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Review article

Exploring machine learning applications in Meningioma Research (2004–2023)

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ABSTRACT

Objective: This study aims to examine the trends in machine learning application to meningiomas between 2004 and 2023.
Methods: Publication data were extracted from the Science Citation Index Expanded (SCI-E) within the Web of Science Core Collection (WOSCC). Using CiteSpace 6.2.R6, a comprehensive analysis of publications, authors, cited authors, countries, institutions, cited journals, references, and keywords was conducted on December 1, 2023.
Results: The analysis included a total of 342 articles. Prior to 2007, no publications existed in this field, and the number remained modest until 2017. A significant increase occurred in publications from 2018 onwards. The majority of the top 10 authors hailed from Germany and China, with the USA also exerting substantial international influence, particularly in academic institutions. Journals from the IEEE series contributed significantly to the publications. "Deep learning," "brain tumor," and "classification" emerged as the primary keywords of focus among researchers. The developmental pattern in this field primarily involved a combination of interdisciplinary integration and the refinement of major disciplinary branches.
Conclusion: Machine learning has demonstrated significant value in predicting early meningiomas and tailoring treatment plans. Key research focuses involve optimizing detection indicators and selecting superior machine learning algorithms. Future efforts should aim to develop high-performance algorithms to drive further innovation in this field.

1. Introduction

Meningiomas, comprising 20 % of all intracranial tumors, are the most common primary tumors of the central nervous system [1–3], with a prevalence rate of 98 cases per 100,000 individuals [4]. Clinical symptoms vary and may include headaches, vision problems, epileptic seizures, memory decline, muscle weakness, or other neurological dysfunctions, largely depending on the tumor's

Abbreviations: ML, machine learning; RCTs, randomized controlled trials; WOSCC, Web of Science Core Collection; SCI-E, Science Citation Index-Expanded; MRI, magnetic resonance imaging; DNA, deoxyribonucleic acid; LR, Logistic Regression; SVM, Support Vector Machine; KNN, K-Nearest Neighbors; RF, Random Forest.

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anatomical location [5–7]. Despite being predominantly benign, these tumors' size and location can lead to significant health complications [8]. Currently, the diagnosis of meningiomas relies on neuroimaging data [9–11]. Due to the often asymptomatic nature of the disease, observation is usually the preferred treatment approach [1,2,12]. However, many patients fail to adhere to regular medical check-ups, increasing the risk of malignant transformation [13–15]. This non-compliance can have severe implications, causing substantial distress and even leading to depression in many patients [16,17]. Therefore, accurately predicting the disease's prognosis at an early stage is crucial in preventing the malignant transformation of meningiomas. In recent years, machine learning (ML) has played a crucial role in improving the accuracy, efficiency, and personalization of treatment plans for the early prediction and diagnosis of meningiomas [18–20]. Various learning algorithms, such as convolutional neural networks [21] and residual networks [22], have demonstrated high predictive accuracy. This reliability has been confirmed by high-level evidence studies, including authoritative multicenter randomized controlled trials (RCTs) [23] and systematic reviews [24]. However, these studies share a common limitation: they do not provide insights into the evolving trends in this field, including research focal points, interdisciplinary collaborations, and the geographical distribution of scientific output. Furthermore, their interpretations often involve subjective judgments and scoring by researchers. In contrast, bibliometric analysis (BA), which leverages theories and methodologies from both bibliometrics and informatics, offers a more profound and insightful perspective by objectively visualizing the quantity, quality, and impact of scientific literature [25–28]. To the best of our knowledge, there remains a notable absence of BA regarding the academic collaborative networks, developmental trajectories, and cutting-edge research in the application of ML to meningiomas. The objective of this study is to comprehensively search the Web of Science Core Collection (WoSCC) using CiteSpace for relevant literature spanning the past twenty years. The aim is to explore the frontiers and development trends of machine learning (ML) applications in meningiomas, with a focus on core authors, their collaboration networks, affiliated institutions, countries, and regions. This effort is intended to enhance clinical practitioners' understanding of the latest research trends and technological advancements, thereby guiding their clinical practice and elevating the standards of diagnosis and treatment for meningiomas. Medical experts can collaborate with specialists in machine learning and bibliometrics to leverage ML techniques in addressing challenges in meningioma research, thereby fostering advancement and progress in this field. Additionally, this bibliometric analysis (BA) can serve as a reference and guide for future research endeavors in the field of meningiomas.

2. Material and methods

2.1. Data sources and search strategy

All the data used in this study were obtained from the Web of Science Core Collection (WoSCC), a citation-based database. Unlike other databases, WoSCC offers a unique advantage in directly computing various bibliometric indicators (such as cited authors, cited journals, impact factors, countries, academic institutions, etc.) without the need for integration from multiple databases. This comprehensive display of core publication information makes WoSCC an authoritative and widely utilized dataset for bibliometric analysis [29,30]. Therefore, this study also relies on this database to enable comparison and verification with similar research outcomes.

A comprehensive search strategy was devised for the period from December 1, 2004, to December 1, 2023, incorporating keywords related to "meningiomas" and "machine learning" (Table 1). The filtering strategy used for the search was illustrated (Fig. 1 and PRISMA_2020_flow_diagram_updated_SRs_v1). To ensure the data's comprehensiveness, we imposed no restrictions on the country of publication, language, or study type.

