



OPEN MRI radiomics in diagnosing high and low grade meningiomas through systematic review and meta analysis

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To evaluate the diagnostic value of magnetic resonance imaging (MRI) radiomics in distinguishing high-grade meningiomas (HGM) from low-grade meningiomas (LGM). A systematic search was conducted in PubMed, EMBASE, Web of Science, and The Cochrane Library databases up to December 31, 2023. Two researchers independently screened studies, extracted data, and assessed risk of bias and quality of included studies as well. Meta-analysis was performed using Stata 14 software to calculate pooled sensitivity (SEN), specificity (SPE), positive likelihood ratio (PLR), negative likelihood ratio (NLR), diagnostic odds ratio (DOR), and area under the curve (AUC). A total of 21 studies with 2253 patients were included (607 HGM, 1646 LGM). Meta-analysis showed an overall SEN of 0.82 (95% CI 0.74–0.88) and SPE of 0.85 (95% CI 0.81–0.89). The PLR and NLR were 5.64 (95% CI 4.17–7.64) and 0.21 (95% CI 0.14–0.31), respectively, with a pooled DOR of 26.66 (95% CI 14.42–49.27) and an AUC of 0.91 (95% CI 0.88–0.93), indicating high diagnostic accuracy. Although additional research is required to validate suitable techniques, MRI radiomics shows strong potential as an accurate tool for meningioma grading. Standardizing radiomics application could enhance diagnostic precision and clinical decision-making for meningioma grading in the future.

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Keywords MRI radiomics, High-grade meningiomas, Low-grade meningiomas, Diagnostic value, Meta-analysis

As the most common primary intracranial tumors, meningiomas account for 25.2% of all intracranial tumors¹. According to the 2021 World Health Organization (WHO) Classification of Central Nervous System Tumors, meningiomas are categorized into grades I, II, and III². The European Neuro-Oncology Society Guidelines for the Diagnosis and Treatment of Meningiomas recommended that the main treatment for meningiomas is surgical resection³. In cases without obvious clinical symptoms, WHO grade I meningiomas can be monitored with regular follow-up. However, some symptoms, such as cognitive impairment, necessitate surgical resection. For WHO grade II or III meningiomas, surgery is mandatory and may be complemented with radiotherapy depending on the patient's condition, or other options, including cytotoxic chemotherapy, hormone therapy, targeted therapy, etc., may be explored⁴. Therefore, accurately distinguishing tumor grades is crucial. MRI is the preferred method for evaluating patients with meningioma⁵, but reliance on visual analysis for medical image interpretation—limited to tumor shape and grayscale information—has led to some controversy in grading meningiomas due to its subjectivity and instability^{6,7}. The advancement of artificial intelligence, particularly in image processing, offers significant support for differential diagnosis, grading, typing, and the prediction of prognosis for meningiomas.

As an emerging discipline, radiomics can objectively and quantitatively capture some valuable tumor characteristics that are difficult to identify with the naked eyes. The method for evaluating tumor heterogeneity involves image analysis^{8–10} that which can extract high-dimensional data and quantitative image features from medical images. Through machine learning algorithms, researchers can mine information related to tumor pathophysiology to diagnose diseases and predict prognosis. This research encompasses four main processes, namely data acquisition, image segmentation, feature extraction and quantification, as well as feature selection

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and model establishment. In previous studies, image analysis has performed well in tumor diagnosis and grading. Furthermore, it has been used to predict tumor gene mutations and protein expression differences, subsequently reflecting tumor heterogeneity and microenvironment. This, in turn, guides the selection of targeted therapy and prognosis¹¹. Meningiomas exhibit many pathological subtypes, and the imaging manifestations of different subtypes, meningiomas, and other intracranial tumors are often similar. Conventional imaging techniques struggle to differentiate them, and the tumors' malignancy levels and prognoses vary significantly. The accuracy of MRI in distinguishing high-grade meningiomas (HGM) from low-grade meningiomas (LGM) has yet to be definitively established, and there has been no systematic evaluation and summary of the value of image analysis in this distinction. Addressing this gap is crucial for providing an effective method for tumor identification. The ongoing development of image analysis offers an opportunity to address this challenge and potentially improve diagnostic precision. To the best of our knowledge, this study is the first meta-analysis aimed at examining the diagnostic value of MRI radiomics in distinguishing HGM from LGM, aiming to guide the clinical diagnosis of meningiomas.

