015 to December 10, 2023, there were 891 articles on breast cancer radiomics in the WOSCC database (Fig. 1), including 731 articles (91.09%) and 160 reviews (8.91%), contributed by 56 countries and regions, 1183 institutions, and 4429 authors.

Since 2015, the number of papers published each year has increased and can be divided into three stages. The field saw minimal growth from 2015 to 2016, as evidenced by the publication of fewer than 10 articles annually, suggesting that researchers have not paid adequate attention. From 2017 to 2019, the publication volume gradually increased, which may indicate that more researchers have attempted to enter this field. Since 2020, the publication volume in this field has increased rapidly, peaking in 2023. It has attracted widespread attention as a hot topic in recent years.

3.2. Countries

Fifty-six countries and regions conducted studies on the application of breast cancer radiomics. The top five countries in this field were China, the United States, Italy, South Korea, and the United Kingdom. Ranked first in the world, China accounted for 47.70% of the total publication volume, far exceeding that of other countries.

Among the top ten countries/regions in the ranking of paper publication volume, the United States has 12090 citations, far beyond other countries/regions. Its paper citation/publication ratio (56.50) ranks second among all the countries/regions. China has the highest publication volume (425 articles) and ranks second with 6329 citations. Its citation-to-publication ratio (14.89) was the lowest, indicating that the quality of the published papers was generally low. The cooperative network is illustrated in Figure 2A. China has close cooperation with countries such as Switzerland, South Korea, the Netherlands, Germany, and Japan, whereas the United States has close cooperation with countries such as Italy, Australia, France, and the United Kingdom. China has a large number of publications, high citation frequency, and a centrality of 0.27, indicating that it is currently a leading country in this field.

3.3. Institutions

One thousand one hundred eighty-three institutions have systematically published articles on breast cancer radiomics. Among the top ten institutions with published papers, six were from China, two were from the United States, and the remaining two were from Austria and Italy (Fig. 2B). Fudan University published the most literature (49 papers, 782 citations, and

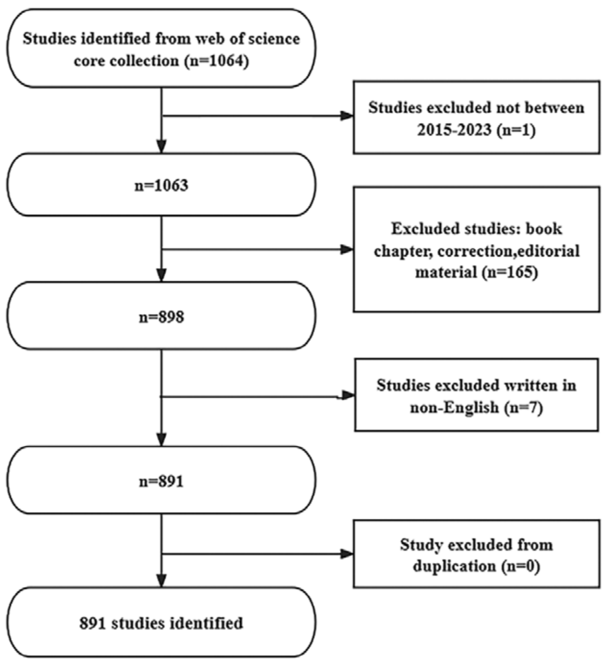

Figure 1. Literature retrieval process diagram.

15.96 citations per paper). The Chinese Academy of Sciences (39 papers, 1637 citations, 41.97 per paper) ranks second, while the Memorial Sloan Kettering Cancer Center (36 papers, 5986 citations, 166.28 per paper) ranks third. Further analysis revealed that institutions were more inclined to cooperate with domestic agencies. Hence, we advocate enhancing collaboration between local and international organizations to dismantle obstacles in academia.

3.4. Journals analysis

Frontiers in Oncology (110 papers, 12.35%) was the journal with the most published papers in this field, followed by Cancers (60 papers, 6.73%), the Journal of Magnetic Resonance Imaging (34 papers, 3.82%), and Academic Radiology (31 papers, 3.48%). Among the top ten most prolific journals, radiology had the highest IF of 19.7. Ninety percent of the journals were classified as zones 1 or 2.

The influence of a journal is determined by its frequency of joint citations, which indicates whether the journal has had a significant impact on the scientific community or not. According to Figure 2C, the journal with the highest number of co-citations is Radiology (761 times), followed by Eur Radiol (616 times), and J Magn Reson Imaging (472 times). Among the top 10 journals with the highest number of joint citations, J CLIN ONCOL was cited 460 times and IF was the highest among the top 10 journals (45.4). All the journals that were jointly cited were in Zone 1 or Zone 2.

The theme distribution of academic publications is displayed by overlaying the two maps (Fig. 2D). Based on the results, we identified two main colored citation paths: research published in medicine/medical/clinical journals is mainly cited by research published in molecular/biology/genetics and health/nursing/medicine journals.

3.5. Contributed authors

Among the authors who have published relevant literature on breast cancer radiomics, the top 10 authors published 160 papers, accounting for 17.96% of all the papers in this field. Pinker, Katja was the most prolific researcher (24 papers), followed by Giger, Maryellen L (22 papers) and Mao, Ning (19 papers). Furtheranalysis showed that of the 10 authors, seven were from China and three were from the United States. CiteSpace visualized the network among authors (Fig. 2E). Further analysis indicated that Li Hui, who ranks seventh in publication volume and third in citation count, is the leading author in this field.

Fifty-six authors were cited more than 50 times, indicating that their research had a high reputation and influence. The largest nodes were associated with authors who have been co-cited the most (Fig. 2F), including Lambin P (367 citations), Gillies RJ (328 citations), and Li H (210 citations). Taking 1 year as the time slot, covering the period from 2015 to 2023, the reference network had 621 nodes and 3169 links (Fig. 2F). Among the top 10 articles with the highest number of co-citations, the article titled “Radiomics: Images Are More than Pictures, They Are Data” in Radiology (IF = 19.7) was the most co-cited reference, with Gillies, Robert J as the first author.