2.2. Analysis tool

This study utilizes CiteSpace 6.2.R6 software as a tool for visualization analysis. Its advantage lies in its ability to identify research hotspots and frontier fields, as well as forecast the future development dynamics of specific areas. The process of conducting bibliometric analysis with CiteSpace 6.2.R6 typically involves several key steps: data collection, importing data into CiteSpace 6.2.R6, data analysis, and interpretation of analysis results. Specifically, we conducted a comprehensive search in the WoSCC database using the keywords detailed in Table 1. We exported the search results in the "download.txt" format supported by CiteSpace 6.2.R6, with the export data parameters set to "Full Record and Cited References." After filtering duplicate data through the CiteSpace 6.2.R6 tool, we set the time slice to "1 year" and the k value for the g-index to 50. Additionally, we employed the Pathfinder network scaling algorithm [31,32]. Finally, we adjusted the network diagrams and clusters to display results that facilitate efficient recognition of core information by the reader.

Table 1
Topic search query (Web of Science Core Collection, December 1, 2004, to December 1, 2023).

Set	Results	Search Query
#1	18,785	TS=((meningioma) OR (meningeal neoplasms) OR (meningeal tumor))
#2	909,543	TS=((machine learning) OR (deep learning) OR (artificial intelligence) OR (machine intelligence) OR (neural network) OR (natural language processing) OR (hybrid intelligent system) OR (CNN) OR (LSTM) OR (RNN))
#3	378	#1 AND #2
#4	342	#3 AND Article (Document Types) AND English (Languages)

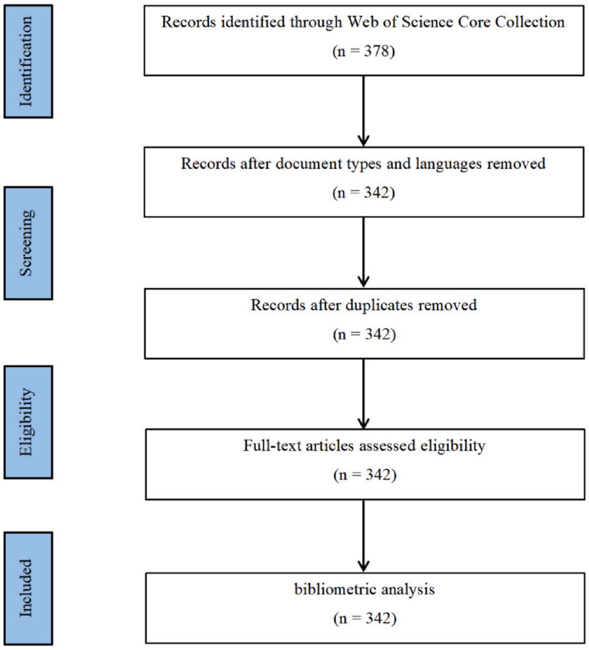


Fig. 1. Map illustrating the literature screening process for machine learning applied to meningiomas.

3. Results

3.1. Annual publications

Fig. 2 illustrates the annual publication trends in ML applications in meningioma research. Before 2007, no publications existed in this domain, and the number remained modest until 2017. This trend significantly correlates with ML's nascent stage as an academic discipline. Since 2018, there has been a marked increase in publications, attributed to advancements in ML's computational capabilities and algorithmic architectures' refinement. These developments have enabled the medical sector to employ more sophisticated ML and deep learning techniques, revolutionizing imaging analysis technology and offering precise diagnostic tools. Recent studies underscore the feasibility of deep learning methods in addressing multiple clinical challenges in meningioma management. This highlights the complexity and varying invasiveness of tumors, necessitating advanced tools for accurate diagnosis and prognosis, thus increasing reliance on ML technologies [33,34].

3.2. Analysis of authors, countries, and institutions

Fig. 3 and Table 2 display the authorship details of the 342 published works. Each node represents an author, with connecting lines indicating collaborative relationships between them. The top ten authors, listed in order of publication count, are: Stummer, Walter (5 publications); Xu, Jianguo (5 publications); Musigmann, Manfred (5 publications); Brokinkel, Benjamin (5 publications); Akkurt, Burak Han (5 publications); Mannil, Manoj (4 publications); Zhang, Lei (4 publications); Heindel, Walter (4 publications); Sartoretti, Thomas (4 publications); Teng, Yuen (2 publications). It is noteworthy that the majority of these top ten authors come from Germany

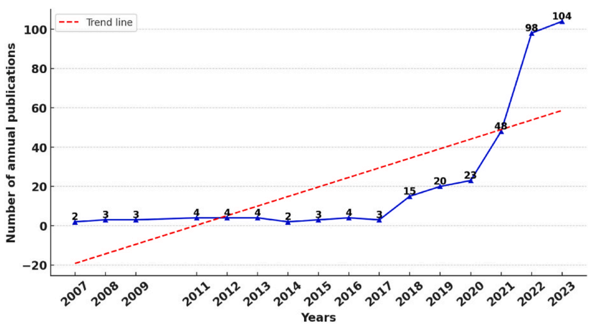


Fig. 2. Map showing the annual publications related to machine learning applied to meningiomas.

