Article

Evolutionary Map And Research Hotspots in Artificial Intelligence-Driven Dermatological Imaging Research: A Bibliometric Study

Jia Lu[1,2#], Dejun Nong[3#], Junjie Ye[4], Fan Long[5], Kezhao Wu[6], Jiaguang Su[7*]

Abstract

Background: Skin diseases impose a major global health burden. Dermoscopic diagnosis relies heavily on the examiner's experience and is time-consuming, a limitation that is particularly consequential for melanoma, which accounts for a disproportionate share of skin-cancer mortality. Artificial intelligence (AI) has the potential to improve the efficiency and accuracy of dermatological imaging diagnostics; no bibliometric analysis has focused specifically on AI-driven dermatological imaging with coverage extending to 2025. **Methods:** This bibliometric study analysed 737 articles from the Web of Science Core Collection (2000–2025) using CiteSpace, VOSviewer, the R package Bibliometrix, and Microsoft Excel. Collaboration networks, co-citation patterns, keyword co-occurrence, cluster analysis, and citation bursts were examined to assess the intellectual structure and dynamic trends of the field. **Results:** Annual publication output rose slowly between 2000 and 2019 and then increased sharply after 2019. China ranked first in publication volume (184 articles), yet its betweenness centrality for international collaboration was negligible (0.00). The USA had the highest centrality (0.49), serving as a key bridge in global cooperation. Research has concentrated on deep learning for the classification, diagnosis, and segmentation of skin cancer and melanoma, with the HAM10000 dataset and deep-learning-based diagnosis emerging as two of the most highly cited foundations of the field. Emerging trends identified through keyword burst analysis include the application of generative adversarial networks (GANs) and vision transformers (ViTs). **Conclusion:** AI-driven dermatological imaging is a rapidly expanding, increasingly interdisciplinary field characterised by close integration of technological development and clinical application. China leads in output but requires stronger international collaboration to enhance its global academic influence. Future research should prioritise the clinical translation of advanced AI models, address real-world validation challenges, and promote data diversity to ensure equitable performance across populations.

Keywords: Artificial intelligence, dermatological imaging, bibliometrics, deep learning, skin cancer

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Introduction

The skin is the largest organ of the human body, and skin disorders are highly prevalent. These disorders constitute a substantial global health problem, adding considerably to the healthcare burden and reducing quality of life worldwide[1]. Diseases of the skin and subcutaneous tissue are also among the leading causes of disability globally, affecting a large proportion of the population across all regions in recent decades[2].

Melanoma accounts for fewer than 5% of skin cancer cases but is responsible for the majority of skin cancer deaths, and its diagnosis depends heavily on visual assessment[3]. It is therefore particularly important to use dermoscopy to assess the likelihood that a pigmented lesion is melanoma. Dermoscopy (also termed dermatoscopy) is a non-invasive, hand-held technique for examining the skin. A modern dermatoscope typically combines a magnifying lens with a light source that can be switched between polarised and non-polarised modes, offers variable magnification, and incorporates a digital camera for image capture. By providing a magnified view, the dermatoscope aids recognition of pigmented and non-pigmented lesions, including melanoma[4]. In conventional dermoscopy, dermatologists diagnose skin cancer by visually inspecting clinical and dermoscopic images. However, visual examination and identification of skin lesions is demanding and time-consuming[5].

Artificial intelligence (AI) has enabled the development of low-cost, widely accessible, and effective tools that can reduce processing time and cost while improving accuracy, thereby extending its reach across multiple disciplines[6]. AI has advanced dermatology considerably, introducing numerous changes to the diagnostic workflow through digital, automated systems[7,8]. Image-based AI models have been used to diagnose skin conditions and to identify various types of skin lesions[9].

Although the relationship between AI research and dermatological diagnosis has attracted increasing discussion in recent years, the overall direction and trends of the field remain unclear, and no bibliometric analysis has focused specifically on AI-driven dermatological imaging with coverage extending to 2025. The present study used bibliometric and visualisation methods to map the global research landscape on AI and dermatological imaging over the past 25 years. Through a comprehensive review of the literature, we aimed to characterise current research and to inform future directions in the diagnosis and treatment of skin diseases.

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Data and Methods

Literature search and strategy

The Web of Science Core Collection (WoSCC; https://www.webofscience.com) was used as the data source. As one of the most widely used and authoritative databases for bibliometric analysis, the WoSCC is recognised across the global academic community for its broad coverage and high-quality indexing.

A topic (TS) search was performed using terms related to AI and dermatological imaging, as follows:
TS = ("artificial intelligence" OR "chatgpt*" OR "gpt*" OR "machine learning" OR "deep learning" OR "transfer learning" OR "reinforcement learning" OR "neural network" OR "convolutional neural network" OR "natural language processing" OR "image segmentation" OR "semantic segmentation" OR "supervised clustering" OR "supervised learning" OR "unsupervised clustering" OR "unsupervised learning" OR "text mining" OR "data mining" OR "graph mining") AND TS = ((skin OR cutaneous) NEAR/1 (imaging* OR radiolog* OR dermatoscop* OR dermoscop* OR photograph* OR image*))

The search covered publications from 1 January 2000 to 31 December 2025. Two researchers independently performed the initial search and screening, and a third researcher resolved any disagreements. A total of 737 articles were ultimately deemed eligible for analysis. The screening process is shown in Figure 1. To ensure comprehensive literature coverage and avoid omitting relevant interdisciplinary studies, our search strategy employed a broad range of AI-related terms, encompassing mainstream algorithm types and technical subfields. This extensive search scope could, in theory, introduce a limited number of irrelevant publications that involve general AI algorithms but are not specifically focused on dermatological imaging. To mitigate this potential noise, we implemented a manual screening process: first screening titles and abstracts, followed by full-text evaluation, thereby excluding, as far as possible, records that did not address dermatological image analysis.

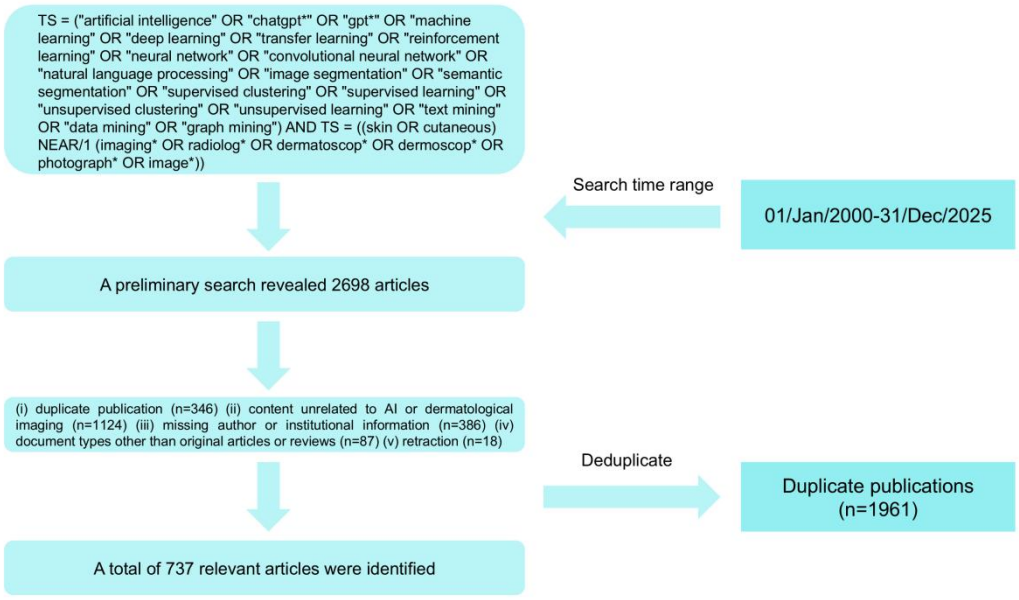


Figure 1. Flowchart of literature screening.

Inclusion and exclusion criteria

Only original research articles and reviews published in peer-reviewed English-language journals were included. Records were excluded for any of the following reasons: (i) duplicate publication; (ii) content unrelated to AI or dermatological imaging; (iii) missing author or institutional information; (iv) document types other than original articles or reviews; or (v) retraction.

Data processing and visualisation

All records were exported in plain text format and imported into three analytical tools for multidimensional bibliometric analysis: CiteSpace 6.4.R1, VOSviewer 1.6.20, and the R package Bibliometrix (version 5.2.1). The detailed parameter settings for CiteSpace 6.4.R1 are as follows: Time span: 2000–2025, with a 1-year time slice; Node selection criterion: g-index with k = 25; a unified pruning method (Pathfinder) was applied, which does not affect statistical data and results; it is solely for optimizing layout and reducing label overlap; link strength calculation: Cosine similarity; Other tuning parameters: LRF = 2.5, L/N = 10, LBY = 5, e = 1.0; Node types: Authors, institutions, countries/regions, subject categories, keywords, cited references, cited journals, and cited authors. Using VOSviewer 1.6.20, keyword co-occurrence and author collaboration networks were constructed and visualized, employing the full-count method, with a similarity threshold set to 0.1 and a minimum node occurrence frequency set to 2. The R package Bibliometrix (version 5.2.1) was used to generate annual publication trend plots. In all network visualizations, the node size is proportional to the frequency of the corresponding item, while the line thickness reflects the strength of collaboration, co-occurrence, or co-citation. Node colors progress from light to dark to indicate the chronological order of publication/occurrence, from earlier to later dates. Nodes with a betweenness centrality exceeding the conventional threshold of 0.1 are highlighted with a purple outer ring, signifying their pivotal bridging role within the knowledge network. For keyword clustering analysis, the reliability and structural clarity of the clustering results were evaluated using modularity (Q) and the weighted mean silhouette score (S). Microsoft Excel 2021 was used to organise the data and to cross-check the quantitative results against the visual outputs.

Results

Annual publication output

A total of 737 articles on AI-driven dermatological imaging have been published since 2000, and overall output has increased over this period, peaking in 2024 (Figure 2). Annual output can be divided into two phases: 2000–2019 and 2020–2025. The first phase (2000–2019) may be described as an exploratory period, during which output increased slowly—fewer than 50 articles per year—as researchers began to recognise the importance of the topic. After 2019, annual output increased markedly, indicating that AI-driven dermatological imaging research has gained considerable momentum worldwide. The apparent decline in 2025 is a statistical artefact most likely arising from database indexing delays at the time of retrieval rather than a genuine reduction in output.