Materials and methods

The study strictly adhered to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) (2020) guidelines.

Inclusion and exclusion criteria

Study type

This meta-analysis includes both prospective and retrospective diagnostic accuracy trials.

Study subjects

The study focuses on patients diagnosed with HGM and LGM.

Diagnostic methods

Evaluated diagnostic approaches include radiomics and image texture analysis. The benchmarks for comparison are puncture tissue biopsy, intraoperative frozen pathological biopsy, or postoperative histological pathological biopsy.

Outcome indicators

Assessment parameters comprise sensitivity (SEN), specificity (SPE), positive likelihood ratio (PLR), negative likelihood ratio (NLR), diagnostic odds ratio (DOR), and the area under the curve (AUC) of the summary receiver operating characteristic (SROC) curve, along with an evaluation of publication bias.

Exclusion criteria

(1) Non-English literature; (2) literature published multiple times; (3) literature with incomplete data or where data cannot be extracted; (4) animal studies, case reports, and conference literature.

Literature search strategy

A comprehensive search was conducted in PubMed, EMBASE, Web of Science, and The Cochrane Library databases from the inception of each database to December 31, 2023 to identify relevant studies on grading meningiomas using MRI radiomics methods. The search strategy utilized a combination of subject headings and free words, which means to carefully tailor to each database's specific characteristics. Concurrently, the references of the included studies were thoroughly reviewed to further enrich our collection of relevant information. Key search terms in English included “radiomics”, “texture analysis”, “meningiomas”, and “MRI”.

Literature screening and quality evaluation

The screening of literature retrieval, data extraction, and quality evaluation were meticulously carried out independently by two physicians. In the event of disputes, a decision was rendered by the chief physician, boasting over 15 years of work experience. The data extraction included: (1) essential information of the included studies, such as the first author, publication time, country of study, age, gender, and sample size; (2) detailed extraction of true-positive (TP), true-negative (TN), false-positive (FP) and false-negative (FN) values. In instances where the precise TP, TN, FP, FN data were not disclosed, SPE, SEN, PLR, and NLR were utilized to retrograde extrapolation to calculate these results. Quality evaluation was conducted using an image radiomics quality score (RQS). The risk of bias was meticulously assessed using the Quality Assessment Tool for Diagnostic Accuracy Studies (QUADAS)-2.

Statistical analysis

The statistical software used in this study included Stata 14.0 and RevMan 5.3. The Cochran-Q and I^2 tests were utilized to identify heterogeneity between studies. In cases where the heterogeneity between groups was low ($I^2 < 50\%$), fixed effect models were employed to synthesize indicators; conversely, when the heterogeneity between groups was significant ($I^2 \geq 50\%$), random effect models were used for indicator synthesis. Quality analysis of the included literature was conducted using RevMan 5.3. Additionally, Stata 14.0 facilitated the derivation of the combined SEN, SPE, PLR, NLR, DOR, and their respective 95% CIs, crafted the SROC curve, and calculated the corresponding AUC. The diagnostic value was assessed based on the AUC magnitude. The AUC of 0.7–0.9 indicated moderate diagnostic accuracy, whereas AUC > 0.9 signified high diagnostic accuracy. Deek's test was conducted to evaluate publication bias, with $P < 0.05$ signaling a statistically significant difference. Subgroup analysis was also conducted using Stata 14.0.

Results

Literature screening process and results

During the preliminary search, a total of 434 relevant articles were identified. Following a meticulous review process, 21 studies were ultimately selected for inclusion. A detailed depiction of the literature screening process and results is illustrated in Fig. 1.

Basic characteristics of included studies

Totally, 21 studies with 2253 meningioma patients were included, among which 607 patients had HGM and 1646 had LGM. Among these, five studies focused on patients from Korea, Europe, and the USA, whereas the remaining studies featured patients from China. Detailed information is provided in Table 1.