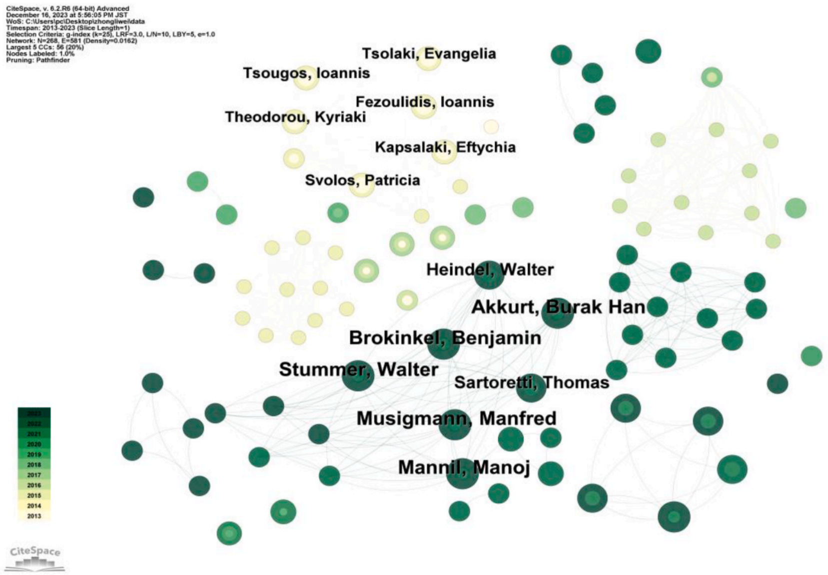


Fig. 3. Map displaying the authors associated with machine learning applied to meningiomas.

Table 2
Top 10 authors related to machine learning applied to meningiomas.

Rank	Author	Frequency	Year	Country
1	Stummer, Walter	5	2022	Germany
2	Xu, Jianguo	5	2021	Peoples R China
3	Musigmann, Manfred	5	2022	Germany
4	Brokinkel, Benjamin	5	2022	Germany
5	Akkurt, Burak Han	5	2022	Germany
6	Mannil, Manoj	5	2022	Germany
7	Zhang, Lei	4	2021	Peoples R China
8	Heindel, Walter	4	2022	Germany
9	Sartoretti, Thomas	4	2022	Switzerland
10	Teng, Yuen	4	2021	Peoples R China

and China. This trend aligns with the advanced research infrastructures and significant investments in technological and medical research of these nations. Furthermore, it reflects their focused attention on neuro-oncology, collaborative efforts in multicentric studies, the high incidence of meningiomas, and a robust base of technical expertise in these countries [33,35].

Fig. 4. Map depicting the countries involved in machine learning applied to meningiomas.

Fig. 4 and Table 3 reveal the collaborative network of countries in this research domain, comprising 61 nodes and 129 connecting edges. The top ten countries by publication count are: People's Republic of China (75 publications); USA (61 publications); India (60 publications); Saudi Arabia (32 publications); Pakistan (31 publications); Germany (24 publications); South Korea (23 publications); Egypt (20 publications); England (16 publications); Turkey (14 publications). Countries with notable centrality (indicated by a purple ring) in this network are: USA (centrality score of 0.60); People's Republic of China (0.24); Germany (0.23); Pakistan (0.21); India (0.16); Egypt (0.14); England (0.10). This demonstrates that in the application of ML to the field of meningioma, the USA and China are at the forefront globally. This underscores the heavy dependence of the ML field on a nation's technological prowess, particularly the technological and talent resources of the USA, which accounts for its leading centrality score (0.60).

Fig. 5 and Table 4 present the cooperative network of institutions, comprising 203 nodes and 314 connecting edges. The top ten institutions by publication count are: Egyptian Knowledge Bank (EKB) with 20 publications; Capital Medical University with 11 publications; University of California System with 10 publications; Chinese Academy of Sciences with 9 publications; Fudan University with 9 publications; Sichuan University with 8 publications; Princess Nourah bint Abdulrahman University with 8 publications; Harvard University with 7 publications; Central South University with 7 publications; and University of California, San Francisco with 7 publications. It is observed that institutions from the USA and China hold prominent positions among the top ten, and there exists a substantial network of collaboration between institutions across different countries. This interconnected network is poised to further catalyze the development of ML applications in studying meningiomas.

3.3. Analysis of cited journals

Fig. 6 and Table 5 illustrate the citation network of journals, encompassing 430 nodes and 1415 connecting edges. The top ten journals by citation count are *PLOS ONE* with 159 citations, *IEEE ACCESS* with 121 citations, *LECT NOTES COMPUT SC* with 106 citations, *COMPUT BIOL MED* with 99 citations, *NEURO-ONCOLOGY* with 98 citations, *IEEE T MED IMAGING* with 91 citations, *PROC CVPR IEEE* with 89 citations, *MED IMAGE ANAL* with 88 citations, *ARXIV* with 87 citations, and *SCI REP-UK* with 87 citations. In addition, journals such as *EUR J RADIOL* (with a centrality score of 0.15), *BIOMED SIGNAL PROCES* (0.13), and *AM J NEURORADIOL* (0.13) demonstrated significant centrality (indicated by a purple ring). Notably, the *IEEE* series of journals recognized for their impact in the field of computer science are highly acknowledged in this domain, as reflected in their prominence in the citation network.