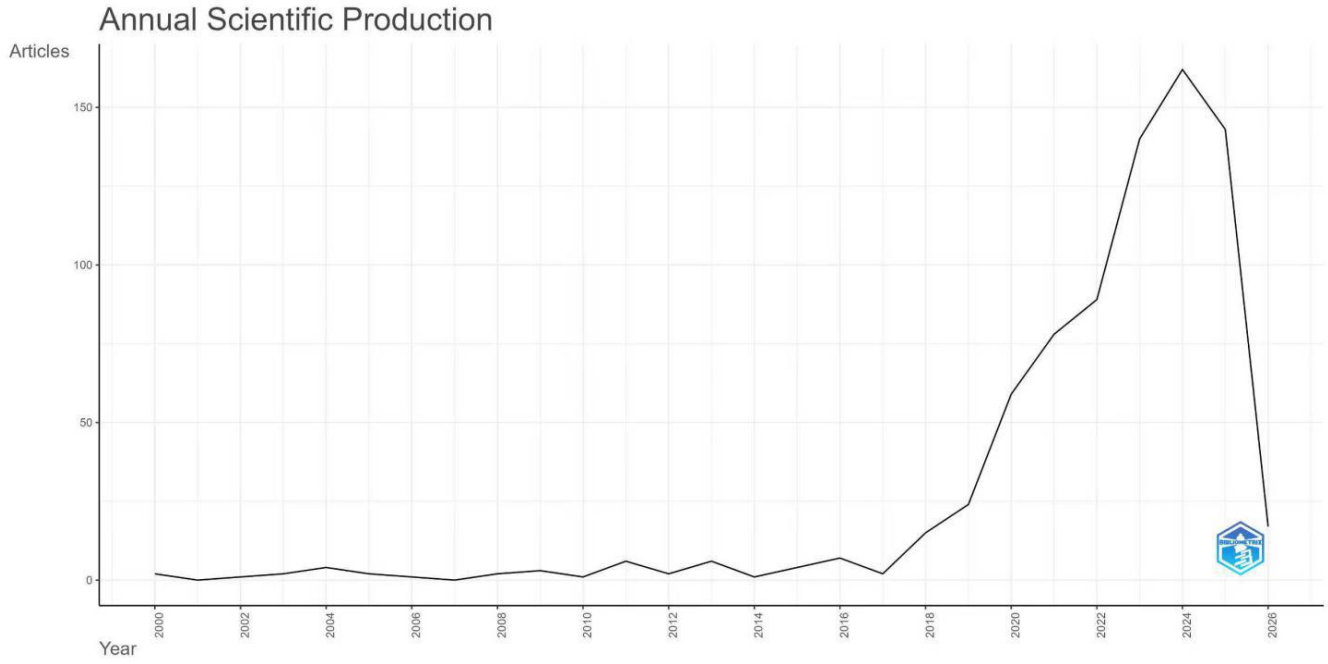


Figure 2. Annual publication volume in the field of AI-driven dermatological imaging.

Note: The 2025 data are incomplete due to the literature retrieval cut-off date (31 December 2025). A proportion of manuscripts published in late 2025 have not yet been fully indexed in the Web of Science Core Collection, so this datum does not represent the real annual publication trend.

Country analysis

Researchers from 80 countries have contributed to AI-driven dermatological imaging. China produced the greatest number of publications (184 articles), followed by India (166 articles) and the USA (128 articles) (Table 1). The inter-country collaboration network is shown in Figure 3. The USA had the highest betweenness centrality (0.49), indicating a pivotal bridging role in international collaboration. Although China led in output, its betweenness centrality was 0.00, indicating that its international collaboration—and, correspondingly, the international influence of its output—remains limited and warrants strengthening.

Table 1. High-productivity countries in AI-driven dermatological imaging research and their betweenness centrality.

Rank	Publications (n)	Centrality	Country
1	184	0.00	China
2	166	0.26	India
3	128	0.49	USA
4	60	0.19	Saudi Arabia
5	43	0.38	Australia
6	42	0.47	Italy
7	41	0.09	England
8	39	0.41	South Korea
9	38	0.06	Spain
10	38	0.39	Pakistan

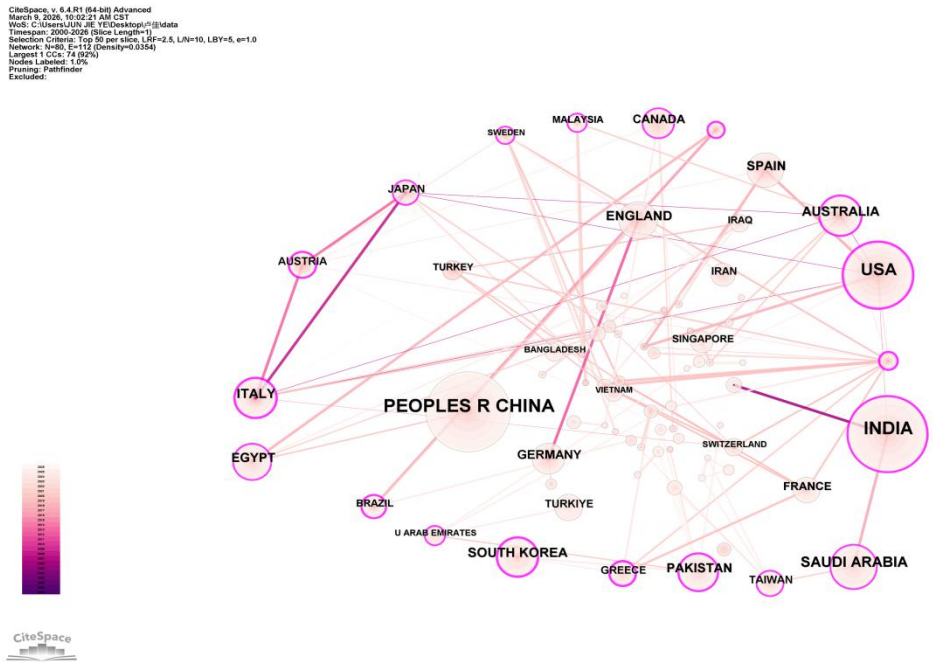


Figure 3. National/regional collaboration network in AI-driven dermatological imaging.

Institutional analysis

The institutional collaboration network comprised 549 nodes and 1,456 links, with a density of 0.0097 (Figure 4). It should be noted that all institutional data are directly extracted from the original institutional affiliations in the Web of Science Core Collection; no standardization of institutional aliases has been performed, nor have different name variants of the same entity been merged. Consequently, the number of publications and betweenness centrality metrics may exhibit certain statistical deviations, and the institutional rankings presented in Table 2 are for reference purposes only. The Egyptian Knowledge Bank (EKB), Memorial Sloan Kettering Cancer Center, and the Vellore Institute of Technology (VIT) had the largest nodes, indicating that they were the most productive institutions in the field. As shown in Table 2, the five most productive institutions were the EKB (36 publications; centrality 0.08), Memorial Sloan Kettering Cancer Center (21; 0.16), VIT (18; 0.05), the University of Queensland (16; 0.04), and Princess Nourah bint Abdulrahman University (14; 0.09). These institutions are located in different countries and span different organisational types, including general universities and specialised research centres. It is important to note that EKB is a national-level literature aggregation and open-access alliance in Egypt and does not represent the independent research output of a single entity. Memorial Sloan Kettering Cancer Center had the highest betweenness centrality (0.16), indicating that it serves as a central hub within the global collaboration network.

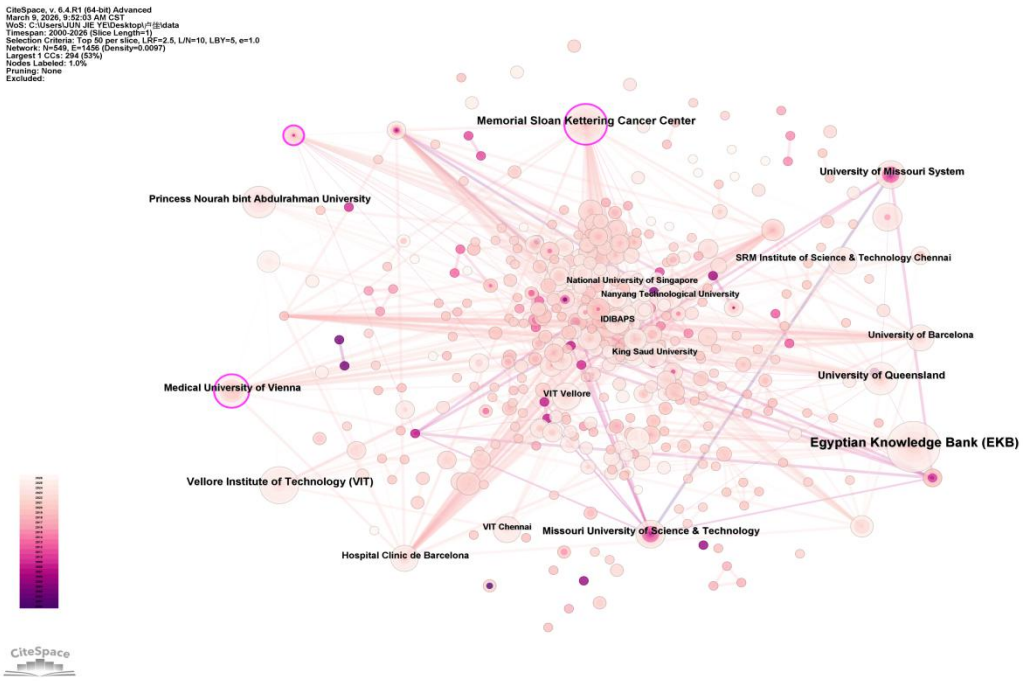


Figure 4. Institutional collaboration network in AI-driven dermatological imaging.

Table 2. Most productive institutions in AI-driven dermatological imaging (for reference only; data based on original WoS affiliation strings without name standardisation).

