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REVIEW

Deep learning applications in dentistry: a bibliometric review analysis and mapping (2014–2024)

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Abstract

The application of deep learning techniques in dentistry has revolutionized the diagnostic and treatment approaches. This study aims to evaluate the impact and trends of deep learning methodologies in dentistry through a bibliometric analysis. A comprehensive search in the Web of Science database yielded 1228 articles published between 2014 and 2024. Bibliometric analyses, including keyword co-occurrence, co-authorship, citation patterns, and collaborative networks, were conducted using VOSviewer software. Remarkably, 94.95% of these publications were released after 2018, showcasing a significant surge in research interest in recent years. The USA and Japan emerged as leading contributors, accounting for 20.6% and 18.48% of the articles, respectively. Notable institutions, such as Tokyo Medical and Dental University, stood out with 88 publications. Key contributors like Orhan Kaan, Schwendicke Falk, Ariji Yoshiko, and Ariji Eiichiro made substantial impacts. The analysis revealed clusters of interconnected research areas, collaborative networks among authors and countries, and influential publications. This study offers valuable insights into the evolving role of deep learning in dentistry, underscoring the growing global interest and collaboration in the field. Understanding these trends is essential for shaping future research directions and fostering interdisciplinary partnerships. The integration of deep learning in dentistry represents a paradigm shift in diagnostic accuracy, treatment effectiveness, and patient-centered care, driving interdisciplinary and international collaborations that promise transformative advancements in dental practice.

Keywords Bibliometric analysis · Deep learning · Dentistry · VOSviewer · Web of science

1 Introduction

The integration of deep learning methodologies into various sectors of dentistry represents an important change in how dental professionals approach diagnosis, treatment planning, and patient care. Deep learning, a subclass of artificial intelligence (AI) distinguished by complex neural network architectures capable of learning intricate patterns from data, has demonstrated remarkable efficacy in analyzing large datasets and extracting meaningful insights. Within dentistry, the application of deep learning spans diverse areas including but not limited to dental imaging analysis, diagnostic decision support systems, treatment optimization, and predictive modeling of clinical outcomes. In recent years, the intersection of deep learning and dentistry has garnered significant attention within the scientific community [8, 10]. Dentistry, a field traditionally reliant on empirical observation and manual expertise, is undergoing a transformative phase driven by the rapid advancements in artificial intelligence, particularly deep learning techniques [30].

In the middle of this expanding surroundings, conducting a bibliometric analysis offers a systematic approach to comprehensively evaluate the scope, trends, and impact of research endeavors leveraging deep learning within the realm

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of dentistry. Bibliometric analyses are essential tools for mapping the knowledge domain [19, 31, 32], identifying significant works, explaining emerging trends, and directing future research directions because they provide a quantitative assessment of the scholarly literature [28].

Through bibliometric factors include citation counts, h-index, as well as journal impact factors, analysis can evaluate the influence and distribution of research findings among scientists. Bibliometric analysis identifies high-impact publications, prolific authors, and collaborative networks. Thus, the educational background and impact in the field of deep learning in dentistry are stated. In the realm of dentistry, the integration of deep learning methodologies has sparked a revolution in dental imaging, particularly evident in the evaluation of the mandibular and maxillary molars [28]. This transformative approach, notably employing convolutional neural networks (CNNs), has exhibited remarkable efficacy in diverse applications within dental imaging, ranging from molar developmental staging to the prediction of eruption and the precise identification and detection of molar conditions [22]. Applications like the relationship between the molar and the nerves, vital for surgical extraction. Cone-beam computed tomography (CBCT) and panoramic imaging are valuable tools for diagnosing various dental issues. Deep learning algorithms enhance this process by enabling accurate detection, segmentation, and classification of dental conditions [2, 15].

Utilizing AI algorithms, panoramic radiographs have become a focal point for diagnosing an array of clinical conditions, from age estimation to gender determination, and beyond. These algorithms allow for accurate delineation of anatomical features such as the mandibular third molar and the inferior alveolar nerve, as well as automated teeth recognition and numbering, identification of apical lesions, and diagnosis of maxillary sinusitis [18].

In the pursuit of optimizing CNN algorithms for dental diagnostics, researchers have combined pretrained deep CNN architectures with self-trained networks, particularly evident in the analysis of periapical radiographic images [13].

Beyond dentistry, convolutional neural networks have demonstrated remarkable success in healthcare, ranging from the detection of breast cancer to diabetic retinopathy. Similarly, pretrained CNN architectures have been harnessed in dentistry for tasks such as detecting carious lesions and periapical pathosis [11].

As researchers delve deeper into the integration of deep learning in dentistry, bibliometric evaluation is a useful technique for assessing the field of academic contributions. Through a comprehensive search employing bibliometric methods, this study identifies and evaluates the corpus of literature surrounding the application of deep learning in dentistry. Specifically, a thorough examination of the Web of Science database yielded a substantial body of literature spanning from 2014 to 2024, shedding light on the evolution and impact of deep learning methodologies in the realm.

2 Materials and methods

2.1 Bibliographic data

Bibliometrics involves analyzing written publications, like books and articles using methods. It is commonly applied in library and information science including scientometrics. For example, bibliometrics help assess literature quantitatively. Evaluate budget allocation. Citation analysis, a technique that focuses on creating a citation graph that illustrates the connections between documents. Various research fields utilize bibliometrics to gauge field impact, researcher influence, paper significance and identify works within research areas. Apart from these uses bibliometrics find application, in linguistics, thesaurus development and reader usage assessment.

A comprehensive search as per the Web of Science database was conducted, employing the specified query terms "deep learning" and "dentistry". The search retrieved a total of 1228 results from the Web of Science Core Collection, specifically from the Science Citation Index Expanded, spanning the publication years from 2014 to 2024 with only English languages. The search was performed on February 13, 2024, and was accompanied by a bibliometric analysis. Figure 1 displays the analysis's flow diagram.

Subsequently, the obtained results were exported in the form of a Tab Delimited File, containing essential bibliographic information such as author names, article titles, publication sources, abstracts, keywords, affiliations, and cited references. The exported file was saved in TXT format, which will facilitate its utilization in bibliometric analyses.

2.2 Analysis and mapping of the data

Bibliometric analysis involves the quantitative evaluation of bibliographic data to discern patterns, trends, and relationships within scholarly literature. It offers insights into the structure and dynamics of research fields, enabling researchers to identify influential works, emerging topics, and collaborative networks.

Within bibliometric analysis, researchers typically examine several key aspects. They conduct publication analysis to understand the distribution of publications over time, by authors, institutions, countries, or journals. Citation analysis is performed to assess the frequency and impact of citations received by individual publications or authors, indicating their influence within the scholarly community. Another important aspect is co-authorship analysis, which investigates collaboration patterns among authors, institutions, or