Quality evaluation and bias risk assessment results of included studies

The quality and risk of bias in the 21 included studies were rigorously evaluated using the diagnostic meta-analysis quality assessment tool QUADAS-2. The outcomes of this qualitative evaluation are depicted in Figs. 2 and 3. Most studies were assessed to possess a low risk of bias, accompanied by minimal concerns regarding their applicability. The quality evaluation content and results included in the study, as shown in Supplementary Table 1, were conducted using the Radiomics Quality Score (RQS)³².

Meta-analysis results

SEN and SPE

The pooled SEN ($I^2 = 76.66$) and SPE ($I^2 = 80.37$) of the studies overall were relatively high, so a random effect model was used for meta-analysis. The SEN and SPE of the overall studies were 0.82 (95% CI 0.74–0.88) and 0.85 (95% CI 0.81–0.89), respectively (Fig. 4).

PLR and NLR

Due to the high heterogeneity of both the PLR ($I^2 = 67.54$) and NLR ($I^2 = 80.07$), a random effects model was used for meta-analysis. The PLR and NLR of the overall study were 5.64 (95% CI 4.17–7.64) and 0.21 (95% CI 0.14–0.31), respectively (Fig. 5).

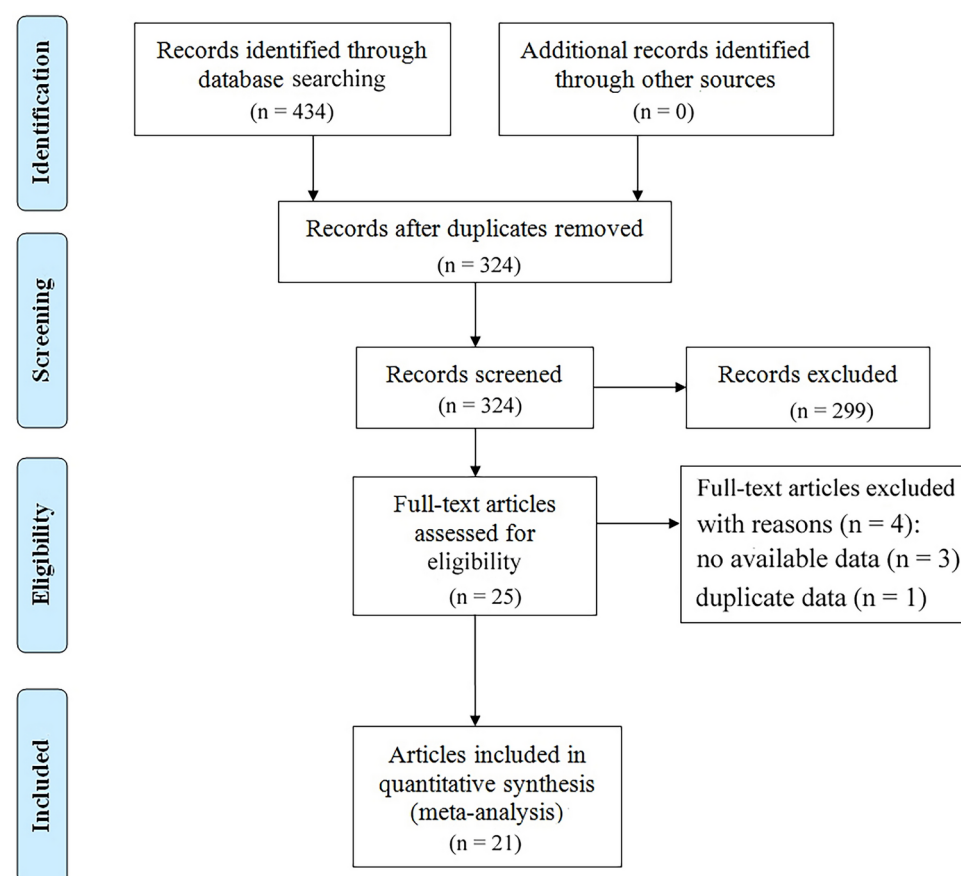


Fig. 1. Flow chart of the meta-analysis. The flowchart was created following the PRISMA 2020 guidelines.