3.6. Clustering analysis

We conducted reference co-citation and temporal clustering analyses (Fig. 3A and 3B). We found that non-small cell lung cancer (cluster9), evolutionary algorithmsbiological imaging (cluster10), and contrast-enhanced ultrasound (cluster12) were the early research hotspots. Cancer (cluster3), ultrasound (cluster4), heterogeneity (cluster6), and computer-aided diagnosis (cluster7) were the mid-term research hotspots. Neoadjuvant chemotherapy (cluster0), pathological complete response (cluster1), axial lymph node metastasis (cluster2), the tumor microenvironment (cluster5), positron emission tomography (cluster8), and lymphovascular invasion (cluster13) are popular topics and trends in this field.

3.7. Keywords

By analyzing keywords, we can quickly understand the situation and development direction of a field. According to the co-occurrence of keywords in VOSviewer, the most popular keywords were MRI (166), machine learning (152), features (150), and images (143) (Table 1, Figure 3C). We removed irrelevant keywords and constructed a network containing 169 keywords that appeared at least eight times, resulting in six clusters. The first group (red) contained 43 keywords, including MRI, dynamic contrast-enhanced (DCE)-MRI, features, magnetic resonance imaging, subtype, radiogenomics, biomarkers, tumor heterogeneity, genomics, associations, and Oncotype dx. The second group (green) contained 43 keywords, including texture analysis, neoadjuvant chemotherapy, f-19-fdg/pet/ct, lung cancer, distant metastasis, reproducibility, impact, convolutional neural-network, and lymph-node metastatic. The third group contained 28 keywords (blue), including diagnosis, machine learning, prediction, artificial intelligence, risk, diagnostic-accuracy, mammography, and selection. The fourth group contained 27 keywords (yellow), including deep learning, preoperative prediction, ultrasound, metastasis, accuracy, nomogram, information, multicenter, and sentinel node. The fifth group contained 27 keywords (purple), including images, classification, lesions, system, differentiation, segmentation, computer-aided diagnosis, benign, performance, and masses. Group 6 contained one keyword (light blue), which is a neural-networks. We created a volcano map using CiteSpace to visually display the changes in research hotspots over time (Fig. 3D).

3.8. Citation bursts

Using CiteSpace, the 50 most reliable citation bursts in the field of breast cancer radiomics were obtained. The reference with the highest citation rate (36.14) is “Radiomics: Images Are More than Pictures, They Are Data” published by Gillies.[26] Of the 50