Rank	Publications (n)	Centrality	First year	Institution
1	36	0.08	2018	Egyptian Knowledge Bank (EKB)
2	21	0.16	2009	Memorial Sloan Kettering Cancer Center
3	18	0.05	2018	Vellore Institute of Technology (VIT)
4	16	0.04	2008	University of Queensland
5	14	0.09	2020	Princess Nourah bint Abdulrahman University
6	14	0.12	2019	Medical University of Vienna
7	13	0.00	2000	University of Missouri System
8	13	0.01	2000	Missouri University of Science & Technology
9	12	0.00	2018	University of Barcelona
10	12	0.03	2018	SRM Institute of Science & Technology, Chennai

Notes: The Egyptian Knowledge Bank (EKB) is a national-level open-access literature alliance in Egypt, and its publication volume includes jointly authored works from multiple domestic collaborating institutions, not the output of a single independent research entity. All institutional names are extracted directly from Web of Science Core Collection without alias merging, so the ranking is for reference only.

Author analysis

The growing integration of AI and dermatological imaging is driving a paradigm shift in the diagnosis and management of skin diseases. This interdisciplinary field combines AI technologies—such as deep learning and computer vision—with visual data, including dermoscopic and clinical images, to automate the detection, risk stratification, and prognostication of skin diseases such as melanoma and basal cell carcinoma.

The field has developed an established academic community, exemplified by a core group of authors (Figure 5). The red cluster is led by H. Peter Soyer (16 publications; 1,074 citations), Josep Malvehy (12 publications; 1,097 citations), and Harald Kittler (11 publications; 1,014 citations), who together constitute a core group in global AI-driven dermatological imaging research. Their high publication and citation counts underscore their standing in the field. The green cluster, centred on Titus J. Brinker and Achim Hekler, maintained strong ties to the red cluster, reflecting collaboration between groups engaged in technological development and clinical validation. Peripheral nodes represent emerging researchers or cross-regional collaborations, indicating that the field is steadily broadening.

Table 3 provides further detail on the influence and collaborative intensity of the leading authors. Each of the top ten authors had total link strength above 80, indicating very close collaboration within the field. H. Peter Soyer was the most productive and collaborative author, with 16 publications and a total link strength of 127. Overall, AI-driven dermatological imaging research has developed a well-defined collaborative structure that provides a solid foundation for future technical innovation and clinical application.

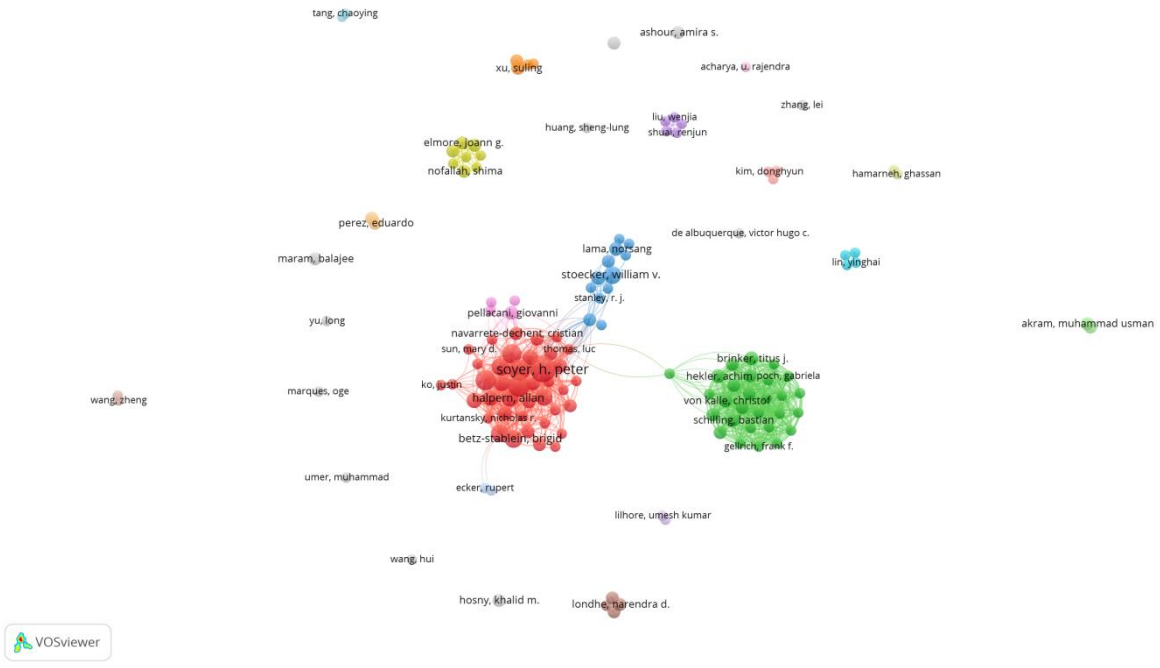


Figure 5. Author collaboration network in AI-driven dermatological imaging.

Notes: Nodes represent authors; node size is proportional to publication count. Lines represent collaborative links, and line width

indicates collaboration intensity. Different colours denote different collaboration clusters.

Table 3. Top 10 most productive authors in AI-driven dermatological imaging research.

Rank	Author	Documents	Citations	Total link strength
1	Soyer, H. Peter	16	1074	127
2	Malvehy, Josep	12	1097	121
3	Kittler, Harald	11	1014	110
4	Rotemberg, Veronica	10	855	101
5	Brinker, Titus J.	5	328	90
6	Hekler, Achim	5	328	90
7	von Kalle, Christof	5	328	90
8	Berking, Carola	4	301	88
9	Haferkamp, Sebastian	4	301	88
10	Hauschild, Axel	4	301	88

Journal co-citation analysis

The co-citation network of the journals comprises 659 nodes and 2,501 co-citation edges, with a network density of 0.0115. The largest connected component covers 86.9% of all nodes, indicating high interconnectivity among core journals in this field (Figure 6). This network exhibits a distinct two-cluster modular structure, forming two primary academic clusters: Computer Science and Engineering, and Clinical Dermatology, with medical imaging journals serving as pivotal hubs for cross-cluster knowledge flow.

Proc CVPR IEEE, IEEE Trans Med Imaging, and Comput Biol Med are the source journals with the highest co-citation frequencies. Journals focused on computer science and AI (e.g., Proc CVPR IEEE and Lecture Notes in Computer Science) constitute a technical source cluster, hosting advancements in fundamental AI algorithms and image processing methodologies. Journals dedicated to clinical dermatology (e.g., British Journal of Dermatology and Journal of the American Academy of Dermatology) form an application-oriented cluster, emphasizing clinical diagnostic practices and dermatological research. Innovative AI algorithms were first validated and applied in the field of general medical imaging, and were subsequently adapted and extended to clinical research in dermatology. This cross-domain knowledge transfer pathway is consistent with the interdisciplinary nature of AI-driven dermatological imaging.

Analysis of disciplinary co-occurrence helps clarify the interdisciplinary support structure of the field (Figure 7A). Node size was positively correlated with the frequency of disciplinary occurrence. The core technical disciplines were Engineering (Electrical & Electronic), Computer Science (Information Systems), Computer Science (AI), and Engineering (Biomedical), whereas the core clinical discipline was Radiology, Nuclear Medicine & Medical Imaging. These disciplines are densely interconnected: the technical foundation formed by electrical/electronic engineering and computer science is strongly linked to the clinical application layer formed by biomedical engineering and medical imaging, with additional support from Oncology and Biology. This structure underscores the convergence of engineering, computational intelligence, and clinical medicine. As shown in Figure 7B, Dermatology (2011–2013; strength 3.10) and Biology (2022–2023; strength 2.49) showed the strongest citation bursts over 2000–2025, with the research focus shifting over time from interdisciplinary areas toward the basic life science.

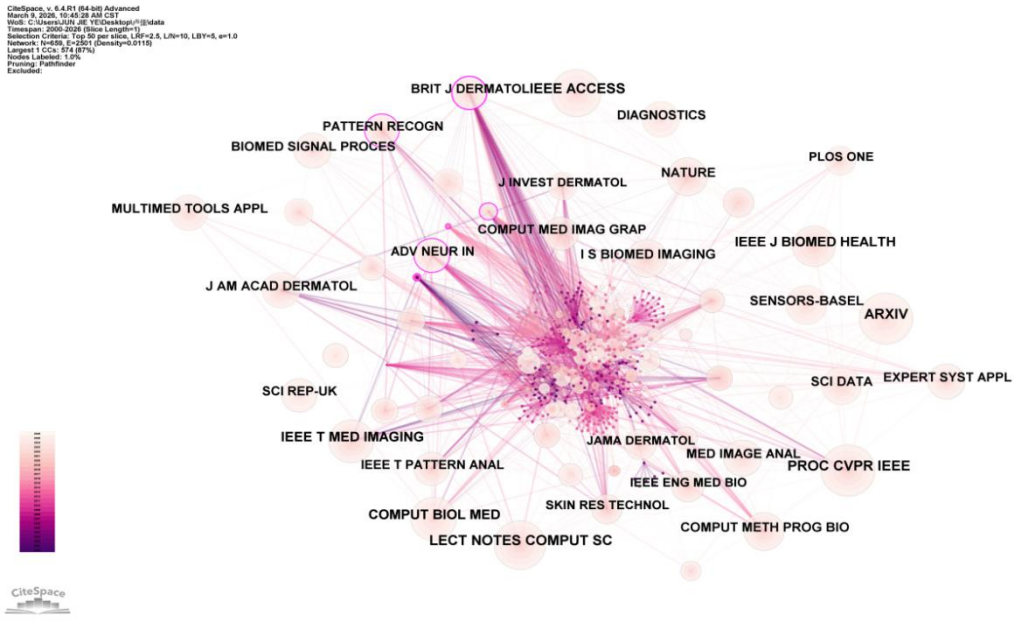
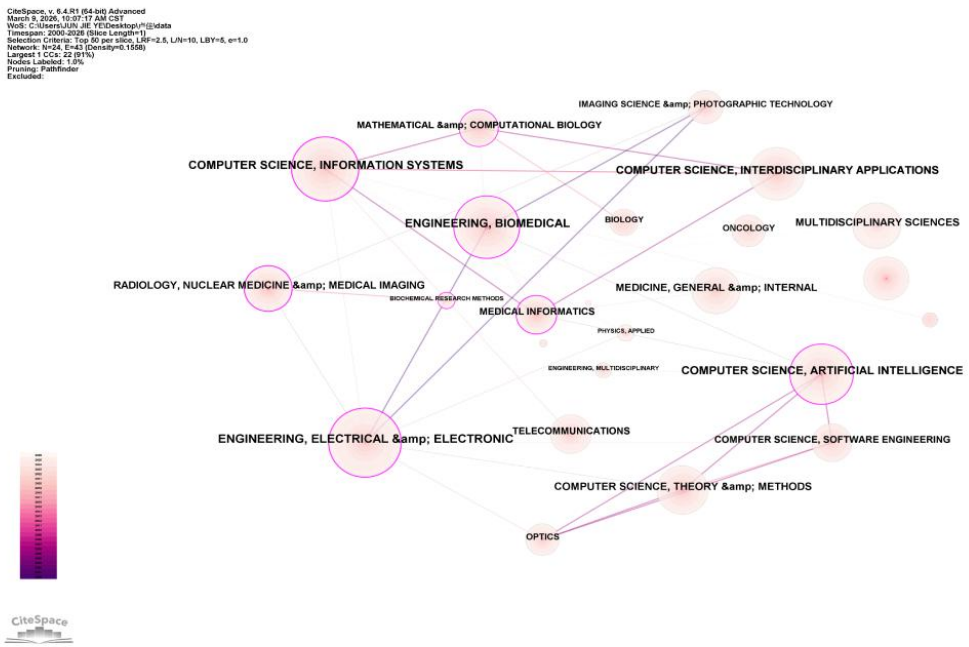