Study (year)	Country	Sample size		Age	Gender (male/female)	TP	FP	FN	TN	Sensitivity (%)	Specificity (%)	(Refs)
		HGM	LGM									
Zhu (2019)	China	13	69	57.37 ± 12.30	23/59	11	14	2	55	0.846	0.797	12
Yang (2022)	China	10	17	–	–	9	1	1	16	0.9	0.924	13
Duan (2022)	China	94	94	HGM:56.28 ± 12.56; LGM:54.16 ± 10.10	HGM:44/50; LGM:17/77	80	15	14	79	0.85	0.87	14
Laukamp (2019)	Germany, USA	25	46	60.2 ± 13.6	31/40	20	5	5	41	0.79	0.89	15
Hamerla (2019)	Germany	45	102	61.9 ± 12.0	39/108	45	3	0	99	1	0.97	16
Park (2022)	Korea	15	46	HGM:56.73 ± 19.25; LGM:55.13 ± 13.61	HGM:5/10; LGM:15/31	13	14	2	32	0.846	0.698	17
Chen (2022)	China	33	31	Median: 49 (13–78)	27/37	29	6	4	25	0.88	0.81	18
Ke (2019)	China	19	60	HGM:47.05 ± 15.13; LGM:50.17 ± 12.04	HGM:7/12; LGM:19/41	16	13	3	47	0.84	0.78	6
Cai (2023)	China	31	129	HGM:64.58 ± 13.38; LGM:62.33 ± 10.35	HGM:16/15; LGM:43/86	20	23	11	106	0.63	0.82	19
She (2023)	China	31	91	HGM:56.35 ± 11.93; LGM:55.26 ± 12.23	HGM:10/21; LGM:20/71	29	27	2	64	0.94	0.7	20
Morin (2019)	USA	18	67	Median: 59 (18–89)	31/84	8	13	10	54	0.46	0.81	21
Hu (2020)	China	87	229	HGM:52.22 ± 12.63; LGM:53.29 ± 10.98	HGM:37/50; LGM:54/175	47	18	40	211	0.54	0.926	22
Han (2020)	China	10	17	52.27 ± 11.30	11/16	9	1	1	16	0.87	0.92	23
Zhao (2023)	China	22	120	52.6 ± 11.3	42/100	17	7	5	113	0.773	0.942	24
Park (2023)	Korea	15	33	Mean:54.9	11/37	11	9	4	24	0.73	0.73	25
Chen (2023)	China	27	127	52.47 ± 12.53	55/99	14	35	13	92	0.518	0.724	26
Han (2023)	China	36	128	53.18 ± 11.35	46/118	30	28	6	100	0.829	0.783	27
Guo (2022)	China	39	49	HGM:median 65; LGM:median 54	HGM:15/24; LGM:14/35	32	8	7	41	0.8205	0.8367	28
Cao (2022)	China	12	57	HGM:mean 60; LGM:mean 55	HGM:6/6; LGM:9/48	9	7	3	50	0.75	0.8772	29
Yan (2017)	China	21	110	52.89 ± 9.00	HGM:10/11; LGM:29/81	18	14	3	96	0.86	0.87	30
Chu (2020)	China	4	24	–	–	4	0	0	24	0.917	1	31

Table 1. Baseline characteristics of the included studies.

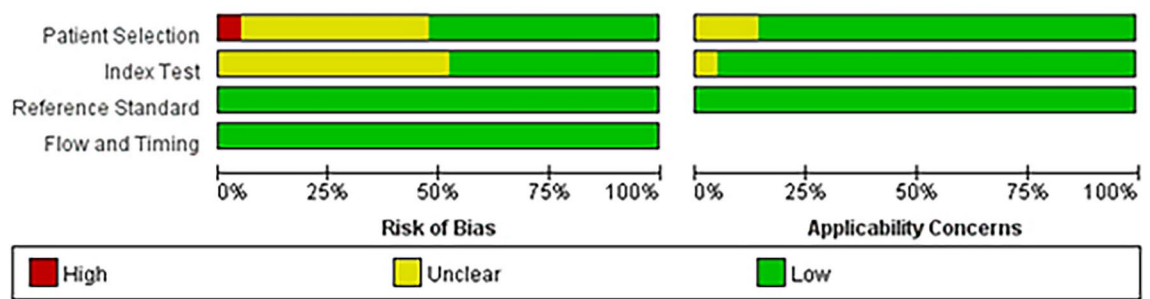


Fig. 2. Methodological quality summary graphs.