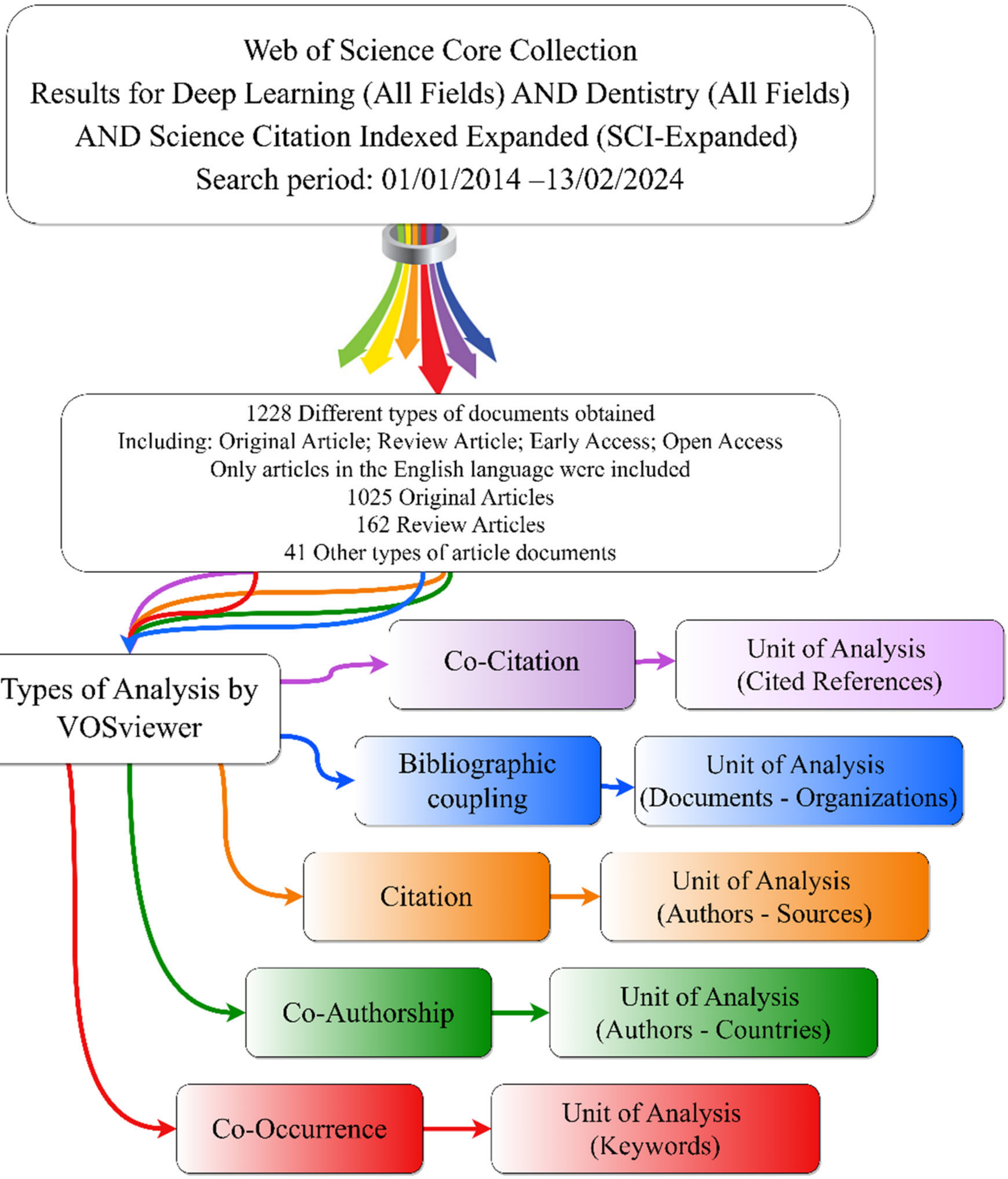

Fig. 1 Bibliometric analysis flowchart

countries, revealing networks of collaboration and interdisciplinary research. Keyword analysis identifies prevalent keywords or terms within a specific research domain, highlighting thematic foci and emerging trends. Cluster analysis involves grouping related publications or authors into clusters based on shared characteristics or co-citation patterns, facilitating the identification of distinct research themes or subfields [23].

VOSviewer was used in this study to conduct bibliometric analyzes and visualize the results. VOSviewer, a widely employed tool for bibliometric analyses and visualization [28], was applied for further examination of the exported data [28]. VOSviewer is an advanced bibliometric software tool that enables researchers to conduct comprehensive bibliometric analyses and visually represent the results in intuitive and insightful ways.

VOSviewer includes network visualization [28], which generates visualizations such as co-authorship networks, citation networks, or keyword networks, allowing researchers to explore the structural relationships between publications, authors, or concepts. The tool also employs advanced algorithms to identify clusters or communities within bibliographic datasets, aiding in the delineation of distinct research themes or intellectual domains.

Moreover, VOSviewer can generate density maps, highlighting areas of high concentration or activity within the analyzed bibliographic space, providing additional insights into research hotspots or emerging trends. Users can interactively explore and manipulate the visualizations generated by VOSviewer, facilitating in-depth exploration and interpretation of bibliometric data. Additionally, VOSviewer allows users to export visualizations for publication or further analysis and seamlessly integrates with other bibliometric software tools and databases, enhancing its utility in scholarly research. VOSviewer serves as a powerful and user-friendly tool for conducting bibliometric analyses and getting an important understanding of the dynamics and structure of academic literature [28].

Following the generation of outcomes, a map representation was produced using VOSviewer software, predicated upon bibliometric information. The database utilized in this investigation was sourced from Web of Science; however, datasets could be acquired through alternative channels such as Scopus, Dimensions, Lens, PubMed, among other repositories. During the map creation process, VOSviewer affords the user the option to select the analytical approach and counting methodology. Fundamentally, VOSviewer 1.6.20 offers five distinct types of analyses, namely Co-occurrence, Co-authorship, Citation, Co-citation, and Bibliographic Coupling [28]. It is pertinent to note that the unit of measurement varies for each analysis type. The typology and unit of analysis are delineated in Table 1**.**

Table 1 shows bibliographic data type where the data source is Bibliographic database files. When generating a map derived from bibliographic data, the Create Map wizard provides a selection among two counting methodologies. Defaulting to, the full counting method is employed. Alternatively, fractional counting can be chosen as an alternative approach [29]. There exists a disparity in the computation of the strength metric across various types of analyses within bibliographic data. Additionally, this discrepancy in strength calculation can be addressed through either full or fractional counting methodologies.

In this analysis, this study focuses on:

- Co-occurrence with keywords.
- Co-authorship among authors.
- Co-authorship across countries.
- Citation of sources.
- Citation for authors.
- Bibliographic coupling with documents.
- Bibliographic coupling among organizations.
- Co-citation of references.

Table 1 Available types and unit analysis for bibliographic data type in VOSviewer creating map wizard

Type of analysis	Unit of analysis
Co-occurrence	*Keywords*
Co-authorship	*Authors* Organizations *Countries*
Citation	Documents *Sources* *Authors* Organizations Countries
Bibliographic coupling	*Documents* Sources Authors *Organizations* Countries
Co-citation	*Cited references* Cited sources Cited authors

For each type, a map was generated, and the later section specifies the top studies identified.

3 Results

A thorough exploration was undertaken using the Web of Science database, utilizing the predefined search terms “deep learning” and “dentistry”. Following each analysis, a map was generated, visually illustrating the network, and highlighting the most notable studies. The search yielded a total of 1228 results from the Web of Science Core Collection, sourced from the Science Citation Index Expanded, covering publications from 2014 to 2024. Conducted on February 13, 2024, the search was complemented by a bibliometric examination. Out of the entire corpus of publications analyzed, an astonishing 94.95% were published after the year 2018. The data show an increase in the quantity of articles that are published per year from 2014 to 2023, with a peak of 378 articles in 2023. As shown in Fig. 2.

Among the 94 nations that contributed to this body of work, the United States and Japan emerged as the predominant leaders, with contributions amounting to 20.6% and 18.48% of the total articles, respectively, as presented in Fig. 3.

Tokyo Medical and Dental University stood out among 2090 organizations with the highest publication count, totaling 88 publications presented in Fig. 4. Important to note that authors such as Orhan, Kaan, and Schwendicke, Falk, each made significant contributions with 28 publications each. They were closely followed by Ariji, Yoshiko, who

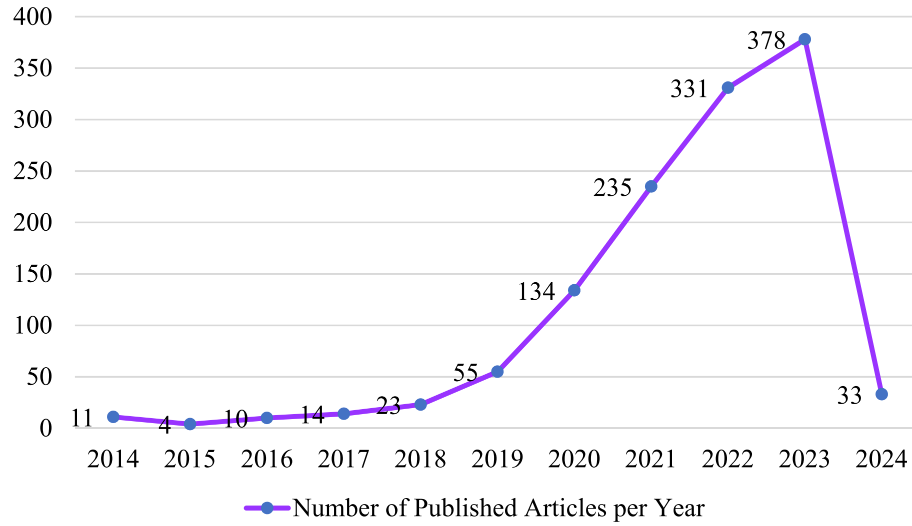

Fig. 2 The annual number of papers about Deep Learning in Dentistry from 2014 to 2024