Figure 6. Journal co-citation network for AI-driven dermatological imaging

Notes: The network was generated by CiteSpace 6.4.R1 with cosine similarity and Pathfinder pruning, containing 659 nodes and 2501 links (density = 0.0115). Nodes represent journals; node size is proportional to co-citation frequency. Lines represent co-citation relationships, and line width is proportional to co-citation strength. Node colour gradient from light to dark reflects the recency of citations (earlier to later). Nodes with betweenness centrality > 0.1 are marked with a purple outer ring, indicating their hub role in cross-journal knowledge flow.

A



B

Top 5 Subject Categories with the Strongest Citation Bursts

Subject Categories	Year	Strength	Begin	End	2000 - 2026
DERMATOLOGY	2002	3.1	**2011**	2013	
COMPUTER SCIENCE, ARTIFICIAL INTELLIGENCE	2003	0.97	**2013**	2014	
ENGINEERING, BIOMEDICAL	2000	0.98	**2015**	2016	
MEDICAL INFORMATICS	2003	1.29	**2019**	2020	
BIOLOGY	2015	2.49	**2022**	2023	

Figure 7. Disciplinary co-occurrence network in AI-driven dermatological imaging.

Notes: (A) Nodes represent disciplines, with node size positively correlated with occurrence frequency; lines represent co-occurrence relationships, with thickness positively correlated with co-occurrence frequency, and node colour (light to dark) reflects the chronological emergence of each discipline. (B) The five disciplines with the strongest citation bursts in AI-driven dermatological imaging research over 2000–2025.

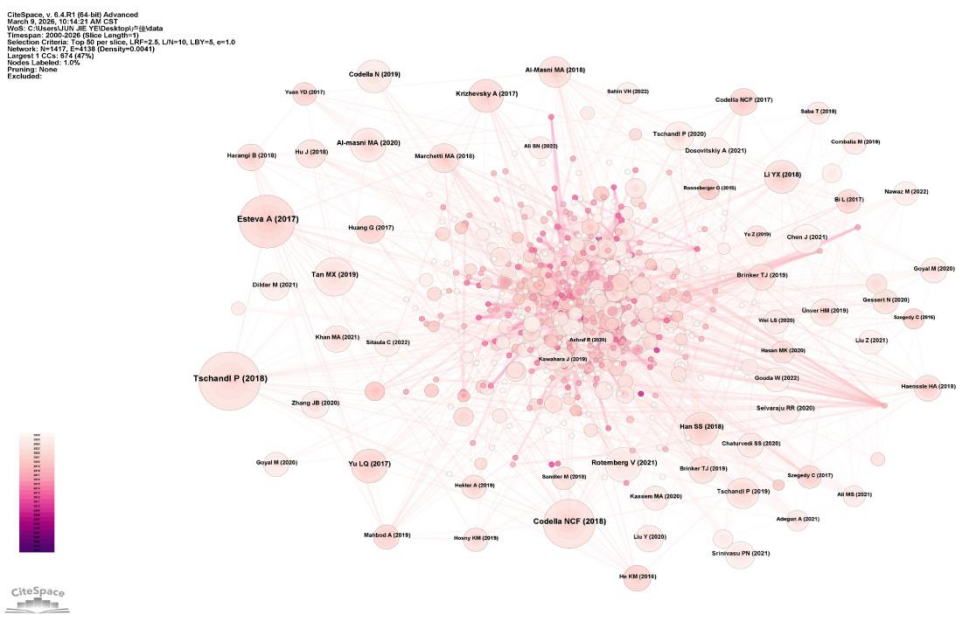
Table 4. Top 10 most co-cited journals in AI-driven dermatological imaging research.

Rank	Co-citations (n)	Centrality	Year	Cited journal
1	389	0.02	2006	Proc CVPR IEEE
2	378	0.01	2019	arXiv
3	362	0.01	2011	Lect Notes Comput Sci
4	322	0.03	2020	IEEE Access
5	300	0.05	2000	IEEE Trans Med Imaging
6	290	0.04	2005	Comput Biol Med
7	255	0.01	2015	IEEE J Biomed Health Inform
8	243	0.05	2013	Comput Methods Programs Biomed
9	237	0.04	2002	J Am Acad Dermatol
10	235	0.03	2019	Sensors (Basel)

Reference co-citation analysis

In the reference co-citation analysis, cited references served as nodes (Figure 8A), and the ten most-cited references are listed in Table 5. References with high centrality or high citation counts represent topics and advances that have attracted the greatest attention in AI-driven dermatological imaging. The most-cited reference was the HAM10000 dataset—a large collection of multi-source dermatoscopic images of common pigmented skin lesions by Tschandl et al.[10]—with 120 co-citations. This finding reflects the capacity of AI to provide intelligent, computer-aided diagnosis and classification of skin diseases using large-scale, multi-source, real-world medical images. As shown in Figure 8B, 2016–2022 was a period of intense output of highly cited literature. The references by Esteva et al.[19] and Tschandl et al.[10] showed especially strong bursts, reflecting their pivotal role in advancing the field. Several references from 2023–2025 remained in a high-burst phase, indicating that the leading research hotspots and key advances in this area are still evolving.

A



B

Top 25 References with the Strongest Citation Bursts

References	Year	Strength	Begin	End	2000 - 2026
Esteva A, 2017, NATURE, V542, P115, DOI 10.1038/nature21056, DOI	2017	33.51	2019	2022	
Yu LQ, 2017, IEEE T MED IMAGING, V36, P994, DOI 10.1109/TMI.2016.2642839, DOI	2017	14.99	2019	2022	
Krizhevsky A, 2017, COMMUN ACM, V0, PP10971105, DOI 10.1145/3065386, DOI	2017	13.18	2019	2022	
Codella NCF, 2017, IBM J RES DEV, V61, P0, DOI 10.1147/JRD.2017.2708299, DOI	2017	9.11	2019	2022	
Li YX, 2018, SENSORS-BASEL, V18, P0, DOI 10.3390/s18020556, DOI	2018	8.84	2019	2023	
Han SS, 2018, J INVEST DERMATOL, V138, P1529, DOI 10.1016/j.jid.2018.01.028, DOI	2018	8.61	2019	2023	
Codella NCF, 2018, I S BIOMED IMAGING, V0, PP168, DOI 10.1109/ISBI.2018.8363547, DOI	2018	21.43	2020	2023	
He KM, 2016, PROC CVPR IEEE, V0, PP770, DOI 10.1109/CVPR.2016.90, DOI	2016	12.6	2020	2021	
Huang G, 2017, PROC CVPR IEEE, V0, PP2261, DOI 10.1109/CVPR.2017.243, DOI	2017	11.12	2020	2022	
Al-Masni MA, 2018, COMPUT METH PROG BIO, V162, P221, DOI 10.1016/j.cmpb.2018.05.027, DOI	2018	9.11	2020	2023	
Mahbod A, 2019, COMPUT MED IMAG GRAP, V71, P19, DOI 10.1016/j.compmedimag.2018.10.007, DOI	2019	8.72	2020	2022	
Tschandl P, 2018, SCI DATA, V5, P0, DOI 10.1038/sdata.2018.161, DOI	2018	32.21	2021	2023	
Tan MX, 2019, PR MACH LEARN RES, V97, P0	2019	9.95	2022	2024	
Sandler M, 2018, PROC CVPR IEEE, V0, PP4510, DOI 10.1109/CVPR.2018.00474, DOI	2018	8.22	2022	2023	
Codella N, 2019, ARXIV, V0, P0	2019	12.77	2020	2024	
Rotemberg V, 2021, SCI DATA, V8, P0, DOI 10.1038/s41597-021-00815-z, DOI	2021	10.31	2023	2026	
Dildar M, 2021, INT J ENV RES PUB HE, V18, P0, DOI 10.3390/ijerph18105479, DOI	2021	9.42	2023	2026	
Goyal M, 2020, COMPUT BIOL MED, V127, P0, DOI 10.1016/j.compbiomed.2020.104065, DOI	2020	9.13	2023	2024	
Srivastva PK, 2021, SENSORS-BASEL, V21, P0, DOI 10.3390/s21082852, DOI	2021	8.72	2023	2026	
Dosovitskiy A, 2021, ARXIV, V0, P0	2021	13.07	2024	2026	
Stania C, 2022, J MED SYST, V46, P0, DOI 10.1007/s10916-022-01868-2, DOI	2022	9.92	2024	2026	
Gouda W, 2022, HEALTHCARE-BASEL, V10, P0, DOI 10.3390/healthcare10071183, DOI	2022	9.92	2024	2026	
Nawaz M, 2022, MICROSC RES TECHNIQ, V85, P339, DOI 10.1002/jemt.23908, DOI	2022	9.23	2024	2026	
Selvaraju RR, 2020, INT J COMPUT VISION, V128, P336, DOI 10.1007/s11263-019-01228-7, DOI	2020	8.59	2024	2026	
Liu Z, 2021, 2021 IEEE/CVF INT ----- VISION (ICCV 2021), V0, PP9992, DOI	2021	8.53	2024	2026	

Figure 8. Reference co-citation network for AI-driven dermatological imaging.