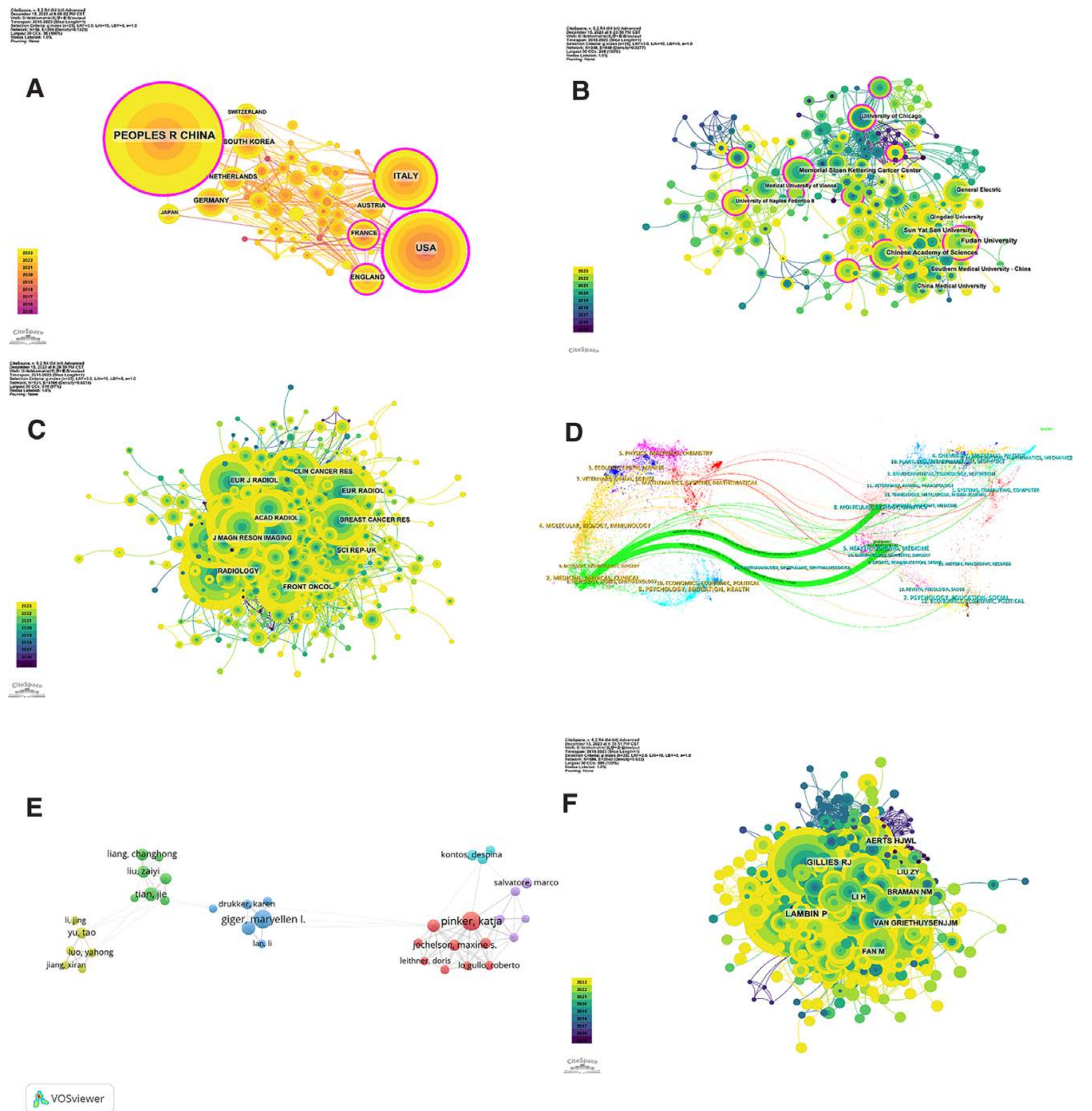

Figure 2. (A) National cooperation network diagram. Each node represents a country. (B) Network diagram of institutional cooperation. (C) Co-cited network diagram of journals. (D) Dual-map overlay of journals. The colored path showcases the interconnections between journals through citations, positioning the cited journal on the left and the citing journal on the right. (E) Author collaboration network diagram. (F) Co-citations network diagram of authors.

references, 42 were published between 2015 and 2023, indicating that these papers have been frequently cited over the past nine years. Importantly, 11 of these papers are currently at the peak of citations (Fig. 4A), indicating that breast cancer radiomics research will still receive considerable attention in the future.

Out of the 257 most prominent burst keywords in this field, we narrowed our focus to 50 with the most robust citation bursts (Fig. 4B), signifying the current research trends and possible future directions in this area of study.

4. Discussion

Our study analyzed the related research literature on breast cancer radiomics from 2015 to 2023. Our findings suggest that this area is progressing swiftly, with a sharp increase in the volume of primary research papers and scholarly reviews. This study has the potential to provide researchers with a deeper understanding of the progression and upcoming trends in this specific field.

To our knowledge, our study is the first to report the trend of breast cancer radiomics using a bibliometrics analysis. Compared to previous studies,[17,27] which published in the form of reviews, this paper used a bibliometrics analysis to help authors understand the change in this field. With vivid images and detailed tables, this new method can provide readers with a more intuitive display of the development in this field. Through a bibliometric analysis of the annual distribution of different nations, institutions, journals, authors, keywords, and references in the field of breast cancer radiomics, we can obtain more

Table 1

High-frequency Keywords.

Rank	Keyword	Counts	Rank	Keyword	Counts
1	MRI	166	11	Ultrasound	94
2	Machine learning	152	12	Deep learning	90
3	Features	150	13	Texture analysis	84
4	Images	143	14	Artificial intelligence	76
5	Neoadjuvant chemotherapy	121	15	Nomogram	67
6	Diagnosis	108	16	Lesions	65
7	Mammography	107	17	Heterogeneity	64
8	Classification	106	18	Therapy	64
9	Magnetic resonance imaging	106	19	Preoperative prediction	62
10	Prediction	104	20	Survival	60