Keywords Co-Occurrence and Citation Burst Analysis; Fig. 7 and Table 6 show a network graph of keywords comprising 313 nodes and 913 connecting edges. The top ten keywords, based on frequency, were deep learning (mentioned 85 times), brain tumor (74 times), classification (66 times), segmentation (59 times), magnetic resonance imaging (49 times), machine learning (48 times), convolutional neural network (38 times), MRI (26 times), images (25 times), and system (23 times). Analyzing the frequency and centrality of these keywords, it becomes apparent that "deep learning," "brain tumor," and "classification" emerge as prominent themes in this field. Fig. 8 shows the top 20 keywords with the most robust citation bursts. The start and end of each burst are denoted as "beginning" and "end," respectively. The increase in influence correlates with the escalation in the "strength" value. The light blue area represents the research period, whereas the red portion indicates the burst onset and climax. It is observed that the keyword with the highest burst strength is "tumors," reaching 3.49. Additionally, in the early phase, keywords such as "high grade gliomas," "magnetic resonance spectroscopy," and "matrix metalloproteinase" garnered significant attention, indicating an early focus on clinical imaging data in medical research. During the mid-phase, keywords like "support vector machine," "artificial neural network," and "model" were more prominent, suggesting that researchers were exploring new ML algorithms. In the later phase, the frequency of keywords such as "image segmentation," "resection," and "management" increased, illustrating that researchers in the field of ML applications for meningiomas have started to systematically assess clinical methods and progressively refine the management of clinical research protocols. Keywords Timeline; Fig. 9 depicts the evolution and interconnection of keywords over time arranged chronologically. This timeline extends from left to right, highlighting the emergence and disappearance of research keywords from 2004 to 2023. In addition, this illustration clusters various types of keywords. Ten clusters (labeled 0–9) are shown. Cluster #0, labeled as "pretrained model," primarily focuses on topics like brain tumor classification, brain tumor, and efficient classification. Cluster #1, termed "diagnosis performance," concentrates on deep neural network-based models, translocator protein, and traditional radiological findings. Cluster #2, marked as "non-linear feature space," emphasizes classification analysis, new convolutional neural network architectures, and related topics. Cluster #3, identified as "clinical outcome," revolves around clinical decision support systems,

Table 3
Top 10 frequency and centrality of countries related to machine learning applied to meningiomas.

Rank	Frequency	Countries	Rank	Centrality	Countries
1	75	PEOPLES R CHINA	1	0.60	USA
2	61	USA	2	0.24	PEOPLES R CHINA
3	60	INDIA	3	0.23	GERMANY
4	32	SAUDI ARABIA	4	0.21	PAKISTAN
5	31	PAKISTAN	5	0.16	INDIA
6	24	GERMANY	6	0.14	EGYPT
7	23	SOUTH KOREA	7	0.10	ENGLAND
8	20	EGYPT	8	0.10	FRANCE
9	16	ENGLAND	9	0.09	U ARAB EMIRATES
10	14	TURKEY	10	0.07	SINGAPORE

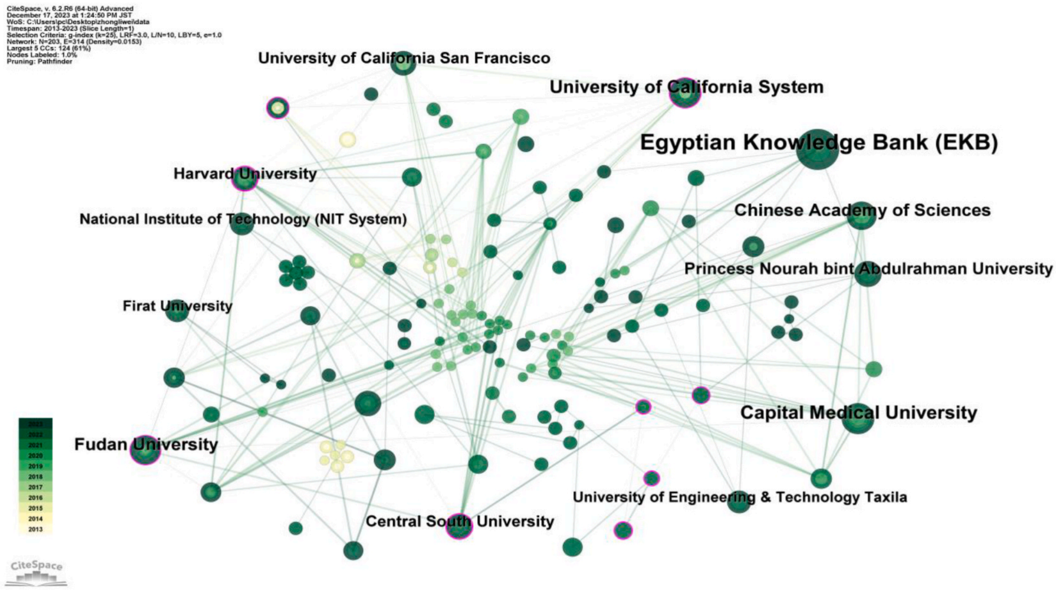


Fig. 5. Map presenting the institutions engaged in machine learning applied to meningiomas.

Table 4
Top 10 publications of institutions related to machine learning applied to meningiomas.

Rank	Frequency	Year	Institutions
1	20	2019	Egyptian Knowledge Bank (EKB)
2	19	2019	Capital Medical University
3	10	2018	University of California System
4	9	2018	Chinese Academy of Sciences
5	9	2019	Fudan University
6	8	2021	Sichuan University
7	8	2022	Princess Nourah bint Abdulrahman University
8	7	2018	Harvard University
9	7	2020	Central South University
10	7	2018	University of California San Francisco

spectroscopic multiple analysis, and similar themes. Cluster #4, named "meningioma classification," focuses on the diagnostic value, meningioma grade, statistical analysis, and associated areas. These clusters represented distinct but interconnected thematic areas within the field, illustrating the dynamic and multifaceted nature of research on ML applications in meningiomas.

3.4. Cluster dependencies of Reference

Fig. 10 illustrates cluster dependency relationships based on referenced literature. Areas coded with different colors represent various reference clusters, while arrows indicate developmental relationships between these clusters. Converging arrows signify the emergence of new disciplinary branches, while interlocking arrows reflect the integration of different disciplines. This occurs because the tail of the arrow represents the latest knowledge frontier, while the head indicates the source of foundational literature.