Notes: (A) Reference co-citation network: node size reflects citation frequency, and line thickness reflects co-citation strength. (B)

Burst analysis of the top 25 most cited references: displays the citation burst strength, start and end years, and high-citation time intervals of highly cited literature, reflecting the influence of key literature and the evolution of academic hotspots in the field.

Table 5. Top 10 most-cited references in AI-driven dermatological imaging research, 2000–2025.

Rank	Citations	Centrality	Year	Cited reference
1	120	0.02	2018	Tschandl P, 2018, Sci Data, V5, DOI 10.1038/sdata.2018.161
2	96	0.01	2017	Esteva A, 2017, Nature, V542, P115, DOI 10.1038/nature21056
3	89	0.04	2018	Codella NCF, 2018, ISBI, P168, DOI 10.1109/ISBI.2018.8363547
4	49	0.01	2019	Tan MX, 2019, PMLR, V97
5	43	0.03	2021	Rotemberg V, 2021, Sci Data, V8, DOI 10.1038/s41597-021-00815-z
6	43	0.03	2017	Yu LQ, 2017, IEEE Trans Med Imaging, V36, P994
7	43	0.01	2020	Al-masni MA, 2020, Comput Methods Programs Biomed, V190
8	40	0.03	2017	Krizhevsky A, 2017, Commun ACM, DOI 10.1145/3065386
9	39	0.00	2019	Codella N, 2019, arXiv
10	39	0.02	2018	Li YX, 2018, Sensors (Basel), V18, DOI 10.3390/s18020556

Research hotspots

Keyword co-occurrence and frequency analysis

Keywords capture the core content of an article, and analysing them helps reveal research trends and hotspots within a field. CiteSpace and VOSviewer were used to construct a research-hotspot map for AI-driven dermatological imaging. The keyword co-occurrence network comprised 482 nodes and 1,925 links, with a density of 0.0166 (Figure 9). The network was highly clustered, with the principal clusters relating to diagnosis, classification, deep learning, and skin cancer. The keyword density map showed high-density regions centred on skin cancer, deep learning, melanoma, and segmentation, with colour grading from bright yellow at the centre to blue–green at the periphery, reflecting a gradient in research intensity. With respect to disease focus, skin cancer clustered with related terms such as melanoma, basal cell carcinoma, and naevi, whereas deep learning was strongly associated with technical terms such as convolutional neural network and transformer, which together form the technical core of the field (Figure 10). The most frequent keyword was deep learning, followed by skin cancer, classification, diagnosis, and melanoma (Table 6).

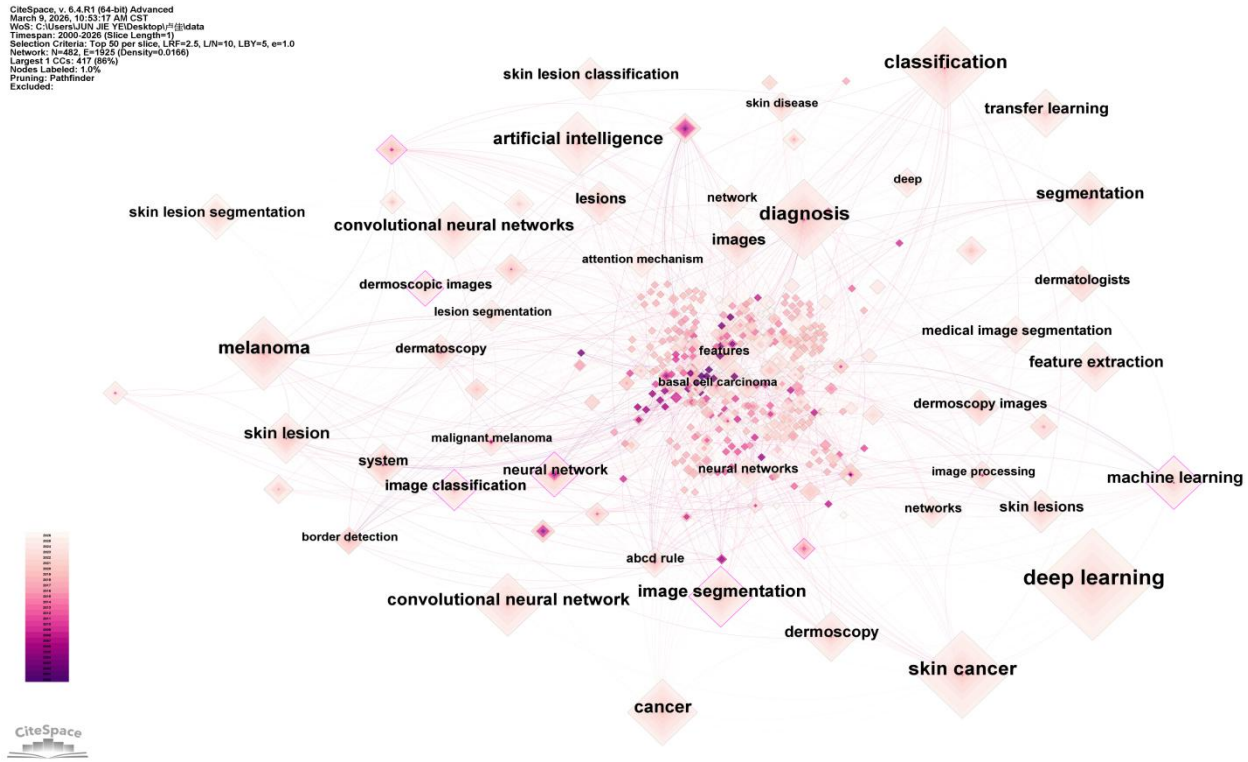


Figure 9. Keyword co-occurrence network in AI-driven dermatological imaging.

Notes: Nodes represent keywords, with node size positively correlated with occurrence frequency. Lines represent co-occurrence relationships, with line thickness positively correlated with co-occurrence frequency. Node colour (light to dark) reflects the year a keyword first appeared (earlier to later). The network comprised 482 nodes and 1,925 edges, with a density of 0.0166.

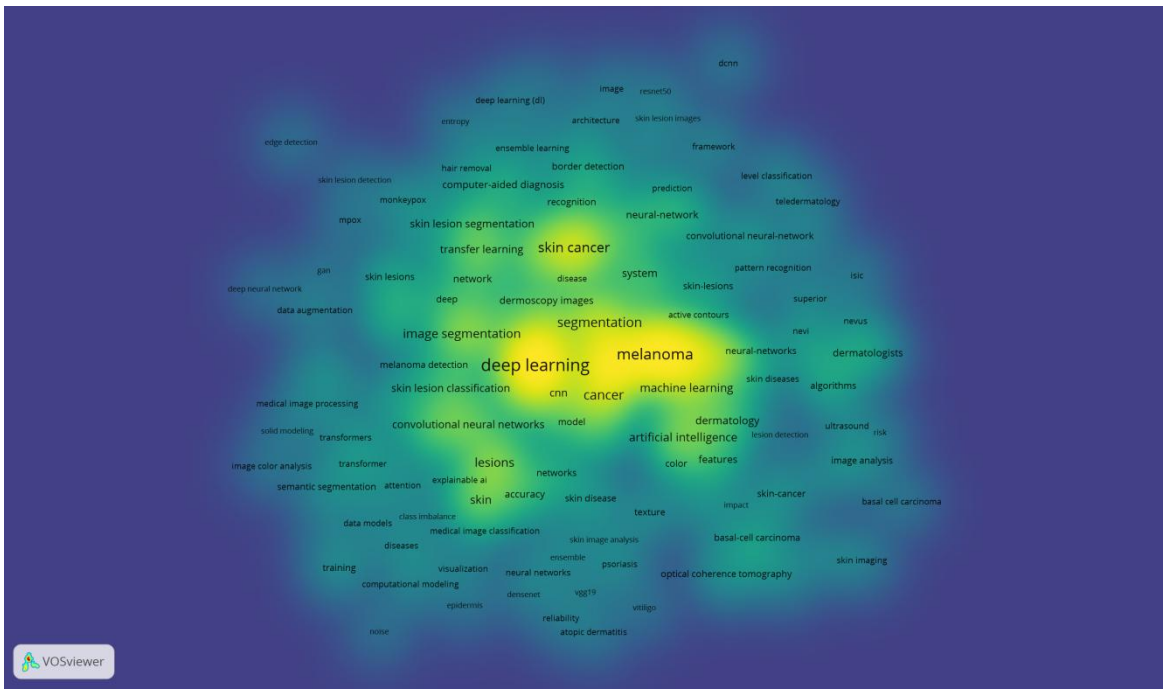


Figure 10. Keyword density map for AI-driven dermatological imaging.

Notes: Colour grading from bright yellow to blue–green represents high to low keyword density, with bright yellow marking the core research hotspots. Higher-density regions indicate more active research and stronger associations among keywords.

Table 6. Top 10 most frequent keywords in AI-driven dermatological imaging research.

Rank	Frequency	Centrality	Year	Keyword
1	224	0.02	2018	deep learning
2	138	0.09	2011	skin cancer
3	126	0.06	2005	classification
4	121	0.06	2002	diagnosis
5	100	0.04	2004	melanoma
6	82	0.04	2018	cancer
7	78	0.09	2011	artificial intelligence
8	73	0.01	2018	convolutional neural network
9	71	0.10	2011	image segmentation
10	61	0.02	2018	convolutional neural networks

Keyword cluster analysis

Keywords summarise the core content of an article, and their analysis provides insight into its main ideas. Comprehensive studies on the application of keywords may help identify tendencies in research and hot topics in specific fields of study[11].