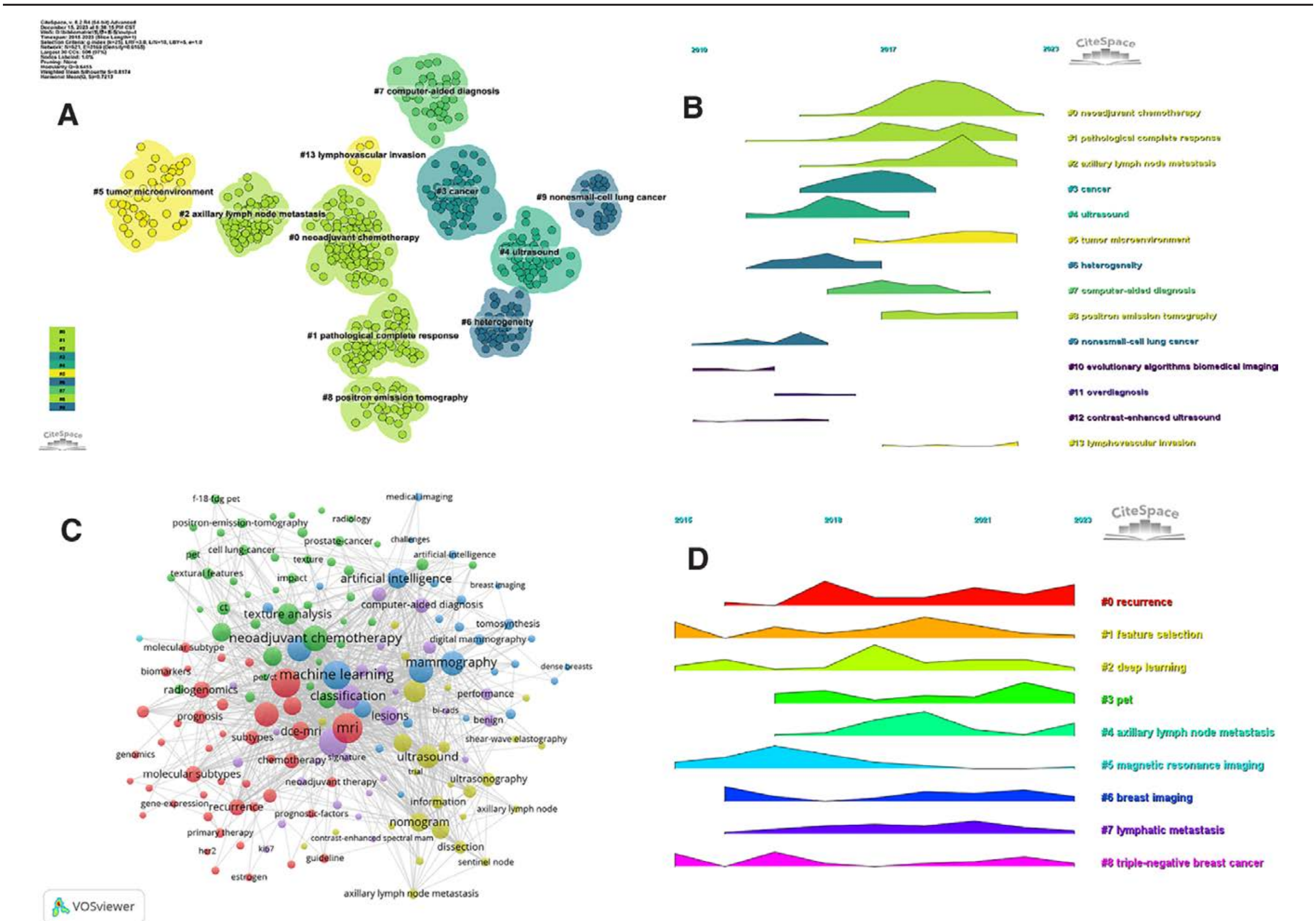

Figure 3. (A) Cluster diagram of co-cited publications. (B) Volcano plot of co-cited literature. (C) Co-occurrence network diagram of high-frequency keywords. Each node resents a keyword, and a larger node means higher frequency. (D) Keyword clustering volcano plot.

detailed information in this area and guide researchers predict the future direction of this field.

4.1. Trend

From 2015 to 2022, the international literature on breast cancer radiomics research has always increased, with a marked surge in publications starting in 2020. Since 2022, the number of academic publications in this field has surpassed 200 annually, signifying a growing interest from researchers in recent times. Significant advancements in the treatment of breast cancer have sparked a shift in the imaging requirements. Advancements in imaging technology and image data processing methods in recent years have also played an important role.

4.2. Countries

At present, a limited number of countries (such as China, the United States, Italy, South Korea, and the United Kingdom) and their educational institutions are primary sources of relevant studies being published. China and the United States ranked first and second in the number of publications, respectively, and made significant contributions to advancements in this field. China's academic research publications comprise nearly half of the total, demonstrating its close collaboration with various countries worldwide. Despite China leading in the number of publications, its citation/publication ratio remains significantly lower than that of the United States, suggesting a potential disparity in the overall quality of the research output. China has a large number of publications, high citation

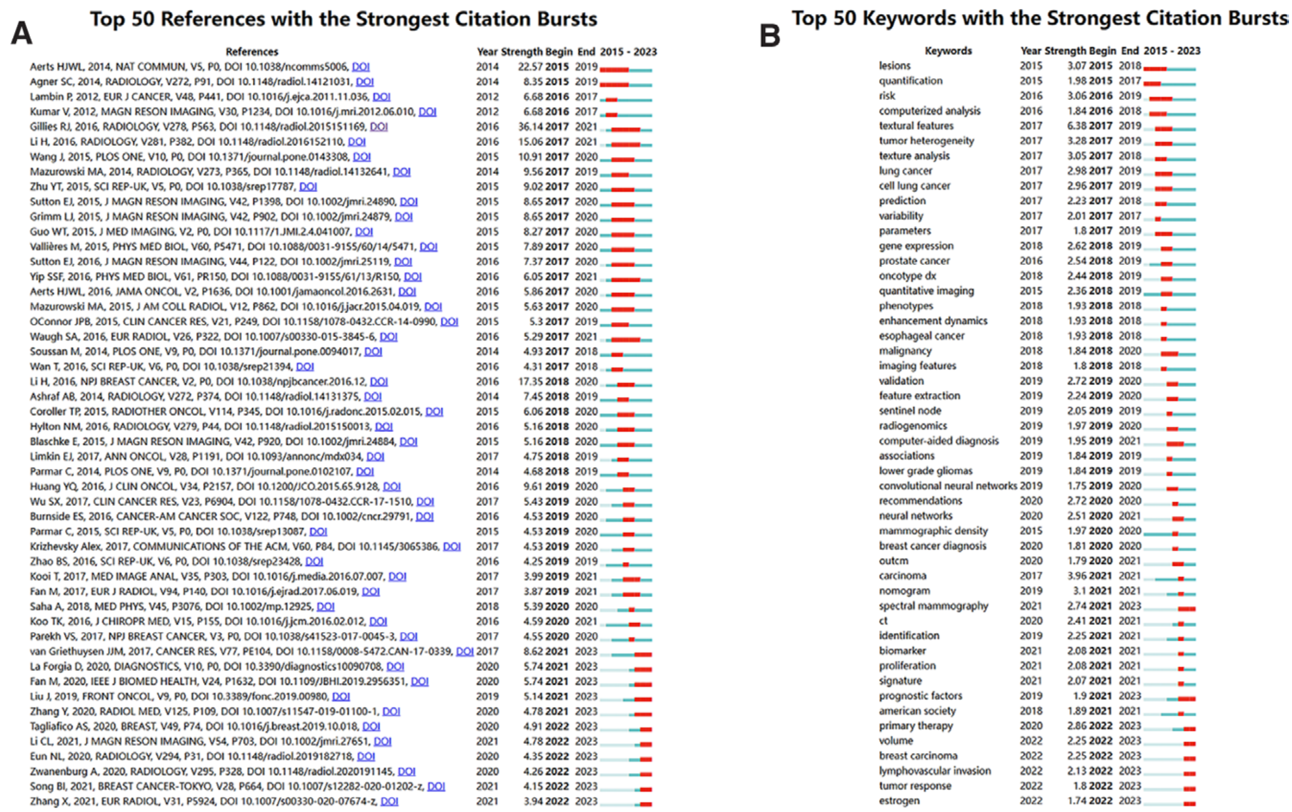

Figure 4. The maps showing the strongest citation bursts. (A) References with the strongest citation bursts. (B) 50 keywords with the strongest citation bursts.

frequency, and centrality of 0.27, indicating that it is currently a leading country in this field. The USA has the highest centrality (0.63), far beyond that of other countries, which shows that this country has also contributed greatly to this field. Among the top ten research institutions in terms of the number of publications, six were from China, far beyond other countries, including Fudan University and the Chinese Academy of Sciences, which were the top two institutions. Despite the significant amount of collaborative research in this field, it is evident that institutions show a higher preference for partnering with their national organizations. Therefore, it is imperative to enhance coordination between local and overseas organizations and dismantle academic obstacles to advance the field of breast cancer radiomics.