In the application of ML to the field of meningiomas, disciplinary development shows a pattern characterized by a combination of interdisciplinary integration and the refinement of major disciplinary branches. For example, Cluster #2 represents both the fusion of two disciplines and the branching off into two others. Meanwhile, Cluster #3, demonstrating collaborative relationships among multiple disciplines, exemplifies the typical manifestation of multidisciplinary integration. This dynamic reflects a complex and evolving landscape in the field, where new insights and approaches emerge from the convergence and divergence of various academic disciplines, driven by advancements and applications of ML in meningioma research.

4. Discussion

CiteSpace was used for a bibliometric analysis covering the years 2004–2023 focusing on key aspects of applying ML to meningiomas. This analysis included core authors, their collaboration networks, affiliated institutions, countries, and regions. We have provided comprehensive data, highlighting focal points and trends in the domain of ML applied to meningiomas.

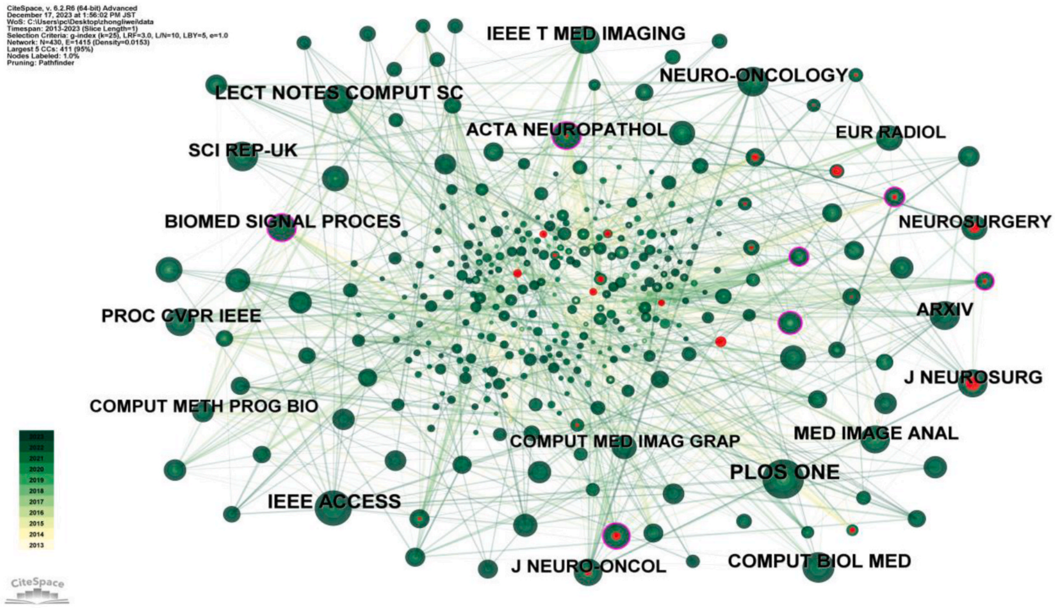


Fig. 6. Map showcasing the cited journals relevant to machine learning applied to meningiomas.

Table 5
Top 10 frequency and centrality of cited journals related to machine learning applied to meningiomas.

Rank	Frequency	Cited Journals	Rank	Centrality	Cited Journals
1	159	PLOS ONE	1	0.15	EUR J RADIOL
2	121	IEEE ACCESS	2	0.13	BIOMED SIGNAL PROCES
3	106	LECT NOTES COMPUT SC	3	0.13	AM J NEURORADIOL
4	99	COMPUT BIOL MED	4	0.11	ACTA NEUROPATHOL
5	98	NEURO-ONCOLOGY	5	0.11	RADIOLOGY
6	91	IEEE T MED IMAGING	6	0.11	NAT COMMUN
7	89	PROC CVPR IEEE	7	0.11	NEW ENGL J MED
8	88	MED IMAGE ANAL	8	0.10	LECT NOTES COMPUT SC
9	87	ARXIV	9	0.09	IEEE ACCESS
10	87	SCI REP-UK	10	0.09	ACTA NEUROCHIR

4.1. General information

This study reveals that over the past 20 years, a total of 342 publications have been publicly available in the field of ML applied to meningiomas. The findings indicate that before 2007, no publications existed in this field, and the number remained modest until 2017, correlating with the nascent stage of ML as an academic discipline. Since 2018, there has been a substantial increase in publications, attributed to enhanced computational capabilities in ML and the refinement of algorithmic architectures. These advancements have enabled the medical sector to utilize more complex ML and deep learning technologies, revolutionizing imaging analysis techniques and providing more accurate and efficient diagnostic tools [18–22,36].

An analysis of authors, countries, and their affiliated institutions with a high number of publications reveals that most of the top ten authors are from Germany and China. Additionally, the influence of the USA and its academic institutions is prominent internationally. This underscores ML's dependence on a country's technological advancement and talent pool. Collaboration in multicenter studies, high incidence rates of meningiomas, and technical expertise are essential factors driving the application and development in this field.

Through keyword network analysis, we have observed a high frequency of key terms such as deep learning, brain tumors, and classification. This prominence likely reflects the central position of these topics in current research. Such focused attention may stem from the successful application of deep learning techniques in medical image processing and diagnosis, as well as the medical and societal significance of brain tumors as a serious ailment. Moreover, the prominent ranking of certain keywords may also indicate ongoing interest among researchers in specific technologies (such as convolutional neural networks), imaging modalities (such as magnetic resonance imaging), and treatment approaches (such as surgical resection). The analysis of citation bursts provides insight into the developmental trajectory and professional trends of deep learning and machine learning in the diagnosis and treatment of brain tumors. From technological innovation to clinical practice, these findings reflect researchers' attention and efforts at various stages, offering valuable guidance and insights for future research and clinical applications.