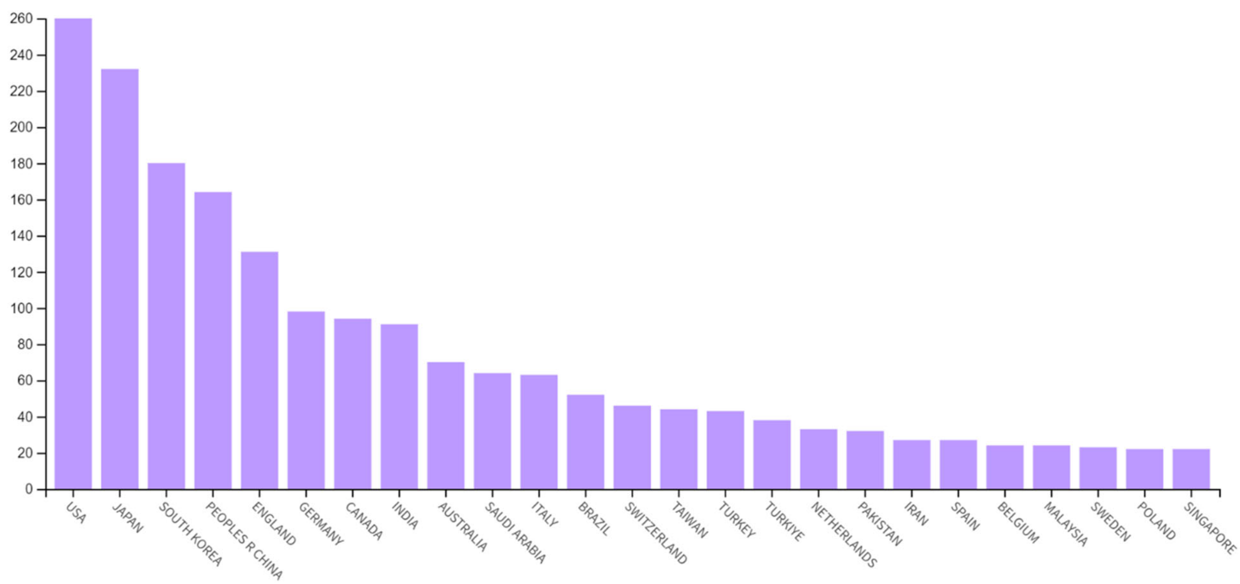

Fig. 3 Top countries among 94 nations from 2014 to Feb 2024

contributed 27 publications, and Ariji, Eiichiro, with 26 publications to their credit.

All maps in this network visualization analysis were generated using the following parameters:

Visualization weights: total links strength.
Layout: attraction set to 2, repulsion set to 0.
Clustering resolution: 1.00, minimum cluster size: 1
Normalization method: association strength.

3.1 Co-occurrence of keywords

The cumulative strength of co-occurrence connections with other keywords computed for each individual keyword. Subsequently, keywords showing the highest aggregated link strength identified and selected.

The threshold for co-occurrence with all keywords was set at a minimum of 5 occurrences out of the total 4491 keywords. Out of these, 250 keywords met the threshold criteria. Consequently, 250 keywords were selected for further analysis, resulting in the identification of 11 clusters. The total number of links found amounted to 4922, with a combined link strength of 11,634 (Fig. 5).

Table 2 displays the most often utilized keywords. In VOSviewer, words are duplicated and analyzed separately;