4.3. Journals

Frontiers in Oncology (110) is a journal with many publications, followed by cancer (60), magnetic resonance imaging (34), and academic radiology (31). Among the top ten journals, Radiology had the highest impact factor, indicating their high academic influence in their fields. The journal with the highest number of co-citations is Radiology (761 times), followed by Eur Radiol (616 times) and J Magn Reson Imaging (472 times). Among the top 10 journals with the highest number of joint citations, J Clin Oncol was cited 460 times and IF was the highest among the top 10 journals (45.4). This suggests that the aforementioned publications have significant academic sway and prestige within their respective disciplines. Numerous research papers in oncology and various clinical publications have highlighted the significant interest among clinical professionals regarding the potential benefits of radiomics tools for patient care.

4.4. References

In our study, information on the top 10 co-cited references, which were classic documents, was extensively explored. Based on these co-cited references, it can be found that the research subjects in this area are mainly the prediction of pathologic complete response to neoadjuvant chemotherapy and the prediction of sentinel lymph node metastasis by radiomics. From the co-cited literature analysis, we can see that in recent years, "neoadjuvant chemotherapy," "pathological complete response," "axillary lymph node metastasis," "tumor microenvironment," "positron emission tomography" and "lymphovascular invasion" have become hotspots. "Neoadjuvant chemotherapy" and "pathological complete response" are related to the treatment of breast cancer. "Tumor microenvironment" and "lymphovascular invasion" are pathological features of this cancer. These terms are related to the application of radiomics in the prediction of diseases. Positron emission tomography, which is not a common method for breast cancer diagnosis, is attracting increasing attention for its application in radiomics. Some studies have reported excellent diagnostic effectiveness of radiomics for many tumors. However, compared to traditional imaging methods, the potential applications of this technology must be further developed to optimize its ability to support clinical decision-making.

The publication titled 'Radiomics: Images Are More than Pictures, They Are Data' in Radiology (IF = 19.7) was the most co-cited reference, and Gillies, Robert J was the first author. Among the ten most cited references, an article written by Gillies et al was cited the most because their study provided crucial information for researchers who wanted to study radiomics, including workflow, clinical applications, challenges, and potential values. The article titled "Global cancer statistics 2020:

Globocan estimates of incidence and mortality worldwide for 36 cancers in 185 countries" had the highest IF (IF = 254.7, CA-A Cancer Journal for Clinicians).

4.5. Authors

Among the researchers involved in these publications, Pinker, Katja was the most prolific author (24 papers), followed by Giger, Maryellen (22 papers), and Mao, Ning (19 papers). We found that Li Hui, who ranks seventh in publication volume and third in citation count, is the leading author in this field. The authors who co-cited the most included Lambin P (367 citations), Gillies RJ (328 citations), and Li H (210 citations). With the most citations among the top 10 co-cited authors, Lambin P is thought to be a leading and powerful researcher in the area. He revolutionized the development of radiomics approaches and displayed dedication towards standardizing research in this field.

4.6. Keywords

Generally, for publications, keywords are extracted from the full texts and main topics of study. Researchers rely on keywords within their chosen academic fields to delve into research topics and identify evolving trends over different time frames. Analyzing keywords provides insight into shifting focus trends within this discipline. After compiling the top 20 high-frequency keywords in the field, we conducted a keyword co-occurrence analysis to cluster them, resulting in the identification of six distinct groups. These clusters offer valuable insights into the current research priorities and potential future trends in breast cancer radiomics.

Keywords can indicate the focus in a certain area, and we confirmed "MRI," "machine learning," "features," "images," and "neoadjuvant chemotherapy" as the focus in this area. These fields are summarized as follows:

1. MRI, features, and images: MRI is frequently selected for radiomics as the primary imaging modality in patients with breast cancer. Through the extraction of pertinent features from MRI scans, we can utilize selected attributes to build models that accurately forecast the disease characteristics, achieving high AUC values.
2. Machine learning: Various algorithms in machine learning, such as Logistic Regression, Random Forest, Decision Tree, and Support Vector Machines, are utilized in the analysis of radiomics data. These components play vital roles in the radiomics workflow. By utilizing these advanced algorithms, we can create precise models that improve prognosis, identify key pathological features, and anticipate treatment outcomes, ultimately enabling healthcare providers to make more informed decisions for their patients.
3. Neoadjuvant chemotherapy: It is a frequently employed method in the treatment of breast cancer, with varying ways depending on the stage of the disease. Conventional medical imaging techniques are ineffective for assessing the effectiveness of this treatment approach. Numerous studies have highlighted the superior predictive capabilities of radiomics in determining response to neoadjuvant chemotherapy, making it a prominent area of interest in recent years with a wealth of pertinent literature. Several studies in medical research have successfully constructed radiomics models that accurately predict the efficacy of neoadjuvant chemotherapy, with high AUC values. By incorporating various clinical indicators into composite models, radiomics has demonstrated enhanced diagnostic accuracy in detecting breast cancer.