By analyzing the timeline graph, we can discern the focus and developmental trends of different research domains during various

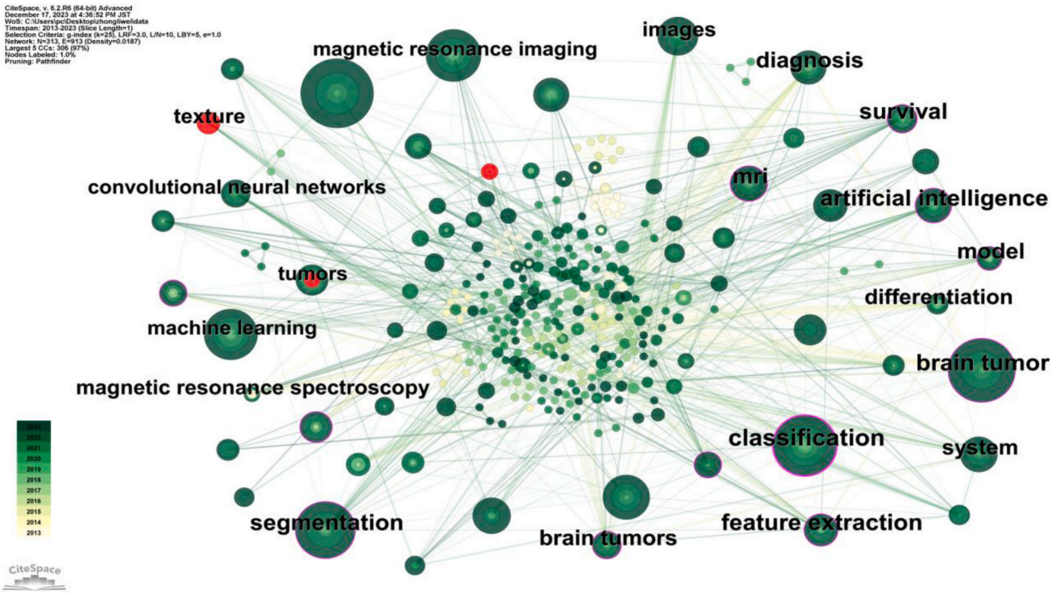


Fig. 7. Map featuring the keywords associated with machine learning applied to meningiomas.

Table 6
Top 10 frequency and centrality of keywords related to machine learning applied to meningiomas.

Rank	Frequency	Keywords	Rank	Centrality	Keywords
1	85	deep learning	1	0.22	classification
2	74	brain tumor	2	0.19	artificial intelligence
3	66	classification	3	0.16	segmentation
4	59	segmentation	4	0.14	model
5	49	magnetic resonance imaging	5	0.13	brain tumors
6	48	machine learning	6	0.13	survival
7	38	convolutional neural network	7	0.12	brain tumor
8	26	mri	8	0.12	feature extraction
9	25	images	9	0.12	features
10	23	system	10	0.12	cancer

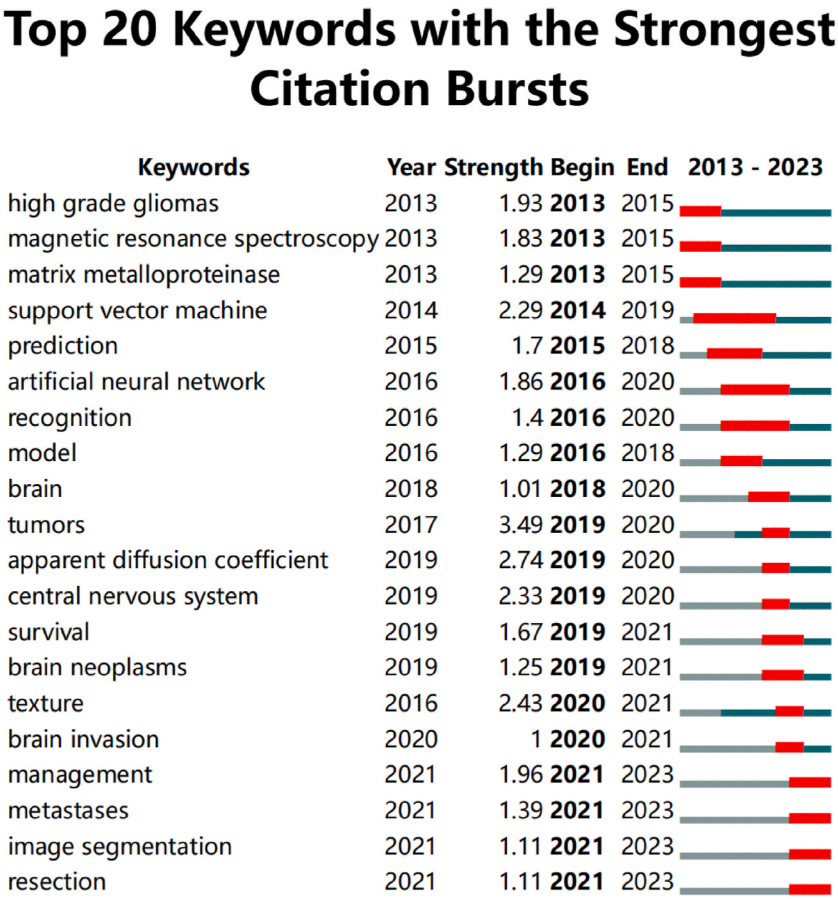
time periods. For instance, in the early stages, researchers may have placed greater emphasis on pre-trained models and fundamental classification methods. However, as time progresses, research into diagnostic performance, nonlinear feature spaces, and clinical outcomes gradually increases, reflecting researchers' deeper exploration and understanding of the field of brain tumor diagnosis and treatment.