Cluster analysis was performed in CiteSpace on the network of 482 nodes and 1,925 links (density 0.0166). The modularity ($Q = 0.6841 > 0.3$) and weighted mean silhouette ($S = 0.8819 > 0.5$) confirmed that the clustering was reliable and internally consistent (Figure 11). Fourteen core clusters were identified (Table 7), forming a coherent knowledge structure: the principal research target was #0 skin lesions; the technical core was #1 medical image segmentation and #2 image segmentation; and the algorithmic support was #3 artificial intelligence and #4 deep convolutional neural network. These clusters follow a clear logical chain—skin lesions as the research target, medical image segmentation as the core technical process, and AI and deep convolutional neural networks as the enabling algorithms. Three further areas have developed around this core: #5 reflectance confocal microscopy as an emerging imaging technique, #12 Swin Transformer as a state-of-the-art algorithm, and #13 receiver operating characteristic analysis as a model-evaluation method. Notably, Cluster #5 reflects a strong association between reflectance confocal microscopy and basal cell carcinoma. As a non-invasive in vivo imaging technique capable of providing cellular-level resolution in en face optical sections, reflectance confocal microscopy serves as a cornerstone clinical tool for the early detection of basal cell carcinoma, delineation of invasive margins, and preoperative localization. The studies within this cluster focus on the application of reflectance confocal microscopy images to achieve AI-assisted automated identification and segmentation of basal cell carcinoma; this explains why this imaging modality is grouped within the same cluster as this specific disease. To

concentrate the discussion on the core knowledge framework and cutting-edge trends in this field, this paper prioritizes an in-depth examination of the clusters that constitute the backbone of the research architecture (#0–#5), represent the most advanced algorithmic developments (#12), and provide the foundational methodology for model evaluation (#13). Clusters #6–#11 comprise specialized technical subfields and niche application scenarios derived from the core themes; these clusters feature relatively fewer publications and garner comparatively less attention within the field. The keyword timeline (Figure 12) clearly shows how research topics have shifted over time. From 2000 to 2010, research focused on clinical and conventional imaging diagnostics, including melanoma diagnosis and dermoscopy. From 2010 to 2020, machine learning, image segmentation, and feature extraction became the core hotspots, reflecting a shift toward intelligent techniques. From 2020 to 2025, advanced algorithms and new imaging techniques—including deep learning, the Swin Transformer, and reflectance confocal microscopy—developed rapidly.

All clusters show continuity and overlap over time: #0 skin lesions and #1 medical image segmentation span the entire period, whereas newer topics such as #12 Swin Transformer have been prominent over the past five years.

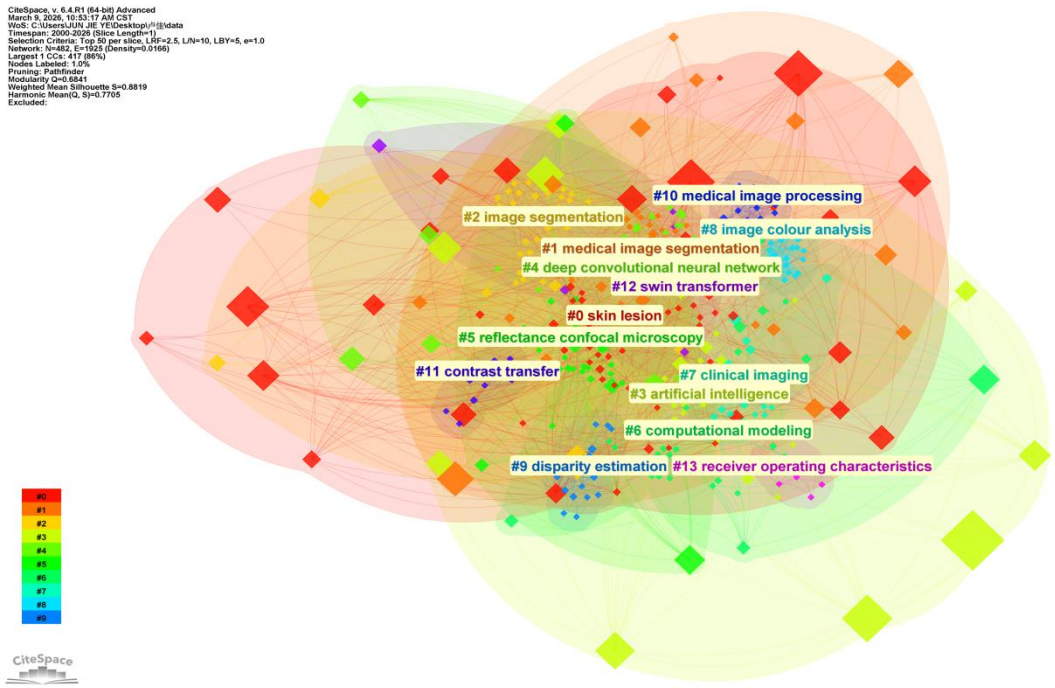


Figure 11. Keyword clustering map for AI-driven dermatological imaging.

Notes: Nodes represent keywords, sized by frequency; lines represent co-occurrence relationships, with width proportional to co-occurrence frequency. Different colours denote different clusters, and the numbers correspond to core research themes.

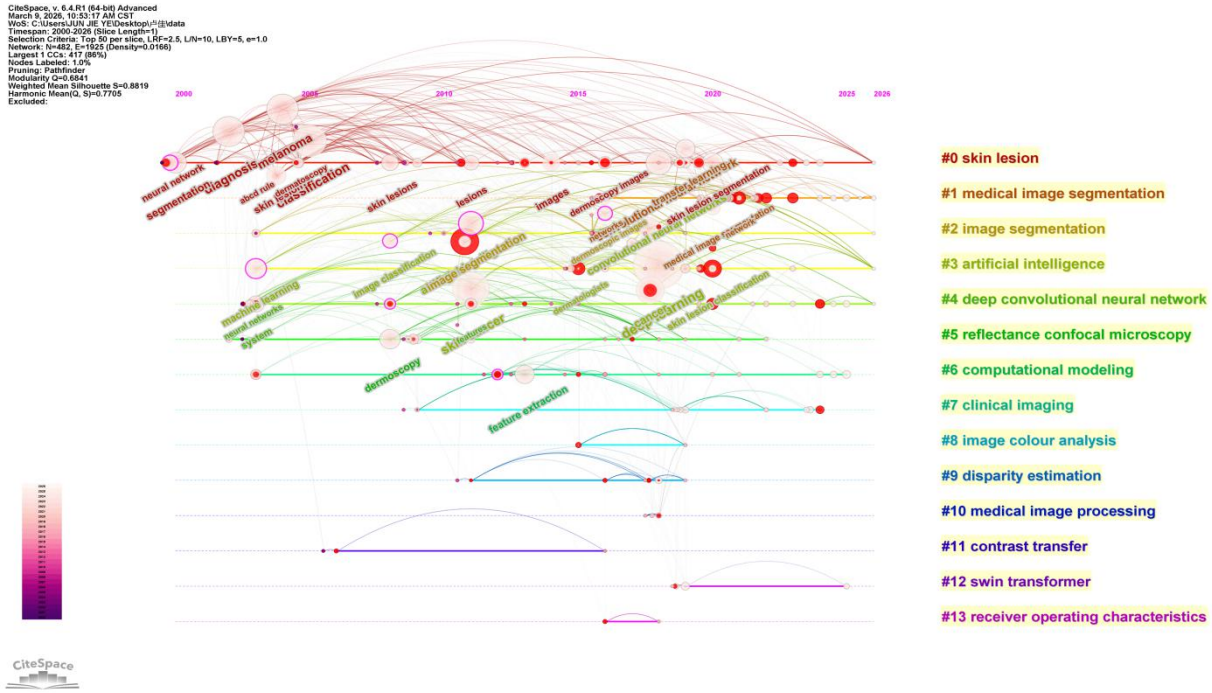


Figure 12. Keyword timeline map for AI-driven dermatological imaging.

Notes: The horizontal axis is the timeline (2000–2025) and the vertical axis lists the 14 core clusters. Nodes are keywords sized by

frequency; node colour reflects the year of first occurrence, and edges represent co-occurrence. Cluster labels appear on the right. Network parameters: Q = 0.6841, S = 0.8819, 482 nodes, 1,925 links.

Table 7. Keyword cluster labels and representative keywords in AI-driven dermatological imaging research.

Cluster	Silhouette	Year	Representative keywords
#0	0.79	2012	deep learning; skin cancer; medical image analysis; biomedical image processing; skin lesions; Wiener filter; image grayscaling; image quantisation; global burden
#1	0.81	2020	deep learning; convolutional neural network; transfer learning; ISIC dataset; Google Colab; skin lesion; activation function; image augmentation
#2	0.91	2017	image segmentation; feature extraction; neural network; attention mechanism; skin cancer; skin lesion; edge detection; automatic segmentation
#3	0.88	2018	machine learning; convolutional neural networks; International Skin Imaging Collaboration; medical imaging; skin cancer diagnosis; dermoscopic images; explainable AI
#4	0.82	2014	machine learning; deep learning; medical imaging; skin cancer; skin lesion segmentation; heterogeneous transfer learning; domain similarity measure
#5	0.91	2013	basal cell carcinoma; deep learning; persistent homology; transfer learning; reflectance confocal microscopy; cutaneous oncology; skin cancer
#6	0.90	2014	feature extraction; skin cancer; image classification; ensemble learning; deep-learning modelling; activation maps; dermoscopic images
#7	0.92	2019	deep learning; monkeypox virus; image classification; vision transformer; digital tools; artificial intelligence; mobile applications; quality assurance
#8	0.99	2018	image classification; image colour analysis; wounds; feature extraction; image segmentation; burn wound assessment; semantic segmentation; digital photography
#9	0.97	2016	skin imaging; disparity estimation; haptic palpation; light-field camera; depth estimation; deep learning
#10	0.95	2018	skin lesion; dermoscopy image; Levenberg–Marquardt neural network; cellular neural networks; segmentation-based classification
#11	1.00	2008	illumination correction; skin colour; contrast transfer; neural network; condensation tracker; fuzzy c-means clustering
#12	0.97	2020	skin cancer detection; Swin Transformer; deep learning; hybrid model; transfer learning; feature selection; hyperparameter optimisation; ensemble classifier
#13	0.99	2017	rheumatoid arthritis; k-means algorithm; fuzzy c-means algorithm; feature extraction; receiver operating characteristics (roc) curve

Keyword burst analysis

Burst keywords are terms whose frequency of use rises abruptly over a defined period; they help identify research frontiers and the dynamic evolution of a field, and burst strength quantifies the intensity of this short-term surge in attention[12,13]. The non-technical term "superior", generated as noise by the automatic keyword-extraction algorithm, was excluded from the interpretation. The keyword "image analysis" showed a strong burst (strength 5.89) from 2002 to 2013, making it one of the earliest dominant themes in the field. During this early phase, keywords such as "pigmented skin lesions" (3.17; 2003–2009), "neural network" (3.45; 2009–2013), and "border detection" (3.38; 2016–2021) indicated a focus on lesion identification, foundational neural networks, and image boundary detection at different times (Figure 13).