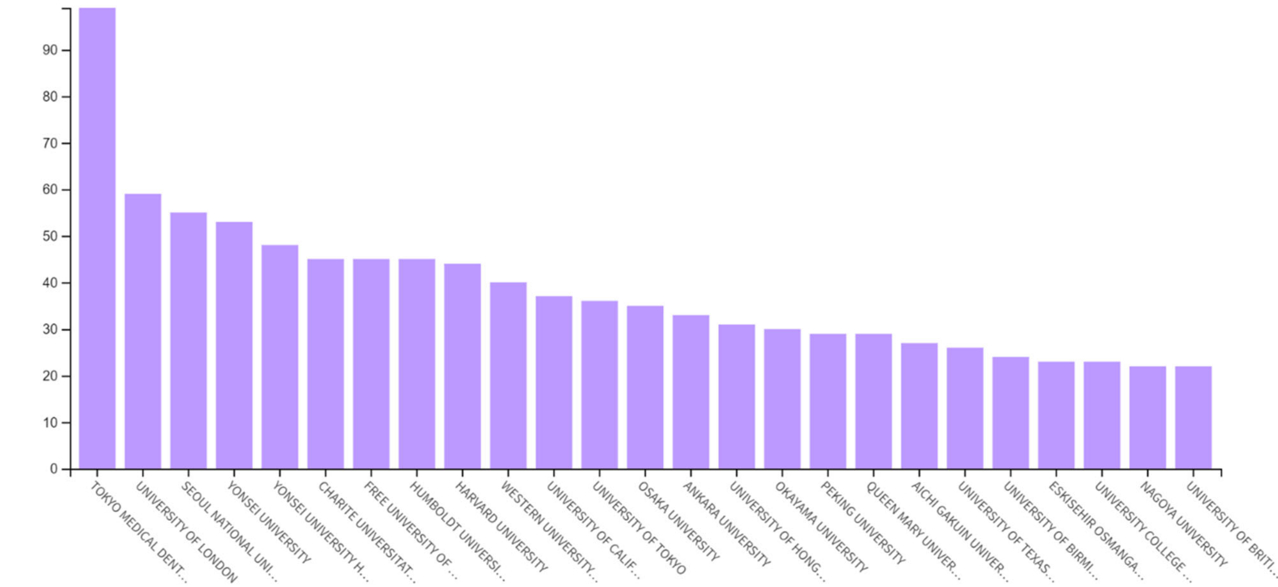

Fig. 4 Top universities among 2090 organizations from 2014 to Feb 2024

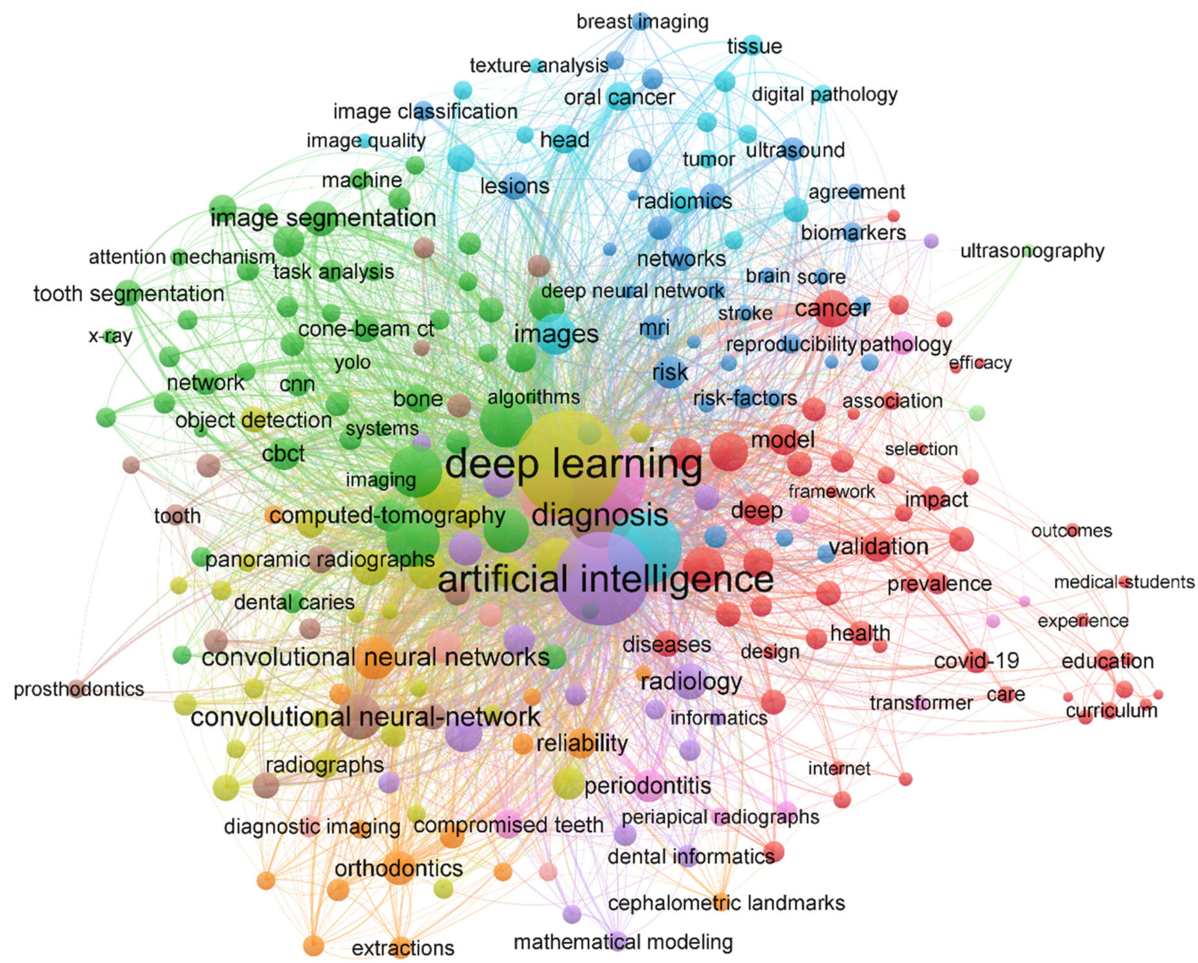

Fig. 5 Keyword occurrence between dentistry and deep learning concepts

Table 2 Most used keywords in the concept of deep learning and dentistry

Sequence no.	Keywords	Occurrence	Total link strength
1	Deep learning	593	2432
2	Artificial intelligence	460	2218
3	Machine learning	198	991
8	Convolutional neural network(s)	180	945
4	Classification	179	965
5	Diagnosis	133	725
6	Segmentation	80	436
9	Teeth	73	447
10	Dentistry	70	432
205	Teeth segmentation	13	79
168	Tooth	7	44
90	Tooth segmentation	6	37

for instance, “deep learning” and “deep-learning” are treated individually. To address this, similar keywords were combined. Although Table 2 lists keywords in descending order of frequency of use, duplicates were merged, resulting in their inclusion only once.

3.2 Co-authorship among authors

The analysis focused on co-authorship with authors, employing the full counting method. Documents with many authors were disregarded, with a maximum of 15 authors per document considered. Authors had to have at least 3 documents and 1 citation to be included in the analysis. Out of the initial pool of 5553 authors, only 396 met these criteria. Despite including all items, the resulting network map displayed considerable dispersion, prompting the exclusion of unconnected items. Of the 396 items initially included, only 72 were found to be interconnected, forming 10 distinct clusters (Fig. 6). As a consequence of discarding unconnected items, the total number of links decreased from 1192 to 268, and the total link strength decreased from 4374 to 834.

Table 3 displays the top 30 authors identified in the co-authorship network analysis. Authors were selected based on study counts and citations accrued within the analysis, shedding light on the collaborative dynamics within the field.

3.3 Co-authorship across countries

The co-authorship analysis focused on collaborations between countries, utilizing the full counting method. Documents with more than 15 countries were excluded, and a minimum threshold of 5 documents and 2 citations per country was set. Out of 94 countries examined, 55 met these criteria, reflecting robust collaborative networks across various nations. The network visualization map is displayed in Fig. 7, generated from the co-authorship analysis, displaying collaborative relationships between countries.

In the network visualization, 55 items were identified and grouped into 6 distinct clusters. These clusters were formed based on 580 links, with a total link strength of 1784. Table 4 highlights the top 15 countries based on their study counts and citations, providing insights into their contributions within the collaborative network.

3.4 Citation of sources

By analyzing 440 varied sources, focusing on their citation patterns as the unit of examination and applying a criterion that mandates at least one document with an accompanying citation for each source, identified 348 noteworthy ones (Fig. 8). This review offers valuable insights into how citations are utilized throughout the data set’s content landscape, revealing both its extent and magnitude to gain further understanding about scholarly domains’ interconnectedness of knowledge across multiple distinct theories or beliefs therein represented within this corpus.

The analysis of 348 items stated a complex network with 180 distinct clusters, showcasing interconnected ideas. With 1148 links found, it highlights information flow and influence across the scholarly landscape. The total link strength of 3304 underscores the robust connections. This overview reveals nuanced dynamics, offering valuable insights into the underlying structures and dynamism within academic discourse. “Scientific Reports” leads with 1706 citations from 79 documents, confirming its significant impact. “The Journal of Dentistry” follows closely behind with 1004 citations from 42 documents (Table 5), highlighting its significance in dental research.

3.5 Citation of authors

The citation analysis focused on authors, examining their scholarly impact within the unit analysis framework. The analysis utilized a maximum threshold of 15 authors per document, while authors were required to have a minimum of 3 documents and 2 citations to be included. Out of the initial pool of 5553 authors, 387 met these criteria, indicating a robust dataset for analysis.

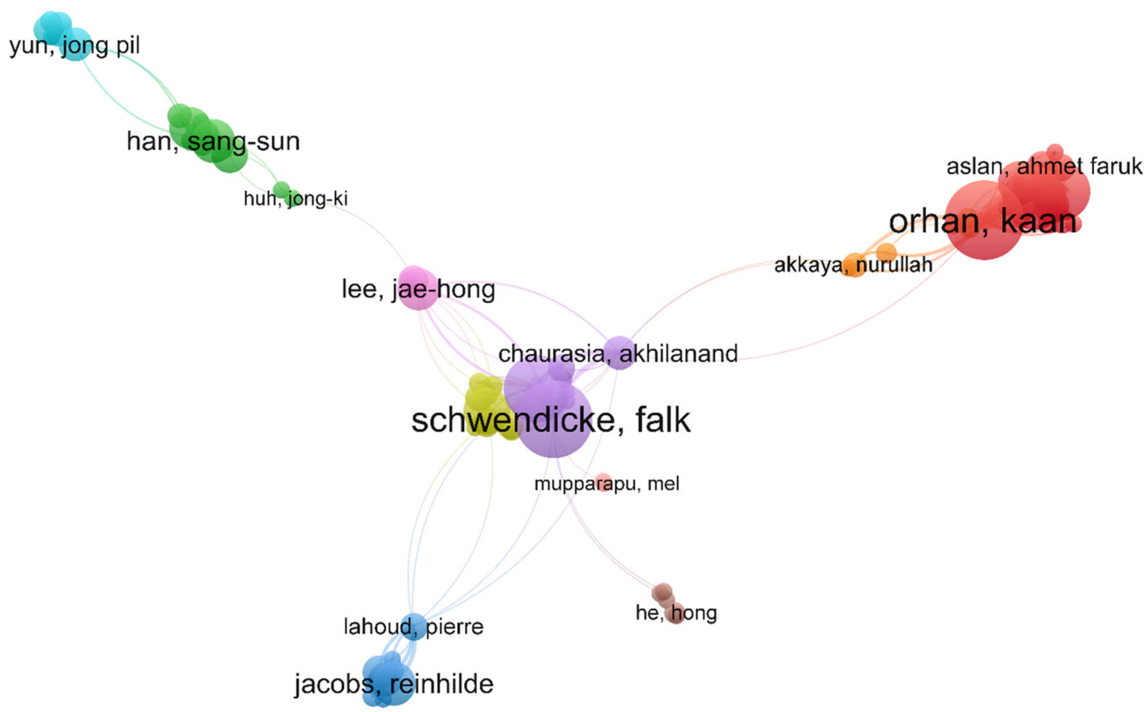

Fig. 6 Co-authorship network visualization analysis between dentistry and deep learning concepts

After removing unconnected items from the network, the analysis focused solely on the interconnected elements. Among the 387 items initially included, only those connected to others were retained. The largest set of connected items formed a cluster comprising 319 items. Following this refinement, the analysis revealed 319 interconnected items distributed across 13 clusters. The network comprised a total of 9255 links, through a combined link strength amounting to 39,349. Figure 9 illustrates the visual representation.