The analysis of interdependencies in referenced literature clusters reveals that the disciplinary development pattern in applying ML to meningiomas predominantly consists of a coexistence of interdisciplinary integration and the refinement of major disciplinary branches. This unique feature is likely to promote resource integration, cross-disciplinary idea exchange, and academic innovation within the field.

In summary, as an emerging discipline, ML has shown immense value in early diagnosis, medical efficiency, and personalized treatment in the field of meningiomas, with a rapid increase in publications in recent years. Given the trends in annual publication numbers and the innovation of ML algorithms, significant progress is anticipated in the next 5–10 years, ultimately offering precision medical services to patients with meningiomas.

4.2. Research hotspots

Keywords encapsulate the core content and central themes within a specific research domain. Through methods like keyword co-occurrence analysis, keyword clustering, and citation burst analysis, one can monitor the development of various hot topics within a field. In the application of ML to meningiomas, two primary research hotspots have emerged: the selection of optimal detection indicators and the determination of the best ML algorithms.



Top 20 Keywords with the Strongest Citation Bursts

Keywords	Year	Strength	Begin	End	2013 - 2023
high grade gliomas	2013	1.93	**2013**	2015	
magnetic resonance spectroscopy	2013	1.83	**2013**	2015	
matrix metalloproteinase	2013	1.29	**2013**	2015	
support vector machine	2014	2.29	**2014**	2019	
prediction	2015	1.7	**2015**	2018	
artificial neural network	2016	1.86	**2016**	2020	
recognition	2016	1.4	**2016**	2020	
model	2016	1.29	**2016**	2018	
brain	2018	1.01	**2018**	2020	
tumors	2017	3.49	**2019**	2020	
apparent diffusion coefficient	2019	2.74	**2019**	2020	
central nervous system	2019	2.33	**2019**	2020	
survival	2019	1.67	**2019**	2021	
brain neoplasms	2019	1.25	**2019**	2021	
texture	2016	2.43	**2020**	2021	
brain invasion	2020	1	**2020**	2021	
management	2021	1.96	**2021**	2023	
metastases	2021	1.39	**2021**	2023	
image segmentation	2021	1.11	**2021**	2023	
resection	2021	1.11	**2021**	2023	

Fig. 8. Top 20 keywords exhibiting the strongest citation bursts.

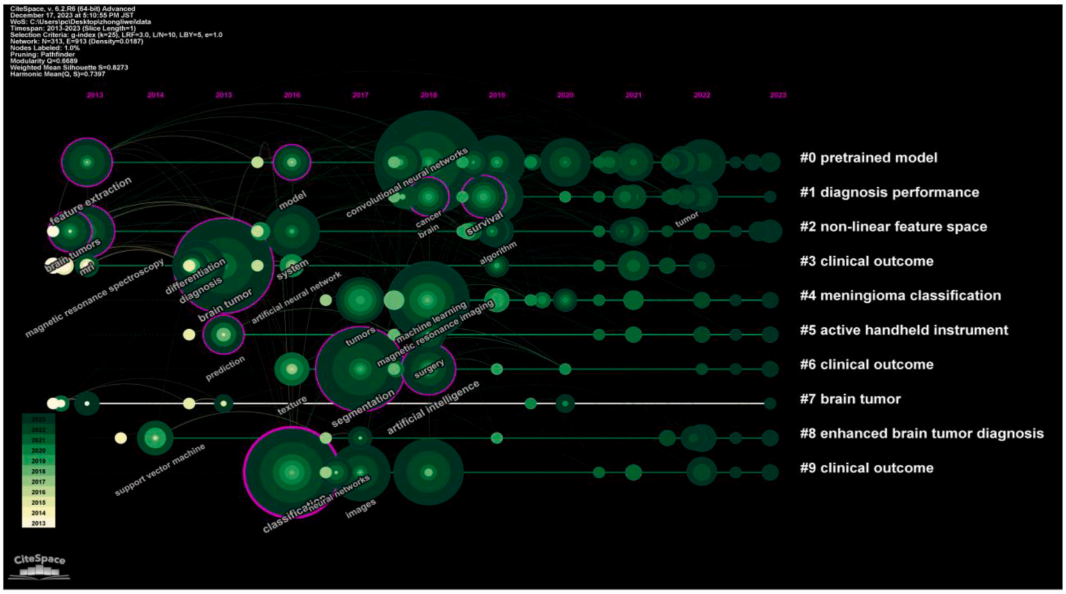


Fig. 9. Map illustrating the timeline of keywords related to machine learning applied to meningiomas.