DOR

Due to the high heterogeneity of DOR ($I^2 = 100$), a random effects model was used for meta-analysis. The overall DOR of the study was 26.66 (95% CI 14.42–49.27; Fig. 6).

The AUC of the integrated SROC curve was 0.91 (95% CI 0.88–0.93). The results indicated that MRI radiomics had high diagnostic value in distinguishing the grading of meningiomas (Fig. 7).

Publication bias

Publication bias was examined, and a Deeks funnel plot was drawn (Fig. 8). Quantitative analysis showed no statistically significant difference ($P = 0.82$), which suggested that there was no publication bias.

Subgroup analysis

To investigate the source of heterogeneity, subgroup analysis was conducted based on country, modeling method, sample size, MRI sequence, and whether clinical factors were combined. According to Table 2, the results of each subgroup analysis were generally in line with the overall results, and there was no significant difference in heterogeneity between subgroups and the overall heterogeneity (all P values were greater than 0.05).

Discussion

Due to different phenotypes of tumors, tumor cell subsets are not consistent in terms of cell proliferation rate, morphology, karyotype, cell surface markers (antigenicity), biochemical metabolism, and invasion and metastasis ability. Imaging features were selected through high-throughput computers, and target data were classified using mathematical models, aiming to explore the correlation between imaging features and tumors at the cellular and molecular levels, which is currently a hot topic in medical research. Based on this, the concept of radiomics emerged in 2012¹⁰. The concept of radiomics is the comprehensive analysis of features using tools, such as MaZda, MATLAB, TexRAD, MISSTA, CAD, and FireVoxel, which can provide new quantitative imaging markers without the need for new acquisition devices or tracers, and it has stronger diagnostic capabilities than ordinary inspection methods. To systematically evaluate the accuracy of radiomics in distinguishing HGM and LGM, the author conducted this meta-analysis. The results proved that the combined SEN and SPE of MRI radiomics were 0.82 and 0.85, respectively, and PLR and NLR were 5.64 and 0.21, respectively. The AUC was 0.91, which indicated that MRI radiomics has high diagnostic value in the grading of meningiomas. Previous meta-analyses³³ systematically reviewed and evaluated the methodological quality of studies using radiomics for the diagnosis and prediction of intracranial meningiomas. The overall quality score and percentage quality score of radiomics have moderate to good inter-reader reproducibility. This meta-analysis showed an overall AUC of 0.88 (95% CI 0.84–0.93) with a standard error of 0.02. The AUC value in this study was 0.91 (95% CI 0.88–0.93), which surpassed that of previous studies. The primary focus of this study was the classification of HGM and LGM based on MRI radiomics. Importantly, this study not only complemented prior research but also underscored the significance of MRI radiomics.

Compared with WHO grade 1 meningiomas, HGM is potentially malignant, with a high risk of local recurrence, poor prognosis, and low overall survival rate. Therefore, the accurate preoperative prediction of meningioma recurrence and brain invasion becomes extremely important. According to a multi-center study²¹, a low spherical shape of meningiomas is associated with a high local recurrence rate and low survival rate. The RF model, which integrates image-based features with clinical features, demonstrates the highest predictive performance, with an AUC of 0.78. Zhang et al.⁸ used a SVM prediction model based on T1-weighted imaging (T1WI) enhancement and T2-weighted imaging (T2WI) sequences to foresee the potential of meningioma invasion before surgery. The research results highlighted that the AUC reached as high as 0.82. Wang et al.³⁴ employed MRI radiomics features to develop a model based on preoperative contrast-enhanced T1WI and T2WI magnetic resonance imaging, aiming to precisely predict meningioma venous sinus infiltration before surgery. The areas under the curve for the training and validation groups were 0.86 and 0.82, respectively, which was helpful for selecting surgical approaches and predicting prognosis. In summary, precise preoperative prediction of meningioma grading holds significant importance.