Table 6 highlights the top 30 authors based on their study counts and citations within the citation analysis. The network analysis demonstrated 319 interconnected items organized into 13 clusters.

3.6 Bibliographic coupling of documents

The bibliographic coupling analysis, conducted at the document unit level, employed the full counting method to assess scholarly connections. Documents were scrutinized based on a minimum citation threshold of 3, ensuring robustness in the analysis. Out of the initial pool of 1228 authors, 724 met these stringent criteria, reflecting a substantial dataset for examination. The visual representation is shown in Fig. 10.

In the analysis, unconnected items were excluded, focusing solely on interconnected elements. The resulting network comprised 676 items distributed across 16 distinct clusters, indicating a complex interplay of relationships. This interconnected network was characterized by a substantial number of links, totaling 40,313, with a remarkable combined link strength of 71,837. Table 7 presents the top 20 authors identified through bibliographic coupling relationships in the document analysis. The table highlights their study counts and citations, offering insights into their scholarly contributions within this analytical framework.

3.7 Bibliographic coupling among organizations

The bibliographic coupling analysis, conducted at the organization's unit level, utilized the full counting method to explore scholarly connections. Organizations were scrutinized based on stringent criteria, including a maximum limit of 15 organizations per document and minimum thresholds of 5 documents and 2 citations per organization. Out of the initial pool of 1997 organizations, 201 met these criteria, underscoring a robust dataset for analysis. Illustration for the analysis shown in Fig. 11.

The analysis revealed a network comprising 201 interconnected items organized into 4 distinct clusters, indicating significant relationships among entities. This network was characterized by a substantial number of links, totaling 18,429, with an impressive, combined link strength of 620,091. Table 8 provides insights into the top 20 organizations based on their contributions within this bibliographic coupling analysis, showcasing their study counts and citations.

Table 3 Top 30 authors in co-authorship network analysis: study counts and citations

Sequence no.	Authors	Documents	Citations	Total link strength
1	Lee, Jae-Hong	11	874	24
2	Schwendicke, Falk	27	861	71
3	Krois, Joachim	22	831	65
4	Ariji, Eiichiro	26	806	145
5	Ariji, Yoshiko	27	806	146
6	Fukuda, Motoki	22	762	127
7	Jeong, Seong-Nyum	7	707	10
8	Katsumata, Akitoshi	19	698	107
9	Fujita, Hiroshi	12	660	81
10	Kise, Yoshitaka	15	628	95
11	Kim, Do-Hyung	3	603	6
12	Nozawa, Michihito	9	440	65
13	Elhennawy, Karim	6	420	19
14	Tateishi, Ukihide	20	362	148
15	Fujioka, Tomoyuki	17	339	139
16	Mori, Mio	15	337	132
17	Khurram, Syed Ali	9	335	17
18	Nakagawa, Tsuyoshi	13	330	121
19	Oda, Goshi	13	330	121
20	Kubota, Kazunori	15	325	124
21	Jacobs, Reinhilde	12	308	38
22	Schwendicke, F	11	302	16
23	van Gerven, Adriaan	8	300	36
24	Willems, Holger	8	300	36
25	Krois, J	9	297	16
26	Orhan, Kaan	28	293	117
27	Kuwada, Chiaki	12	285	75
28	Chen, Hu	6	280	9
29	Chaurasia, Akhilanand	8	277	22
30	Katsuta, Leona	10	273	93

3.8 Co-citation of references

The co-citation analysis, conducted at the cited reference unit level, employed the full counting method to explore scholarly connections. Cited references were scrutinized based on a minimum citation threshold of 10, ensuring robustness in the analysis. Out of the initial pool of 38,906 cited references, 355 met these stringent criteria, reflecting a substantial dataset for examination. Figure 12 displays the visual map depicting the co-citation of references.

The analysis revealed 355 items organized into 6 distinct clusters, indicating notable relationships among cited references. This network was characterized by 24,806 links, contributing to a total link strength of 56,671. Table 9 presents insights into the top 20 cited references based on their prominence within the co-citation analysis.

4 Discussion

A bibliometric analysis focused on dental caries research, aiming to quantitatively and qualitatively analyze publications in this field. Using the Scopus database, the study identified trends and patterns in dental caries research, resulting in 1630 scientific articles. Key bibliometric indicators like the h-index, total citations, and publication count were used for analysis. Findings revealed the United States and Brazil as leading countries in single-country publications, while top authors and cited countries/institutions were found [6]. Another bibliometric analysis aimed to investigate research trends in digital dentistry, examining the feedback from institutions, researchers, countries, and journals. Using the Web of Science (WoS) database, publications on digital dentistry published between 2012 and 2022 were analyzed. A total

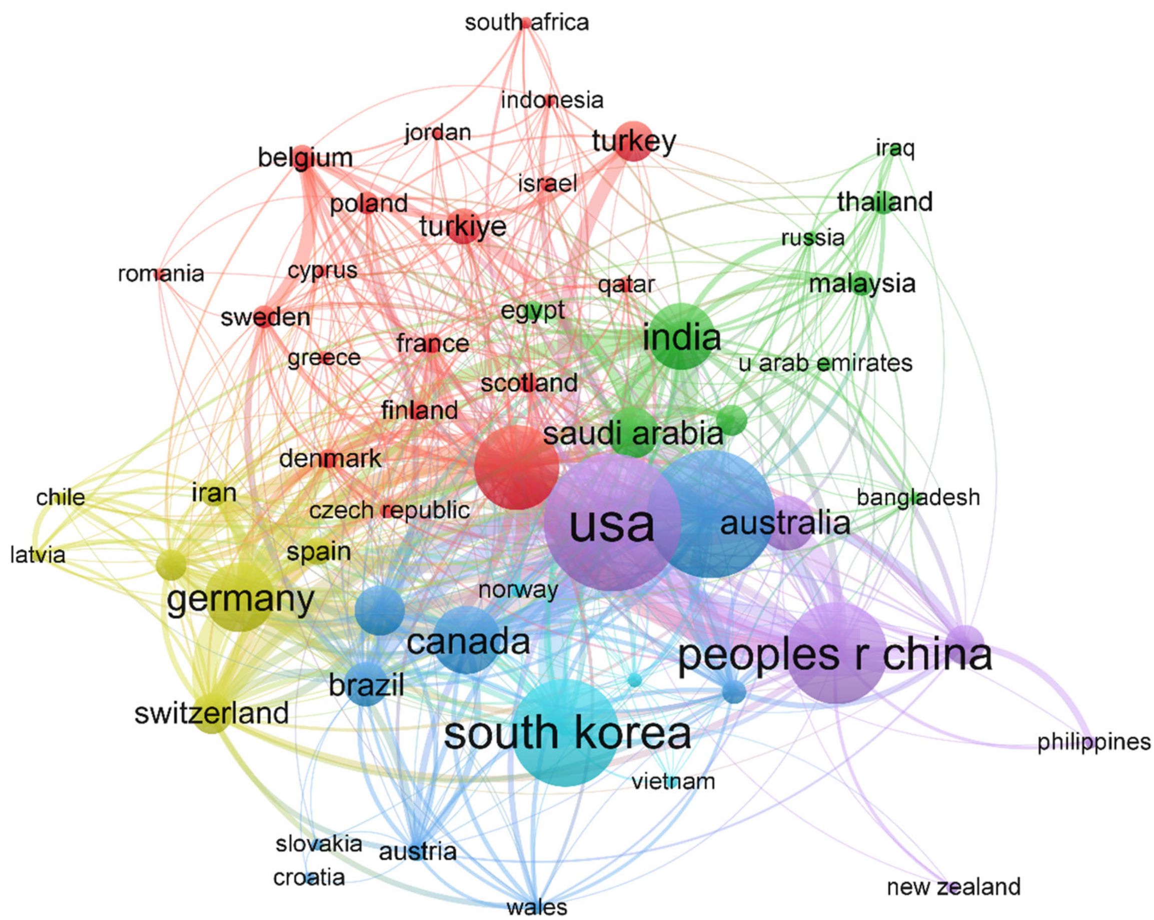

Fig. 7 Visualization of networks for co-authorship relationships between countries