Our investigation indicated that studies in the field of breast cancer radiomics recently emphasize five crucial components with strong citation bursts: prognostic factors, primary therapy, lymphovascular invasion, tumor response, and estrogen. These five keywords highlight emerging areas of interest in the field of radiomics for breast cancer and can be consolidated as follows:

1. Prognostic factors, lymphovascular invasion, and estrogen levels: various factors can influence breast cancer prognosis. The utilization of radiomics can provide researchers with a clearer insight into these influencing factors. For example, Ki-67 is considered an important factor in the prognosis of breast cancer. A number of studies have indicated that radiomics has the potential to provide a more accurate assessment of Ki-67 status. The occurrence of lymphovascular invasion significantly contributes to a diminished survival rate and an unfavorable prognosis. This sign has received increasing attention worldwide as a relatively new research field. As another prognostic factor for breast cancer, high estrogen levels can promote the advancement and metastasis of tumors; therefore, it is often an essential part of breast cancer research. Further exploration is essential to understand the ways in which it affects the progression of this illness.
2. Primary therapy and tumor response: neoadjuvant chemotherapy and surgical intervention are typically employed as the primary treatment plans. The scope of radiomics expands beyond predicting tumor response to neoadjuvant chemotherapy, assessing lymph node metastasis and immune factor expression prior to surgery, and offering enhanced direction for perioperative care.

The surge of the prominent terms from 2018 highlighted a shift in research emphasis over the previous five years, transitioning from mainstream technology to more nuanced investigations into the clinical characteristics of breast cancer. This trend was also observed in the clustering analysis. This conforms to the general rules of disease research, and the latest keywords highlight the cutting-edge subjects within this discipline.

4.7. Application of radiomics in breast cancer

4.7.1. Distinguishing between benign and malignant breast tumors. Identifying whether a breast tumor is benign or malignant poses a challenge even for seasoned radiologists. The implementation of radiomics technology has shown a remarkable increase in diagnostic precision in this field, as evidenced in previous studies.[15,28–31] In a previous analysis, the research conducted by Zhang et al[32] attempted to identify the most effective radiomics approach using multimodal MRI to distinguish between benign and malignant breast masses. The researchers developed several integrated models and validated a superior model that integrates T2WI, DKI, and pharmacokinetic parameter maps, resulting in an AUC value exceeding 0.9. Diffusion-weighted imaging (DWI) is a promising adjunctive imaging sequence to traditional DCE-MRI that uniquely enables the observation of water molecule diffusion. The differentiation of benign and malignant breast lesions through assessment of the apparent diffusion coefficient is a prominent area of research focus in the field of medical imaging. Naranjo et al[33] used radiomics methods based on two MRI sequences (DWI and DCE imaging) to distinguish between benign and malignant breast masses. This study found that multiparametric imaging radiomics methods (AUC = 0.85) could distinguish between benign and malignant lesions better than traditional DWI alone (AUC = 0.79).

4.7.2. Prediction of tumor information. For accurate clinical decisions, more detailed and microscopic information about tumors, such as pathological and immunohistochemical results, is required for further analysis. Wang et al[34] enrolled 901 patients with invasive breast cancer to predict their histological grades by using MRI radiomics. Of the 529 features extracted from these images, 26 were used to construct a radiomics model. This model showed a relatively high diagnostic efficacy in their study. Li et al[35] conducted a radiomic analysis of 91 cases of invasive breast cancer confirmed by biopsy and found that the tumor phenotype based on MRI radiomics can effectively distinguish the molecular classification of these breast cancers, including distinguishing ER + from ER -, PR + from PR -, HER2 + from HER2-, and triple-negative from non-triple-negative breast cancer, all with high AUC values. The results showed that radiomics technology is a good tool for reflecting the characteristics of tumors.

4.7.3. Prediction of the treatment effect. Radiomics has proven to be highly effective in predicting treatment outcomes, especially neoadjuvant chemotherapy (NAC).[36–40] NAC is used before surgery to optimize surgical options, minimize tumor size, and lower the likelihood of distant metastasis. Typically, it is the treatment of choice for individuals diagnosed with advanced breast cancer in a local area, serving as the primary form of defense against the disease. To predict NAC response using radiomics, Fan et al[41] combined various radiomics features extracted from DCE-MRI and found that background parenchymal features were among the most representative features for prediction, especially in the normal breast. By utilizing an evolutionary algorithm for feature confirmation, their classifier demonstrated remarkable predictive accuracy with a selection of 12 features. Braman et al[42] reported that a combination of imaging features inside and around the tumor could accurately predict the likelihood of pathological complete response to NAC (AUC = 0.74). By factoring in the receptor status, the AUC can be increased to 0.83.

4.7.4. Prediction of the prognosis. Radiomics can also help doctors better predict the prognosis of patients with breast cancer. Evaluation of axillary lymph node status helps to analyze prognosis and is still a mandatory requirement in the diagnosis of breast cancer. Yu et al[43] found that DWI-MRI features extracted using software could be used to evaluate sentinel lymph node metastasis in breast cancer. In this study, the AUCs of DWI-MRI combined with T2-SF were more than 0.8 in the training and validation groups. Ki-67, an important prognostic marker of breast cancer, can be used to estimate the therapeutic response. Liang et al[44] proposed a T2W image–based radiomics classifier based on 16 features extracted from T2W images and found good discrimination for predicting Ki-67 status. Ha et al[45] confirmed that the metabolic characteristics of positron emission tomography CT imaging are related to Ki-67 expression, which can be used to predict the recurrence risk of breast cancer and provide personalized management for patients with locally advanced breast cancer.

4.8. Problems

In recent years, radiomics has been increasingly used for the treatment of breast cancer, but there are still many problems: (1) At present, radiomics is mainly conducted in a few nations' academic institutions and usually simply in a single center, thus limiting its broader application. (2) The lack of big data studies, obvious differences in imaging parameters, and scanning methods limits the reproducibility and accuracy of radiomics for breast cancer.