In the intermediate phase, keywords such as "dermatologists" (4.35; 2022–2023), "dermoscopy images" (3.26; 2020–2022), and "recognition" (3.42; 2022–2023) reflected a shift toward the clinical use of dermoscopic images and intelligent recognition.

In the most recent phase, the burst strengths of "generative adversarial networks" (3.42; 2023–2024), "artificial intelligence" (3.50; 2024–2025), "medical imaging" (3.05; 2024–2025), and "vision transformers" (2.87; 2024–2025) all rose, with their bursts beginning between 2023 and 2024. These findings indicate that deep-learning approaches—including generative adversarial networks, vision transformers, and AI-based diagnostics—represent the emerging research directions in the field.

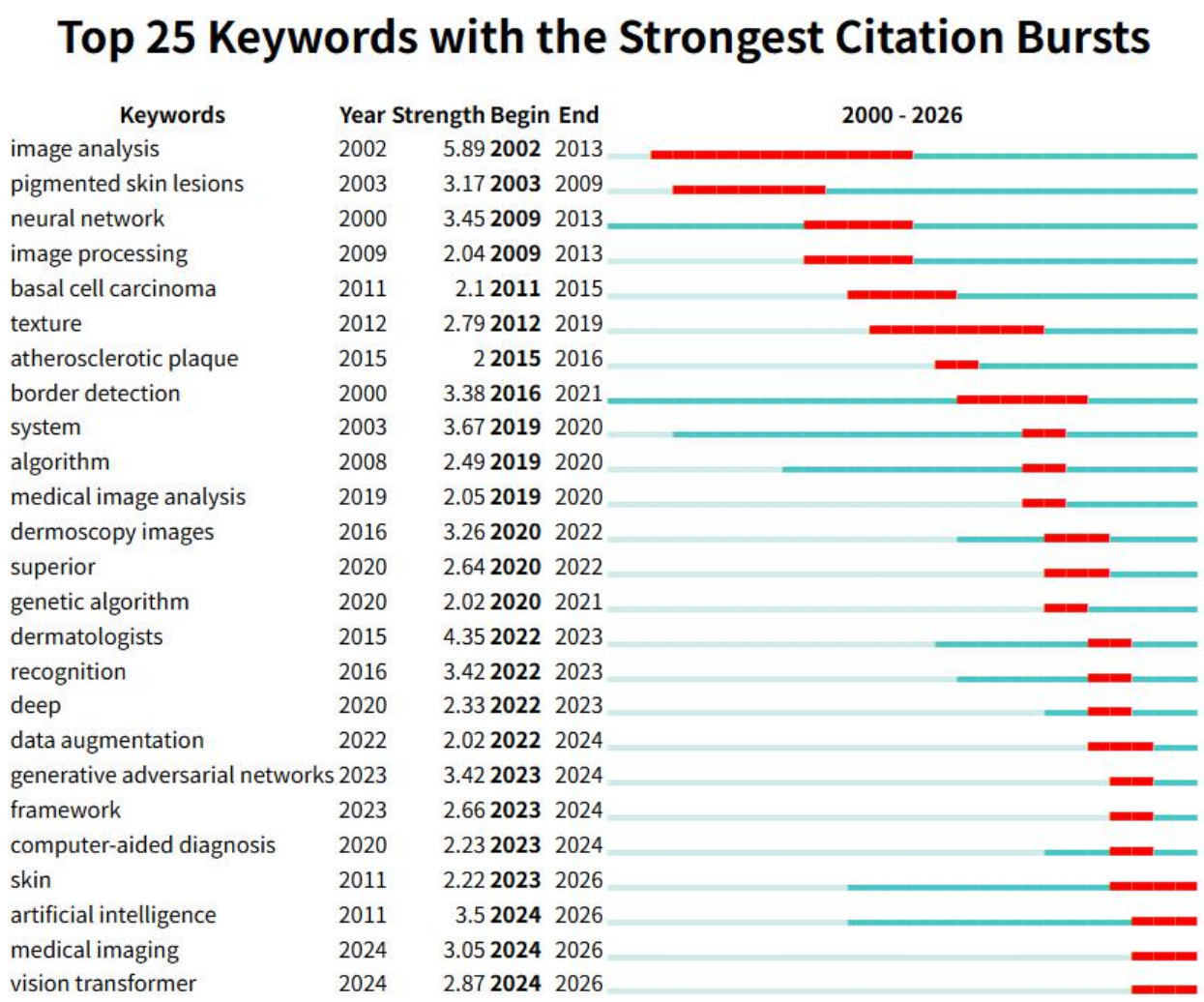


Fig 13. Ranking map of keyword bursts in AI-driven skin imaging.
Notes: The blue lines indicate the years of emergence and the red lines represent high-frequency citations during this period.

Discussion

Research status

The present study analysed 737 articles, and research output on the relationship between AI and dermatological imaging has risen substantially in recent years. This is a strongly interdisciplinary field spanning computer science, engineering, and medicine. Publication output has grown rapidly since 2019, with 96.6% (712/737) of articles published between 2019 and 2025. This rapid growth points to the field's considerable developmental potential and academic value.

China, India, and the USA are among the largest contributors, reflecting substantial investment of funding and personnel. China's high output may be partly attributable to the national New Generation Artificial Intelligence Development Plan[14] and to sustained governmental support for dermatological imaging research. Such support has enabled intensive research on key issues—such as the integration of dermatological imaging with healthcare and interdisciplinary collaboration—thereby advancing both research and clinical translation in China.

The top ten most productive institutions belong to different countries and encompass diverse organizational types, including comprehensive universities and specialized research centers. This diversity indicates that AI and dermatological imaging is a cross-disciplinary field requiring the involvement of institutions with varied backgrounds and expertise. They have contributed to overlapping research areas, helping to improve access to dermatological imaging-based care.

Analysis of author contributions helps to gauge academic impact by revealing collaborative relationships and identifying influential authors and teams. H. Peter Soyer was the most prolific author, and his publication rate has increased consistently in recent years. Soyer's research focuses on dermatology and skin cancer, including early melanoma detection[15], AI-assisted skin cancer diagnosis[16], and remote monitoring of skin lesions[17]. Another leading author, Brigid Betz-Stablein of the University of Queensland, Australia, works on skin cancer epidemiology and the use of three-dimensional total-body photography[18] for naevus monitoring. The Dermatology Research Centre at the University of Queensland anchors a cross-institutional group (the red cluster in the collaboration network), with strong ties to major medical and research institutions worldwide and an active focus on skin cancer prevention and accurate diagnosis.

The three most co-cited journals were Proc CVPR IEEE, IEEE Trans Med Imaging, and Comput Biol Med. Journals in this field tend to have high impact factors, suggesting that the corresponding articles are of high quality and academic value. The most-cited journals address medical imaging, AI algorithms,

clinical dermatological diagnosis, and biomedical information processing, and they define the research hotspots and frontiers of the field. This breadth indicates that AI and dermatological imaging has attracted scholars from multiple disciplines and reinforces the case for greater interdisciplinary collaboration and resource sharing.

The most-cited reference was the HAM10000 dataset by Tschandl et al.[10]—a large-scale, multi-source, publicly available dataset—in which more than half of the lesions were confirmed by histopathology— of dermoscopic images. It provides an essential foundation for developing AI-based skin cancer diagnostic systems and has substantially advanced the field. The second and third most-cited references, by Esteva et al.[19] and Codella et al.[20], relied on deep-learning methods and large dermatological imaging datasets and represent two landmark advances in the integration of AI with dermatological imaging. The former demonstrated, in a leading journal, that AI-assisted skin cancer diagnosis is technically feasible, whereas the latter established a benchmark through a public challenge that spurred global technical progress. Together, these works have accelerated the clinical application of AI in dermatology.

Research hotspots

Keyword analysis provides a direct representation of a field's research hotspots[21]. As shown in Table 6, deep learning ranked first among all keywords, appearing 224 times, and together with skin cancer, classification, diagnosis, and melanoma, it constitutes a core hotspot cluster in this field. The keyword clustering results further demonstrate that deep learning has permeated multiple key research topics—including skin lesions (#0), medical image segmentation (#1), and artificial intelligence (#3)—thereby validating its role as a foundational technological pillar for AI-driven dermatological imaging. The application of deep learning-based AI in the classification and diagnosis of skin cancer and melanoma has emerged as a highly concentrated research direction in this domain.

Over the past decade, deep learning has emerged as the dominant technological paradigm, a trend consistent with the rapid growth in related publications observed in this study since 2019. It employs multi-layer artificial neural networks to learn hierarchical representations of data and performs complex tasks at a level comparable to, or even surpassing, that of human experts[22]. During the preceding decade, deep-learning approaches have improved the accuracy and efficiency of medical image registration. Unlike conventional methods, they optimise a global objective function over a training set to train a general-purpose network; at inference, a fixed-weight network is applied directly to image pairs without further optimisation. These techniques offer three main practical advantages: the diversity of training data can act as an implicit regularizer and may reduce the risk of overfitting; the combination of pretrained weights with advanced optimisation improves convergence toward the global optimum; and inference can be completed in a single forward pass, making these methods faster than conventional approaches. Affine registration networks, by contrast, use encoder-only networks to estimate the relevant parameters, with supervision provided by transformation matrices rather than dense displacement fields[23].

The evolution of these technological hotspots is closely related to the clinical needs of patients with skin cancer. Skin cancer is among the most common malignant tumours worldwide. Skin cancers are broadly divided into melanoma and non-melanoma skin cancers (NMSC); the latter include basal cell carcinoma (BCC) and squamous cell carcinoma (SCC). BCC typically arises from the basal cells of the lower epidermis; although slow-growing and unlikely to metastasise, it can invade adjacent tissues if not diagnosed and treated promptly[24]. Late diagnosis of skin cancer, particularly melanoma, is associated with increased mortality, underscoring the need for automated early-detection systems to reduce mortality; visual inspection through scanning or imaging is one common detection approach[25]. This clinical urgency explains why "diagnosis" (frequency 121) and "classification" (frequency 126) have remained high-frequency keywords in the field since their first appearances in 2002 and 2005, respectively. However, it is noteworthy that "melanoma" (frequency 100) ranks only fifth as a keyword, lower not only than "deep learning" (224 times) but also than general terms such as "classification" and "diagnosis". This phenomenon suggests that the current research focus in the literature may lean more toward the universality and transferability of algorithms rather than optimization for specific disease types, which aligns with our finding that "image segmentation" has a relatively high betweenness centrality (0.10).