Table 4 Top 15 countries in co-authorship analysis: study counts and citations

Sequence no.	Country	Documents	Citations	Total link strength
1	USA	252	4804	444
2	Japan	227	3645	141
3	South Korea	176	3552	96
4	England	126	3202	261
5	Germany	93	2802	204
6	Peoples R China	162	1950	178
7	Canada	91	1545	128
8	Switzerland	43	1351	143
9	India	88	1254	171
10	Italy	59	1042	87
11	Australia	67	1005	111
12	Saudi Arabia	61	928	100
13	Brazil	49	603	112
14	Turkey	42	597	31
15	Pakistan	29	535	41

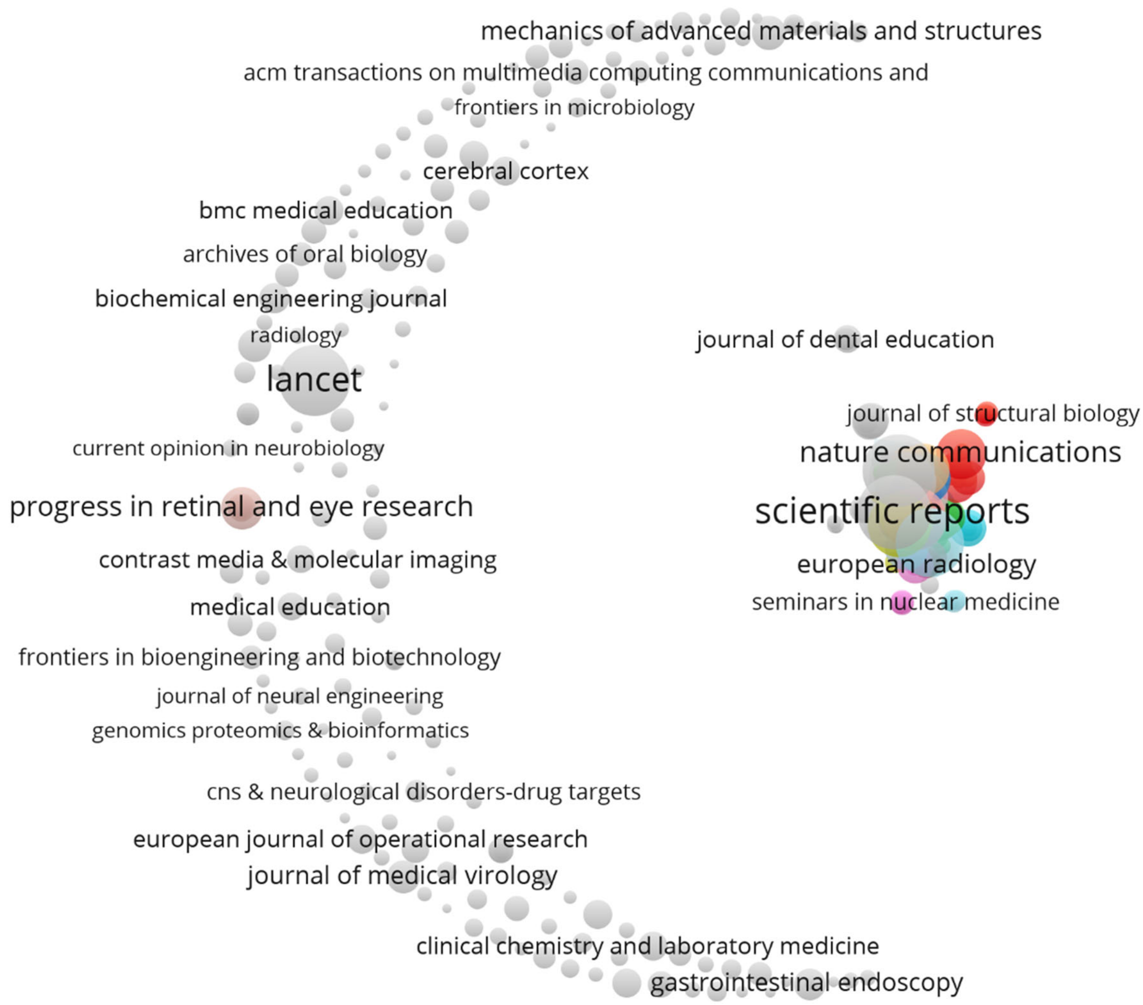

Fig. 8 Network visualization of citation for source journals

of 254 studies were identified, with 2112 citations in total, 8.31 articles on average, with a 25 H index [7]. The analysis revealed extensive collaborations and citations among authors, institutions, and countries, indicating the global expansion of digital dentistry research.

In a research, 165 publications from Web of Science and Scopus published between 2010 and 2022 were examined to examine the expanding application of deep learning (DL) in crack detection for civil inspection. It talks about state-of-the-art techniques in crack detection using DL, concentrating on datasets, network design, domain, and performance. It also draws attention to the sharp rise in publications since 2018. Serving as a reference for researchers, it addresses challenges and future directions, including automated identification of the specific type of fracture, dataset availability, preprocessing techniques, labeling approaches, parameter tuning, 3D imaging, real-time detection, and improving segmentation accuracy [1]. A comprehensive bibliometric analysis of deep learning (DL) publications from 2007 to 2019, utilizing data from Web of Science conducted. With 5722 publications analyzed using tools like VOS viewer and Cite Space, the study examines annual publication trends, institutions, productive countries/regions, and authors. It visualizes co-citation networks and cooperation networks, identifying influential entities and collaboration patterns. Furthermore, it uses Cite Space for keyword analysis to detect hotspots and research trends [16]. A comprehensive bibliometric analysis of deep learning research using 3599 publications from 1968 to 2018 was conducted in the Web of Science database. It reveals significant global collaboration, especially between institutions in China and Western countries, and thriving international academic communication. Three different levels of research fronts are classified, and research hotspots like modeling and algorithm development are noted: modeling research, algorithm research, and application research in computer vision technologies [20].

The assimilation of deep learning methodologies into the field of dentistry has brought about significant advancements,

Table 5 Top 20 sources with most citation analysis: study documents and citations

Sequence no.	Sources	Documents	Citations
1	Scientific Reports	252	4804
2	Journal of Dentistry	227	3645
3	Lancet Digital Health	176	3552
4	Journal of Dental Research	126	3202
5	BMC Oral Health	93	2802
6	Dentomaxillofacial Radiology	162	1950
7	IEEE Access	91	1545
8	Diagnostics	43	1351
9	Computational and Structural Biotechnology Journal	88	1254
10	Oral Surgery Oral Medicine Oral Pathology Oral Radiology	59	1042
11	Oral Radiology	67	1005
12	Journal of Clinical Medicine	61	928
13	Journal of Endodontics	49	603
14	IEEE Transactions on Medical Imaging	42	597
15	Biomolecules	29	535
16	Angle Orthodontist	5	227
17	Sensors	13	225
18	Cancers	12	210
19	Journal of Dental Sciences	7	207
20	Progress in Retinal and Eye Research	1	205