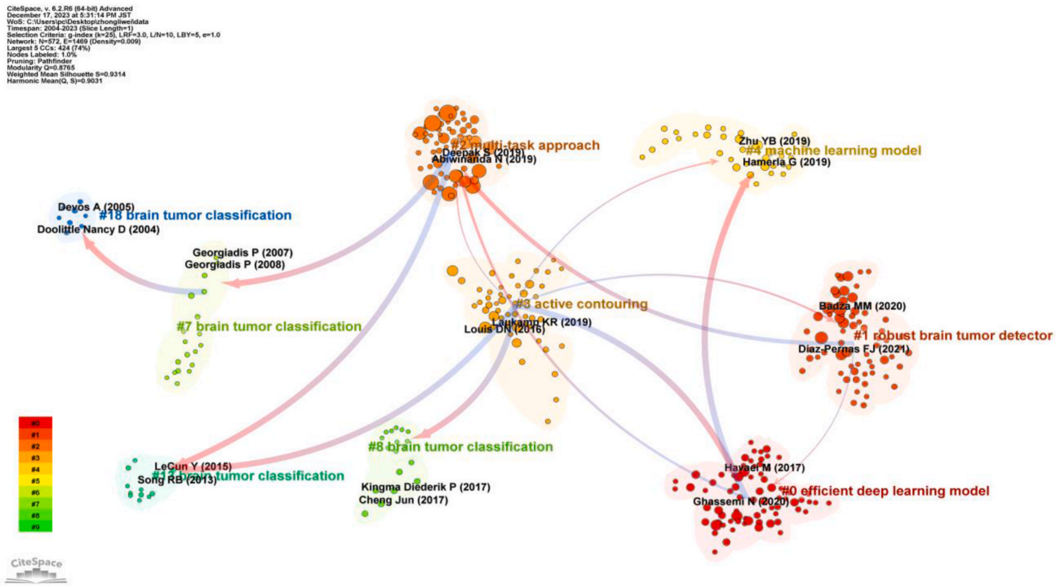


Fig. 10. Map illustrating the dependencies among clusters of references related to machine learning applied to meningiomas.

4.3. Selection of optimal detection indicators

Researchers have primarily focused on neuroimaging and related metrics to select the best detection indicators. For instance, Herrgott [37] discovered that tumor-specific deoxyribonucleic acid (DNA) methylation in patient blood could serve as an effective biomarker for noninvasive methods. Park [38] found that diffusion tensor imaging could accurately predict the grading and histological subtypes of meningiomas. Additionally, multiple studies [39–42] have shown that various magnetic resonance imaging (MRI) parameters can effectively diagnose the early stages of meningioma progression. Interestingly, Jelke [43] suggested that Raman spectroscopy could be a reliable supplementary tool for neuroimaging, particularly useful for distinguishing meningiomas from the dura mater during the perioperative period.

4.4. Determination of the best machine learning algorithms

With the diversification of algorithms in high-tech ML, researchers have explored various approaches. For instance, many studies have identified deep convolutional neural networks as having the best sensitivity for the diagnostic classification of meningiomas [19,21,44,45]. Zahoor [46] suggested advancements in traditional algorithms, including the addition of new deep-feature-enhancement spaces and integrated classifiers. Abdelaziz [22] reported that residual networks exhibit good performance. Teng [47] compared and evaluated common ML algorithms (such as F1 score, recall, accuracy, area under the ROC curve, calibration plot, and decision curve analysis) to determine the performance of models such as Logistic Regression (LR), XGBoost, AdaBoost, Support Vector Machine (SVM), K-Nearest Neighbors (KNN), and Random Forest (RF); Logistic Regression was used to obtain the best performance. Thus, with rapid technological advancements, new ML algorithms will continue to be developed, and their validation will likely remain a hot topic in this discipline in the coming years.

5. Conclusion

The application of ML in the early prediction of meningiomas and the development of individualized treatment plans has provided substantial value. Currently, the most prominent research hotspots are the selection of optimal detection indicators and determination of the best ML algorithms. In future, researchers will continue to develop high-performance algorithms to bring greater innovation to this field. This progressive approach promises to significantly enhance the accuracy and effectiveness of diagnostic and therapeutic strategies, and ultimately improve patient outcomes in meningioma management.

5.1. Limitations

This study has several limitations. First, it focuses primarily on the data available in the WOSCC database. CiteSpace cannot integrate data from different databases or perform citation analyses of sources outside the WOSCC. Secondly, although CiteSpace is valuable for detecting and visualizing emerging trends, it does not delve deeply into the fundamental mechanisms underlying ML applications in meningiomas. Therefore, this study did not provide a comprehensive understanding of the underlying processes.

Despite these limitations, we used CiteSpace to highlight the latest research trends in the field of ML applications for meningiomas.

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Declaration of figures authenticity

All figures submitted have been created by the authors, who confirm that the images are original with no duplication and have not been previously published in whole or in part.

Data availability

Raw data can be directly obtained from the WoSCC, and further inquiries can be directed at the corresponding author.

Disclosure

The authors declare no potential conflicts of interest in this study.

CRediT authorship contribution statement

Li-wei Zhong: Writing – review & editing, Writing – original draft, Supervision, Software, Project administration, Methodology, Funding acquisition, Data curation, Conceptualization. **Kun-shan Chen:** Writing – original draft, Visualization, Data curation, Conceptualization. **Hua-biao Yang:** Writing – original draft, Visualization, Software, Data curation, Conceptualization. **Shi-dan Liu:** Writing – review & editing, Software, Resources, Investigation, Formal analysis. **Zhi-tao Zong:** Writing – original draft, Supervision, Formal analysis, Data curation. **Xue-qin Zhang:** Writing – review & editing, Supervision, Software, Project administration, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare no conflict of interest related to the manuscript titled "Exploring the Research Trends in the Application of Machine Learning to Meningiomas (2004–2023)." The research conducted and presented in this manuscript is independent and impartial.

The authors have no financial relationships with any organizations that might have an interest in the submitted work, nor were there any other relationships or activities that could appear to have influenced the submitted work.

The data for the study was extracted from the Science Citation Index Expanded (SCI-E) within the Web of Science Core Collection (WOSCC), and the analysis was performed using CiteSpace 6.2.R6. The selection of data, process of analysis, and interpretation of results were conducted without any influence or input from these platforms.

All authors have contributed significantly to the research and preparation of the manuscript and have approved the final version for submission to *Heliyon*. Additionally, all authors agree to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

This statement confirms the absence of any personal, financial, or other conflicts of interest that could be construed to influence the outcomes of this research study.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.heliyon.2024.e32596.

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