Research trends

Keyword bursts can indicate how research hotspots evolve over time and how they may develop in the future[26]. As shown in Figure 8B, two advanced deep-learning architectures—generative adversarial networks (GANs) and vision transformers (ViTs)—have successively shown keyword bursts in recent years, representing the cutting-edge technological trends in this field.

Advances in computing and graphics processing units (GPUs) have driven the growth of AI and machine learning. Deep learning, an important subfield of machine learning, extracts useful information from large-scale data; GPU-based training is efficient and produces strong results in tasks such as image processing and speech recognition, and AlexNet has been influential since its introduction.

Machine learning can be divided into supervised and unsupervised approaches: supervised learning requires labelled data, whereas unsupervised learning does not. Because labelling is costly and time-consuming, deep generative models—which can synthesise new data consistent with the distribution of the input data—offer an advantage over traditional machine-learning models. Classical generative models such as the variational autoencoder (VAE) and the deep belief network (DBN) are typically based on maximum-likelihood estimation and Markov chains.

In 2023–2024, the keyword "generative adversarial networks" showed a burst (strength 3.42), reflecting a rapid increase in research interest in generative AI within the field of dermatological imaging. GANs were originally proposed by Goodfellow et al. in 2014 as an unsupervised model based on a two-player game, in which adversarial training enables the generation of realistic samples[27]. GANs are now widely applied to image enhancement, image synthesis, and medical imaging. In image enhancement, the generator improves contrast, colour saturation, sharpness, and detail while reducing noise, producing images that are perceptually close to the originals. In image synthesis, the generator produces images that are difficult to distinguish from real ones, and the

discriminator assesses their authenticity. In medicine, GANs can improve image quality by reducing noise and artefacts, helping clinicians interpret images for diagnosis[28].

Vision transformers (ViTs), as a cutting-edge technology, showed a keyword burst between 2024 and 2025 (strength 2.87). A transformer is a deep neural network built primarily on self-attention that has proven highly effective for sequence-modelling tasks, including natural language processing (NLP). The transformer architecture is now used in video analysis, document generation, and, through vision transformers (ViTs), as a general-purpose method for computer-vision tasks such as image classification[29].

Clinical implications and translational challenges

This study demonstrates that core technologies in the field have evolved from early traditional image feature extraction and CNN iterations to the current ViT and GAN, with technological advances potentially translating into improvements in clinical diagnostic and treatment capabilities. On the basis of these technological evolution trends, we further analyse the potential application value and translational barriers of these cutting-edge technologies in real clinical scenarios, aiming to provide more actionable references for clinicians and policymakers.

Deep learning models exhibit high diagnostic accuracy for common skin tumors such as melanoma and basal cell carcinoma and serve as auxiliary diagnostic tools for primary healthcare institutions and general practitioners, thereby facilitating early screening of skin tumors. Furthermore, newer-generation models such as ViT show superior recognition capabilities in small-sample and rare dermatological conditions, potentially addressing the lack of diagnostic experience in rare skin diseases. GANs can be utilized for skin image data augmentation and lesion simulation, mitigating the scarcity of rare disease data while also being applicable in educational settings. Additionally, automated lesion segmentation and quantitative assessment can provide objective quantitative indicators for monitoring disease progression and evaluating treatment efficacy.

However, the real-world clinical implementation of AI dermatological imaging tools still faces multiple obstacles. Although several AI-assisted dermatology products, such as Google's DermAssist and SkinVision, have been introduced, the majority of research remains at the stage of algorithm performance validation, lacking real-world clinical study evidence. The stability of the models in real clinical scenarios has not been fully verified. Additionally, unified industry standards have not yet been established for ethical and legal issues such as the delineation of responsibility for AI diagnosis and the privacy and security of medical data, which are crucial for the large-scale clinical application of the technology. Furthermore, this study reveals that the core datasets in the current research field, such as HAM10000, and many high-output institutions are predominantly located in high-income regions such as Europe and the United States. The resulting bias may exacerbate health inequities in this field. Current mainstream datasets primarily consist of skin images from light-skinned populations, with low representation of data from dark-skinned individuals. This may lead to significantly reduced diagnostic accuracy of AI models in dark-skinned populations and insufficient recognition capabilities for skin diseases that are common among them. Future research needs to prioritize the construction of multi-population, multi-skin-tone datasets and optimize model fairness.

Comparison with previous bibliometric studies

Previous bibliometric analyses have explored the development of AI in dermatology from diverse perspectives; however, gaps remain regarding specific research focuses, temporal coverage, and analytical depth. Two representative studies are most comparable to our work: one conducted a global bibliometric analysis of AI applications across the entire field of dermatology up to 2022[30], and another focused on AI in skin cancer research, with literature coverage extending to 2023[31]. Compared to these published studies, our work offers the following unique contributions and incremental findings:

In terms of research scope and temporal window, this study specifically targets the niche domain of AI-driven dermatological imaging, rather than the broader applications of AI in general dermatology or skin cancer research. This more precise focus enables a more targeted analysis of the technological evolution and clinical applications of AI-based diagnostic technologies in imaging. Furthermore, this study extends its temporal coverage to 2025, incorporating the latest research findings from the past two years—a critical consideration given the rapid iteration pace of AI technologies: most prior analyses concluded between 2022 and 2023, thereby failing to capture the recent emergence of cutting-edge architectures such as Vision Transformers and Generative Adversarial Networks in dermatological imaging.

Regarding analytical dimensions, this study conducts a more systematic examination of the knowledge structure within this field, whereas existing research has primarily focused on basic metrics such as the number of publications, author productivity, and keyword frequency. Building on this foundation, we further integrated journal co-citation networks and cross-domain knowledge flow analyses, revealing the dual-clustering structure of journals in computer science and clinical dermatology, as well as the bridging role of journals in medical imaging, while delineating the knowledge pathway from fundamental algorithmic research to clinical applications.

Moreover, owing to the use of a more recent time window, this study has identified emerging research directions in the recent past. While prior studies predominantly regarded convolutional neural networks and deep learning as core technological focal points, our burst detection analysis further demonstrates that GANs (2023–2024) and vision transformers (2024–2025) have successively entered the "burst phase". These findings update our understanding of the latest frontiers in this field and provide more timely references for subsequent research.

Limitations and prospects

This study has several limitations. It relied solely on the Web of Science Core Collection, which may not capture all relevant publications, and it included only English-language literature, potentially excluding valuable work in other languages; the findings should therefore be interpreted with these constraints in mind. Furthermore, this study employed a relatively broad range of AI-related keywords in the literature search to maximize the recall rate. Although two rounds of manual screening were conducted to exclude irrelevant records, there remains a risk that residual noise may persist in the final dataset; a limited

number of studies addressing general AI methodologies but not specifically applied to dermatological imaging may not have been completely excluded. Additionally, this study has limitations, including non-standardized reporting across affiliated institutions and the absence of robustness validation across multiple databases.

Future bibliometric analyses should incorporate more recent and broader data, minimise language restrictions and the effects of publication lag, and combine literature from multiple databases to provide a more complete picture of the relationship between AI and dermatological imaging.

Compared with earlier bibliometric work, this study systematically maps the knowledge structure at the interface of AI and dermatological imaging. It offers an international perspective on research directions, hotspots, and areas of strength, and it suggests that further work on the application of AI in dermatological imaging will be increasingly important. Future research in this field should not only focus on improving algorithm performance but also pay attention to clinical translation efficiency, the refinement of regulatory systems, and the optimization of health equity, thereby promoting the true integration of AI technology to benefit broader clinical scenarios and populations.

Conclusion

Drawing on the Web of Science Core Collection, this study analysed the literature on AI and dermatological imaging over the past 25 years from multiple perspectives, providing an intuitive overview of the field's development. By visualising research trends, clinical progress, and current hotspots, we found that this field has undergone two distinctly different developmental stages: a slow exploration phase from 2000 to 2019, and a rapid expansion phase after 2019, with the annual number of publications peaking in 2024. China ranks first in the world in terms of publication volume, yet its betweenness centrality in the international collaboration network is extremely low. We also found that the knowledge structure of this field exhibits a clear framework: skin lesions serve as the research objects, medical image segmentation constitutes the core component, and deep learning provides the foundational technical support, thereby forming a knowledge chain from clinical needs to technical implementation. Furthermore, research hotspots have evolved from early conventional dermoscopy diagnostics, to image feature extraction and segmentation based on machine learning, and further to deep learning-driven intelligent diagnosis. Our burst analysis also indicates that generative adversarial networks and vision transformers have emerged as frontier research directions, representing the latest evolutionary trends in this field.

Overall, AI-driven dermatological imaging is still in a phase of rapid development and deep integration with clinical practice. Future research should further advance the clinical translation of advanced AI models and strengthen real-world clinical validation. Additionally, researchers in high-output countries should deepen international academic collaborations to jointly promote the global development of AI-driven dermatological imaging technologies. This study aims to provide a systematic reference for understanding the overall landscape and evolutionary trends in this field, as well as to support the selection of subsequent research directions and interdisciplinary collaborations.

Abbreviations

AI	Artificial Intelligence
CNN	Convolutional Neural Network
GAN	Generative Adversarial Network
ISIC	International Skin Imaging Collaboration
ViT	Vision Transformer
WoSCC	Web of Science Core Collection
SCI	Science Citation Index
IF	Impact Factor
Q	Modularity Score
S	Silhouette Score

Statement of Ethics

A statement of ethics is not applicable, as this study was based exclusively on previously published literature.

Conflict of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data supporting the findings of this study are available in the Web of Science Core Collection (https://www.webofscience.com/). The processed bibliometric data are not publicly available owing to data-management restrictions but are available from the corresponding author upon reasonable request.

Author Contributions

Conceptualization, Jia Lu, Dejun Nong and Jiaguang Su; Methodology, Junjie Ye; Software, Fan Long; Formal analysis, Jia Lu and Dejun Nong; Data curation, Jia Lu; Investigation, Junjie Ye and Dejun Nong; Resources, Junjie Ye; Validation, Junjie Ye; Visualization, Jia Lu and Junjie Ye; Writing ─ original draft preparation, Jia Lu and Dejun Nong; Writing ─ original draft preparation, Kezhao Wu and Jiaguang Su; Supervision, Jiaguang Su; Funding acquisition, Jiaguang Su. All authors gave final approval for this work.

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