The included literature used a variety of MRI sequences, and functional imaging sequences can provide more information on physiology, hemodynamics, and other information that conventional sequences cannot provide. However, unconventional sequences are not widely used in clinical practice as conventional MRI sequences.

	Risk of Bias				Applicability Concerns		
	Patient Selection	Index Test	Reference Standard	Flow and Timing	Patient Selection	Index Test	Reference Standard
Yan 2017	+	?	+	+	+	+	+
Hamerla 2019	?	?	+	+	+	+	+
Ke 2019	+	?	+	+	+	+	+
Laukamp 2019	●	?	+	+	+	+	+
Morin 2019	?	+	+	+	+	+	+
Zhu 2019	?	+	+	+	+	+	+
Chu 2020	+	?	+	+	+	+	+
Han 2020	?	?	+	+	?	?	+
Hu 2020	+	+	+	+	+	+	+
Cao 2022	+	+	+	+	+	+	+
Chen 2022	+	?	+	+	+	+	+
Duan 2022	?	?	+	+	+	+	+
Guo 2022	+	?	+	+	+	+	+
Park 2022	+	+	+	+	+	+	+
Yang 2022	?	+	+	+	+	+	+
Cai 2023	?	+	+	+	+	+	+
Chen 2023	+	+	+	+	+	+	+
Han 2023	?	+	+	+	?	+	+
Park 2023	?	+	+	+	?	+	+
She 2023	+	?	+	+	+	+	+
Zhao 2023	+	?	+	+	+	+	+

● High
? Unclear
+ Low

Fig. 3. Methodological quality of individual studies.

Image-based radiomics data that were extracted from conventional MRI seems to be a more practical and direct solution. How to standardize image-based radiomics in conventional sequences may help its clinical application.

The entire process of image-based radiomics research involves repeatability and quality control, including data acquisition, feature extraction and selection, modeling, and validation. Particularly, patient inclusion and exclusion criteria can lead to different usability analyses for different populations, especially for small cohort studies. Therefore, it is necessary to adopt standardized inclusion and exclusion criteria and use open dataset to proceed model validation and improve the reproducibility and quality control of radiomics research³⁵. In