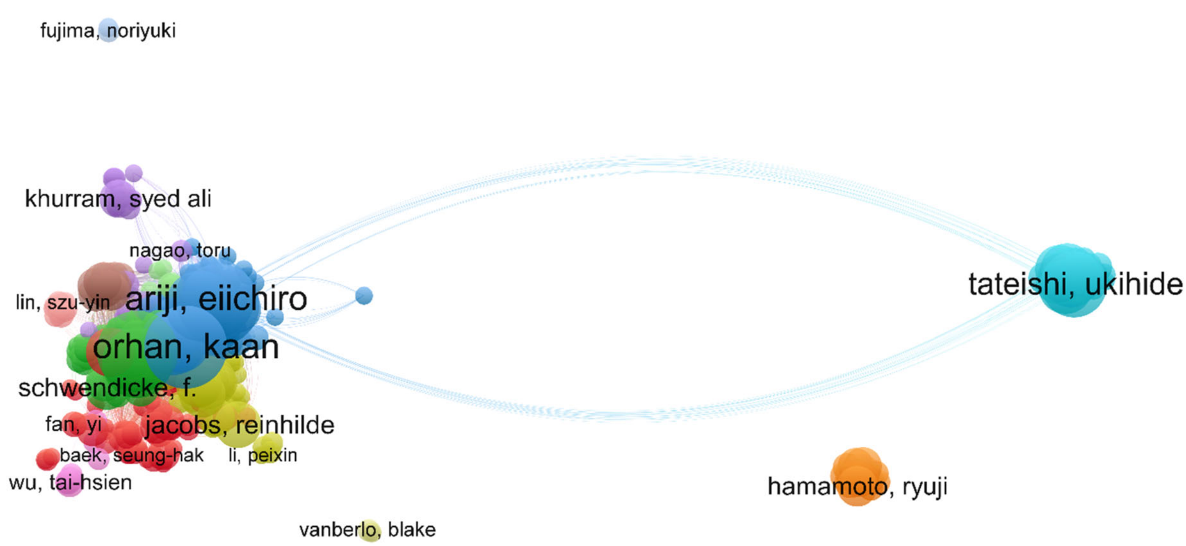

Fig. 9 Network visualization of citation relationships of authors

revolutionizing various aspects of diagnosis, treatment planning, and patient care. This shift, driven by the capabilities of artificial intelligence (AI) and deep learning techniques, has not only enhanced the accuracy and efficiency of dental procedures but also opened doors to new possibilities and innovations.

One of the key areas where deep learning has made a substantial impact is dental imaging analysis. With the utilization of convolutional neural networks (CNNs), deep learning algorithms have shown remarkable efficacy in tasks such as molar developmental staging, prediction of eruption, and detection of various dental conditions. By leveraging

Table 6 Top 30 authors in citation analysis: study counts and citations

Sequence no.	Author	Documents	Citations	Total link strength
1	Lee, Jae-Hong	11	874	1113
2	Schwendicke, Falk	27	861	1552
3	Krois, Joachim	22	831	1235
4	Ariji, Eiichiro	26	806	2183
5	Ariji, Yoshiko	27	806	2207
6	Fukuda, Motoki	22	762	2036
7	Jeong, Seong-Nyum	7	707	809
8	Katsumata, Akitoshi	19	698	1899
9	Fujita, Hiroshi	12	660	1565
10	Kise, Yoshitaka	15	628	1527
11	Kim, Do-Hyung	3	603	626
12	Nozawa, Michihito	9	440	1002
13	Elhennawy, Karim	6	420	514
14	Tateishi, Ukihide	20	362	911
15	Fujioka, Tomoyuki	17	339	885
16	Mori, Mio	15	337	800
17	Khurram, Syed Ali	9	335	40
18	Nakagawa, Tsuyoshi	13	330	755
19	Oda, Goshi	13	330	755
20	Kubota, Kazunori	15	325	804
21	Jacobs, Reinhilde	12	308	481
22	Schwendicke, F	11	302	317
23	Van Gerven, Adriaan	8	300	378
24	Willems, Holger	8	300	378
25	Krois, J	9	297	299
26	Orhan, Kaan	28	293	1385
27	Kuwada, Chiaki	12	285	1003
28	Chen, Hu	6	280	318
29	Chaurasia, Akhilanand	8	277	393
30	Katsuta, Leona	10	273	604

techniques like CBCT and panoramic imaging, deep learning algorithms enable precise detection, segmentation, and classification of dental issues, facilitating more accurate diagnoses and treatment planning.

Moreover, the collaborative nature of deep learning methodologies has fostered robust networks among researchers, institutions, and countries. Co-authorship analysis reveals the collaborative dynamics among authors, shedding light on the collective efforts driving research in this domain. Similarly, co-authorship across countries highlights the global collaboration that contributes to the advancement of deep learning in dentistry, emphasizing the interdisciplinary nature of this field.

Furthermore, bibliometric analysis serves as a valuable tool for understanding the landscape of research in deep learning and dentistry. By quantitatively assessing publications, citations, and collaborative networks, bibliometric analysis provides insights into the evolution, impact, and emerging trends within this field. Through techniques like co-occurrence of keywords, citation analysis, and bibliographic coupling, researchers can identify influential works, thematic foci, and key contributors, guiding future research directions and fostering innovation.

5 Conclusion

The inclusion of deep learning techniques into dentistry signifies a fundamental change in how dental professionals approach diagnosing and treating patients. The combination of AI and deep learning is revolutionizing dental care, making

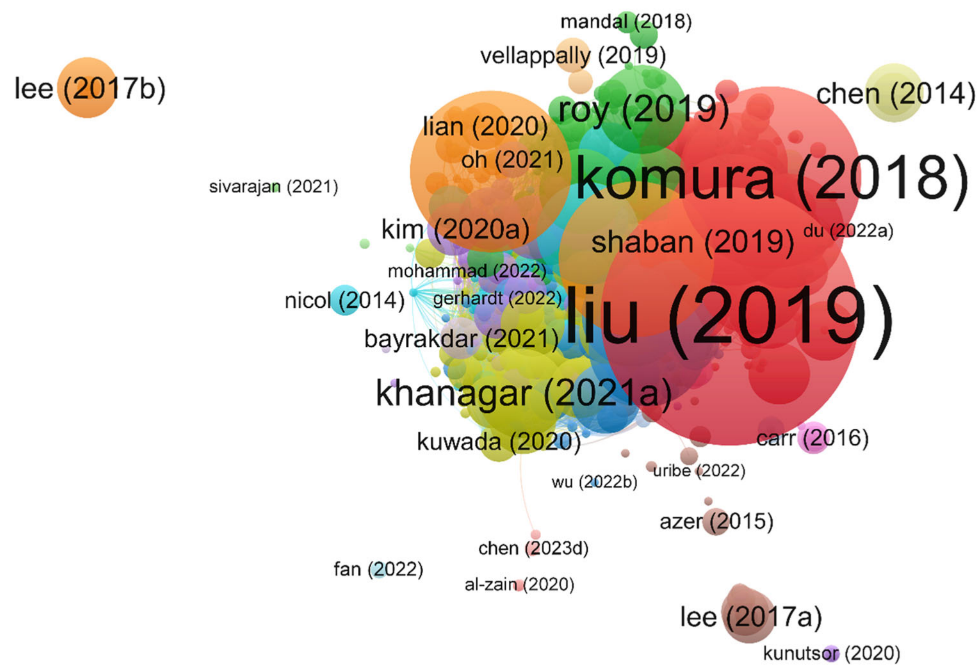

Fig. 10 Bibliographic coupling relationships with documents network visualization

Table 7 Top 20 authors in bibliographic coupling relationships with documents analysis: study counts and citations

Sequence no	Authors	Citations	Total link strength
1	Liu (2019)	674	441
2	Komura (2018)	404	203
3	Mangano (2017)	340	5
4	Lee (2018a)	321	328
5	Jamshidi (2020)	251	57
6	Schwendicke (2020a)	213	80
7	Li (2021b)	205	305
8	Lee (2018b)	188	240
9	Lee (2019a)	177	57
10	Chen (2019)	174	386
11	Kim (2019)	173	54
12	Krois (2019)	172	385
13	Ekert (2019)	143	476
14	Khanagar (2021a)	142	895
15	Roy (2019)	141	236
16	Casalegno (2019)	131	526
17	Urakawa (2019)	127	60
18	Ong (2023)	123	0
19	Kulkarni (2020)	114	219
20	Quoc Dang Vu (2019)	113	362