4.9. Limitations

First, our study only included English literature and did not analyze Chinese literature, so we may have missed some important papers. Second, this study visually showed the number of studies in different countries, authors, and journals but did not conduct a statistical analysis. Finally, we did not conduct further analyses of a single important paper. In this field, we are optimistic that upcoming research endeavors will offer in-depth analyses accompanied by thorough findings.

5. Conclusions

We conducted a comprehensive analysis of publications related to breast cancer radiomics by using bibliometric tools to reveal the bibliometric features of the field. A synthesis of the relevant publications identified the current state of research and hotspots in the field. With a high number of publications, China and the USA are the two most important countries that have contributed to major achievements in this area, indicating their leading roles in this field. Numerous publications on breast cancer radiomics published in clinical journals, which showed increasing interest among clinical professionals, highlighted the value of radiomics in this field. The hotspots have changed from mainstream technology to more nuanced investigations into the clinical characteristics of breast cancer, which reflected this area had been deeply explored in recent years, and the prediction of these characteristics may be the future direction in this field. Although radiomics is a rapidly expanding field, its application in breast cancer is still at the stage of clinical exploration and there are many obstacles to overcome in the future. In the future, more efforts should be made to exploit the application value of radiomics in clinical practice rather than simply regarding it as a research tool.

Acknowledgments

The authors thank the Imaging Department of the Second Affiliated Hospital of Shandong First Medical University for their support.

Author contributions

Conceptualization: Zhe Yang.
Formal analysis: Zhe Yang.
Investigation: Zhe Yang.
Methodology: Zhe Yang.
Resources: Zhe Yang.
Software: Zhe Yang.
Supervision: Zhe Yang.
Visualization: Zhe Yang.
Writing – original draft: Zhe Yang, Chenglong Liu.
Writing – review and editing: Zhe Yang, Chenglong Liu.
Data curation: Chenglong Liu.
Project administration: Chenglong Liu.
Validation: Chenglong Liu.

References

[1] Brem RF, Lenihan MJ, Lieberman J, Torrente J. Screening breast ultrasound: past, present, and future. AJR Am J Roentgenol. 2015;204:234–40.
[2] Hu W, Xu D, Li N. Research status of systemic adjuvant therapy for early breast cancer. Cancer Control. 2023;30:10732748231209193.
[3] Grabinski VF, Brawley OW. Disparities in breast cancer. Obstet Gynecol Clin North Am. 2022;49:149–65.
[4] Tao Z, Shi A, Lu C, Song T, Zhang Z, Zhao J. Breast cancer: epidemiology and etiology. Cell Biochem Biophys. 2015;72:333–8.
[5] Liu Z, Wang S, Dong D, et al. The applications of radiomics in precision diagnosis and treatment of oncology: opportunities and challenges. Theranostics. 2019;9:1303–22.
[6] Lambin P, Rios-Velazquez E, Leijenaar R, et al. Radiomics: extracting more information from medical images using advanced feature analysis. Eur J Cancer. 2012;48:441–6.
[7] Napel S, Mu W, Jardim-Perassi BV, Aerts H, Gillies RJ. Quantitative imaging of cancer in the postgenomic era: Radio(geno)mics, deep learning, and habitats. Cancer. 2018;124:4633–49.
[8] Yu Y, He Z, Ouyang J, et al. Magnetic resonance imaging radiomics predicts preoperative axillary lymph node metastasis to support surgical decisions and is associated with tumor microenvironment in invasive breast cancer: A machine learning, multicenter study. EBioMedicine. 2021;69:103460.
[9] Wang X, Xie T, Luo J, Zhou Z, Yu X, Guo X. Radiomics predicts the prognosis of patients with locally advanced breast cancer by reflecting