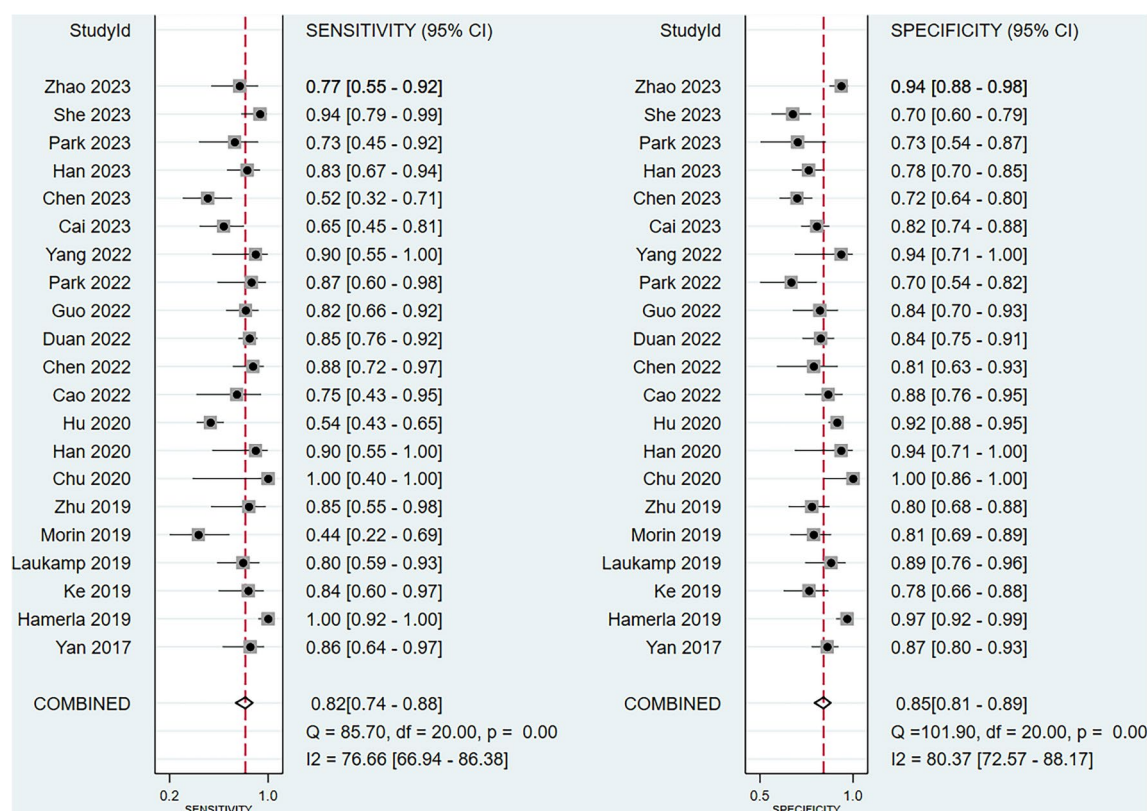


Fig. 4. Forest plot of the sensitivity and specificity of magnetic resonance imaging radiomics for the diagnosis of Meningiomas.

total, 76.2% (16/21) of the literature included in this article underwent external validation, thus enhancing the reproducibility and quality control of MRI radiomics and mitigating the risk of false positives and overly optimistic results. Currently, the application of MRI radiomics in meningiomas is still in its initial stage. The small sample size involved in most studies may lead to overfitting of the model. What's more, 57.1% (12/21) of the studies included in this article took measures to avoid overfitting. In the future, additional prospective, multi-center, and large-scale studies are required to enhance the applicability of findings across diverse populations. Due to differences in scanning sequences, feature extraction algorithms, and screening methods, radiomics features exhibit significant variations. To address these challenges, future research should follow standardized guidelines for radiomics research and incorporate the RQS scoring system. RQS, as a quality assessment tool in the field of radiomics, can provide objective quality evaluation standards for various stages of research, further improve the transparency and overall quality of research, and ensure the reproducibility and reliability of research results. By strictly implementing scoring criteria such as RQS, radiomics research will be able to better standardize its development process and gain wider application in clinical practice.

To explore the sources of heterogeneity, subgroup analysis was conducted in this study. There was no significant difference, which highlighted that the results of this study are reliable and highly representative. However, this study has certain limitations. (1) Most of the radiomics studies included in this research were single-center and retrospective in nature (20/21), and thus the case number was relatively small. Due to the lack of sufficient data to train the models, the statistical results may lack generalizability and reproducibility, with selection bias, which could be one of the reasons for the high accuracy observed in this study. Therefore, prospective large-sample multi-center collaborative studies are required in future research to provide reliable evidence for the clinical application of radiomics. (2) Although radiomics models help in distinguishing between HGM and LGM, they involve a variety of analytical methods. In terms of modeling approaches, various factors, such as model generalizability, feature selection methods, lack of standardization in model selection and evaluation, and model interpretability and robustness, could all impact data accuracy. (3) The included literature exhibited high heterogeneity, and subgroup analyses did not identify the sources of this heterogeneity, but was only preliminarily explored. (4) It is challenging to standardize the specifics of imaging techniques or algorithms, which leads to differences in model generalizability, challenges in reproducibility, and difficulties in clinical application. These discrepancies not only affect the integration of research findings in the field of radiomics but also hinder the application of these models in clinical practice. However, using specific imaging techniques or algorithmic details, such as high-quality imaging data or strategies to avoid overfitting during model training, the high accuracy of MRI radiomics in distinguishing between HGM and LGM can be further explained.

Radiomics provides a new and effective approach for preoperative assessment of meningioma malignancy, especially in cases where traditional imaging analysis struggles to accurately differentiate tumor grades.