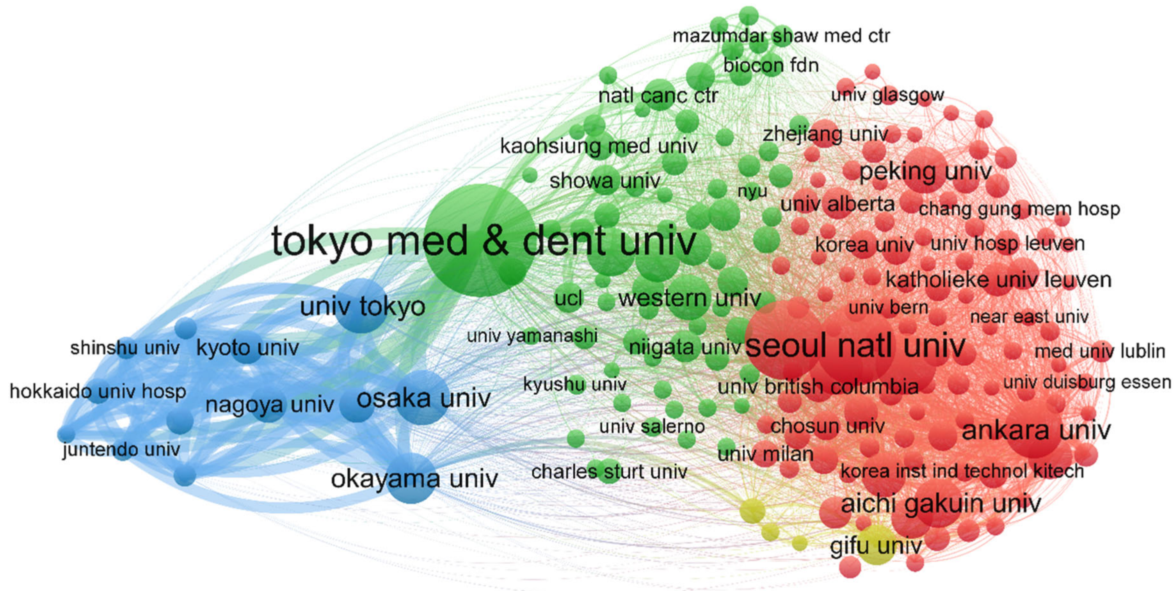

Fig. 11 Network visualization of bibliographic coupling relationships with organizations

Table 8 Top 20 organizations in bibliographic coupling relationships with organizations analysis: study counts and citations

Sequence no.	Organization	Documents	Citations	Total link strength
1	Tokyo Med & Dent Univ	86	1528	43,705
2	Yonsei Univ	51	1247	24,216
3	Charite Univ Med Berlin	35	1163	26,955
4	Univ Birmingham	22	1062	6585
5	Wonkwang Univ	22	1003	16,125
6	Seoul Natl Univ	52	982	25,578
7	Univ Hosp Birmingham Nhs Fdn Trust	6	830	3181
8	Moorfields Eye Hosp Nhs Fdn Trust	5	829	3036
9	Aichi Gakuin Univ	26	815	12,717
10	Gifu Univ	19	775	12,711
11	Asahi Univ	20	732	10,768
12	Peking Univ	24	470	10,134
13	Univ Warwick	10	468	5193
14	Univ Toronto	13	467	5238
15	Ankara Univ	33	440	33,586
16	Univ Sheffield	14	438	6313
17	Karolinska Inst	14	419	8820
18	Minist Hlth	9	413	6270
19	Univ Naples Federico Ii	6	390	1646
20	Univ Hong Kong	29	375	15,208

it more accurate, efficient, and patient-focused. Additionally, the collaborative research evident in bibliometric analysis underscores the importance of interdisciplinary cooperation in driving innovation and advancing dental healthcare. As deep learning continues to progress, it has the potential to significantly enhance the quality of dental care and improve patient outcomes. The bibliometric analysis undertaken in this study offers a thorough assessment of scholarly literature on deep learning in dentistry. Utilizing specialized tools such as VOSviewer, researchers have been able to identify

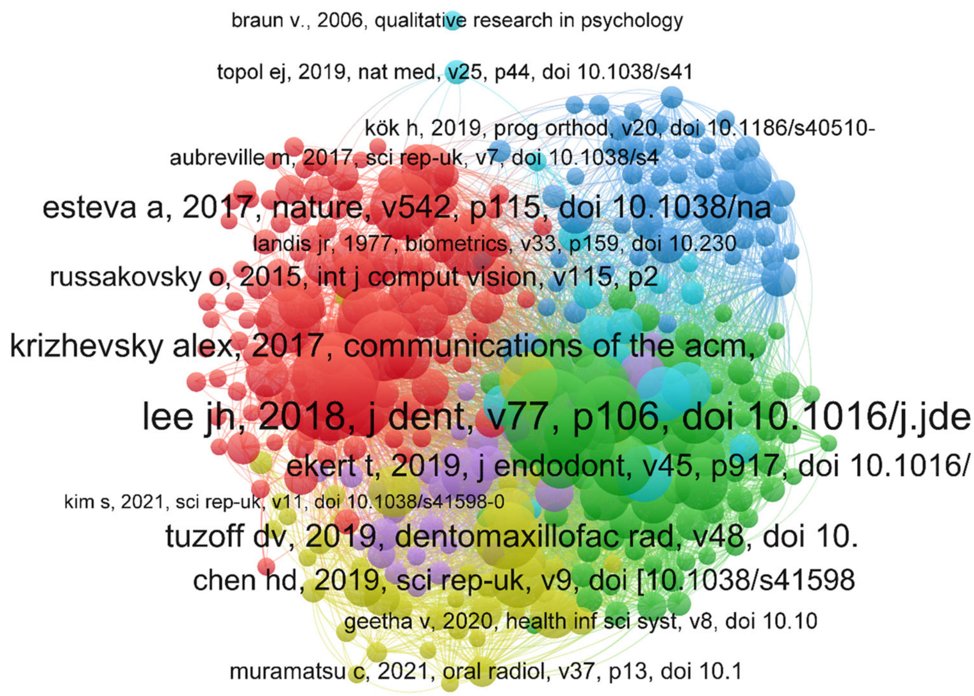

Fig. 12 Network visualization of co-citation relationships with references

Table 9 Top 20 cited references analysis: study counts and citations

Sequence no.	Cited references	Citations	Total link strength
1	[13]	128	2019
2	[22]	125	1249
3	[8]	111	1078
4	[10]	80	894
5	[14]	78	1467
6	[11]	77	1537
7	[4]	76	752
8	[26]	76	983
9	[27]	76	1452
10	kingma d.p., 2014, arxiv	72	501
11	[17]	71	734
12	[25]	69	1127
13	[3]	67	1415
14	[12]	66	643
15	[24]	61	1050
16	[9]	59	1197
17	chen hd, 2019, sci rep-uk, v9, doi [https://doi.org/10.1038/s41598-019-40414-y https://doi.org/10.1038/s41598-018-36228-z]	57	1095
18	[21]	56	1001
19	[5]	54	1193
20	hwang jj, 2019, imagng sci dent, v49, p1	54	823

patterns, trends, and connections within the literature, providing insights into the structure and evolution of research in this area. This analysis has highlighted influential works, prominent authors, collaborative networks, and emerging trends, underscoring the growing importance of deep learning in the field of dentistry.

Author contributions Elham Tahsin YASIN: Conceptualization, Methodology, Formal Analysis, Investigation, Writing—Original Draft, Visualization. Mediha ERTURK: Conceptualization, Investigation, Writing—Review and Editing. Melek TASSOKER: Conceptualization, Methodology, Investigation, Writing—Review and Editing, Supervision. Murat KOKLU: Conceptualization, Methodology, Formal Analysis, Investigation, Writing—Review and Editing, Supervision, Administration.

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Data availability You can access the search query link for this study through the following link: [https://www.webofscience.com/wos/woscc/summary/c8b543b5-bc05-4f4f-8040-6cf8179a31e1-cbfcc8d6/relevance/1]. For detailed visual representations of each map and closer examination, you can access the VOSviewer bibliometric analysis software with the given parameters in the study. No datasets were generated or analysed during the current study.

Declarations

Conflict of interest The authors declare that they have no competing interests.

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