the heterogeneity of tumor cells and the tumor microenvironment. Breast Cancer Res. 2022;24:20.
[10] Liu C, Zhao W, Xie J, et al. Development and validation of a radiomics-based nomogram for predicting a major pathological response to neoadjuvant immunochemotherapy for patients with potentially resectable non-small cell lung cancer. Front Immunol. 2023;14:1115291.
[11] Neri E, Del Re M, Paiar F, et al. Radiomics and liquid biopsy in oncology: the holons of systems medicine. Insights Imaging. 2018;9:915–24.
[12] Wang H, Zhou Y, Li L, Hou W, Ma X, Tian R. Current status and quality of radiomics studies in lymphoma: a systematic review. Eur Radiol. 2020;30:6228–40.
[13] Zheng YM, Xu WJ, Hao DP, et al. A CT-based radiomics nomogram for differentiation of lympho-associated benign and malignant lesions of the parotid gland. Eur Radiol. 2021;31:2886–95.
[14] Kocher M, Ruge MI, Galldiks N, Lohmann P. Applications of radiomics and machine learning for radiotherapy of malignant brain tumors. Strahlenther Onkol. 2020;196:856–67.
[15] Yap FY, Varghese BA, Cen SY, et al. Shape and texture-based radiomics signature on CT effectively discriminates benign from malignant renal masses. Eur Radiol. 2021;31:1011–21.
[16] Liu Z, Zhang XY, Shi YJ, et al. Radiomics analysis for evaluation of pathological complete response to neoadjuvant chemoradiotherapy in locally advanced rectal cancer. Clin Cancer Res. 2017;23:7253–62.
[17] Conti A, Duggento A, Indovina I, Guerrisi M, Toschi N. Radiomics in breast cancer classification and prediction. Semin Cancer Biol. 2021;72:238–50.
[18] Su GH, Xiao Y, Jiang L, et al. Radiomics features for assessing tumor-infiltrating lymphocytes correlate with molecular traits of triple-negative breast cancer. J Transl Med. 2022;20:471.
[19] Wang M, Perucho JAU, Hu Y, et al. Computed tomographic radiomics in differentiating histologic subtypes of epithelial ovarian carcinoma. JAMA Netw Open. 2022;5:e2245141.
[20] Limkin EJ, Sun R, Dercle L, et al. Promises and challenges for the implementation of computational medical imaging (radiomics) in oncology. Ann Oncol. 2017;28:1191–206.
[21] Bakkouri I, Afdel K. DermoNet: A Computer-Aided Diagnosis System for Dermoscopic Disease Recognition. Germany: Springer International Publishing; 2020:170–177.
[22] Bakkouri I, Afdel K. Convolutional Neural-Adaptive Networks for Melanoma Recognition. Germany: Springer International Publishing; 2018:453–460.
[23] Tagliafico AS, Piana M, Schenone D, Lai R, Massone AM, Houssami N. Overview of radiomics in breast cancer diagnosis and prognostication. Breast. 2020;49:74–80.
[24] Ai S, Li Y, Tao J, et al. Bibliometric visualization analysis of gut-kidney axis from 2003 to 2022. Front Physiol. 2023;14:1176894.
[25] Wang R, Shan Y. Hot spots and frontiers of postpartum depression research in the past 5 years: a bibliometric analysis. Front Psychol. 2022;13:901668.
[26] Gillies RJ, Kinahan PE, Hricak H. Radiomics: images are more than pictures, They Are Data. Radiology. 2016;278:563–77.
[27] Valdora F, Houssami N, Rossi F, Calabrese M, Tagliafico AS. Rapid review: radiomics and breast cancer. Breast Cancer Res Treat. 2018;169:217–29.
[28] Wang S, Sun Y, Li R, et al. Diagnostic performance of perilesional radiomics analysis of contrast-enhanced mammography for the differentiation of benign and malignant breast lesions. Eur Radiol. 2022;32:639–49.
[29] Romeo V, Cuocolo R, Apolito R, et al. Clinical value of radiomics and machine learning in breast ultrasound: a multicenter study for differential diagnosis of benign and malignant lesions. Eur Radiol. 2021;31:9511–9.
[30] Sun W, Liu S, Guo J, et al. A CT-based radiomics nomogram for distinguishing between benign and malignant bone tumours. Cancer Imaging. 2021;21:20.
[31] Xu M, Fang M, Zou J, et al. Using biparametric MRI radiomics signature to differentiate between benign and malignant prostate lesions. Eur J Radiol. 2019;114:38–44.
[32] Zhang Q, Peng Y, Liu W, et al. Radiomics based on multimodal MRI for the differential diagnosis of benign and malignant breast lesions. J Magn Reson Imaging. 2020;52:596–607.
[33] Daimiel Naranjo I, Gibbs P, Reiner JS, et al. Radiomics and machine learning with multiparametric breast MRI for improved diagnostic accuracy in breast cancer diagnosis. Diagnostics (Basel). 2021;11:919.
[34] Wang S, Wei Y, Li Z, Xu J, Zhou Y. Development and Validation of an MRI Radiomics-Based signature to predict histological grade in patients with invasive breast cancer. Breast Cancer (Dove Med Press). 2022;14:335–42.
[35] Li H, Zhu Y, Burnside ES, et al. Quantitative MRI radiomics in the prediction of molecular classifications of breast cancer subtypes in the TCGA/TCIA data set. npj Breast Cancer. 2016;2:16012.
[36] Gu J, Tong T, He C, et al. Deep learning radiomics of ultrasonography can predict response to neoadjuvant chemotherapy in breast cancer at an early stage of treatment: a prospective study. Eur Radiol. 2022;32:2099–109.
[37] Xu Q, Sun Z, Li X, et al. Advanced gastric cancer: CT radiomics prediction and early detection of downstaging with neoadjuvant chemotherapy. Eur Radiol. 2021;31:8765–74.
[38] Lin P, Yang PF, Chen S, et al. A delta-radiomics model for preoperative evaluation of Neoadjuvant chemotherapy response in high-grade osteosarcoma. Cancer Imaging. 2020;20:7.
[39] Antunovic L, De Sanctis R, Cozzi L, et al. PET/CT radiomics in breast cancer: promising tool for prediction of pathological response to neoadjuvant chemotherapy. Eur J Nucl Med Mol Imaging. 2019;46:1468–77.
[40] Liu Z, Li Z, Qu J, et al. Radiomics of multiparametric MRI for pretreatment prediction of pathologic complete response to neoadjuvant chemotherapy in breast cancer: a multicenter study. Clin Cancer Res. 2019;25:3538–47.
[41] Fan M, Wu G, Cheng H, Zhang J, Shao G, Li L. Radiomic analysis of DCE-MRI for prediction of response to neoadjuvant chemotherapy in breast cancer patients. Eur J Radiol. 2017;94:140–7.
[42] Braman NM, Etesami M, Prasanna P, et al. Intratumoral and peritumoral radiomics for the pretreatment prediction of pathological complete response to neoadjuvant chemotherapy based on breast DCE-MRI. Breast Cancer Res. 2017;19:57.
[43] Dong Y, Feng Q, Yang W, et al. Preoperative prediction of sentinel lymph node metastasis in breast cancer based on radiomics of T2-weighted fat-suppression and diffusion-weighted MRI. Eur Radiol. 2018;28:582–91.
[44] Liang C, Cheng Z, Huang Y, et al. An MRI-based radiomics classifier for preoperative prediction of Ki-67 status in breast cancer. Acad Radiol. 2018;25:1111–7.
[45] Ha S, Park S, Bang JI, Kim EK, Lee HY. Metabolic radiomics for pretreatment (18)F-FDG PET/CT to characterize locally advanced breast cancer: histopathologic characteristics, response to neoadjuvant chemotherapy, and prognosis. Sci Rep. 2017;7:1556.