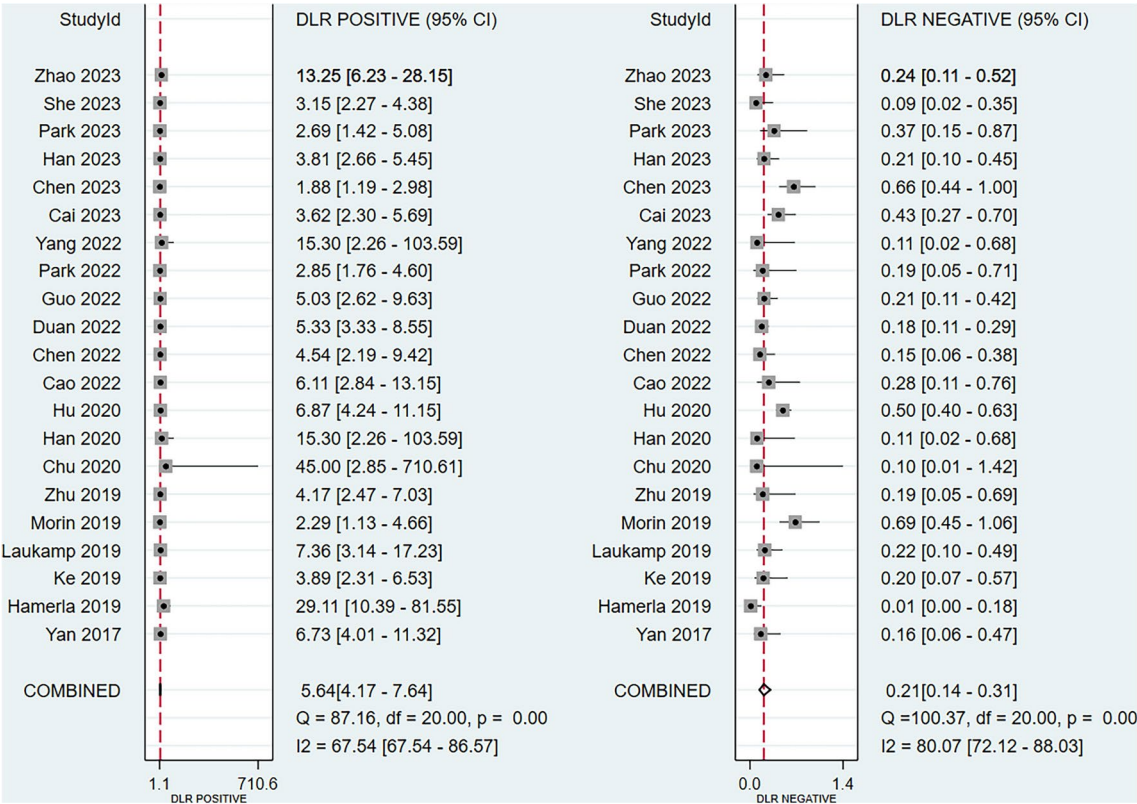


Fig. 5. Forest plot of the PLR and NLR of magnetic resonance imaging radiomics in the diagnosis of Meningiomas.

Meanwhile, this technology offers clinicians more precise diagnostic information for the development of personalized treatment plans, such as optimizing surgical strategies and evaluating the necessity of postoperative radiotherapy. To further enhance its clinical value, the current focus of research should be on standardizing radiomics techniques. Standardization encompasses all stages, from data acquisition and feature extraction to model validation, which could not only improve the reproducibility of radiomics research results but also enhance cross-center comparability. Such standardization will lay a solid foundation for the widespread application of radiomics in clinical practice. We suggest that future studies should focus on establishing unified technical standards and guidelines to ensure consistency in research outcomes and promote the adoption of this technology in clinical settings. At the same time, future research may benefit from using updated evaluation tools, such as CLEAR³⁶ and METRICS³⁷, which can help further improve the transparency and methodological rigor of radiomics research.

Conclusion

In summary, although additional research is required to validate the most suitable techniques, radiomics holds promise as an accurate tool for the identification of the grading of meningiomas. The establishment of a standardized application of radiomics will significantly enhance the diagnostic precision and the accuracy of clinical decision-making for the grading of meningiomas in the future.

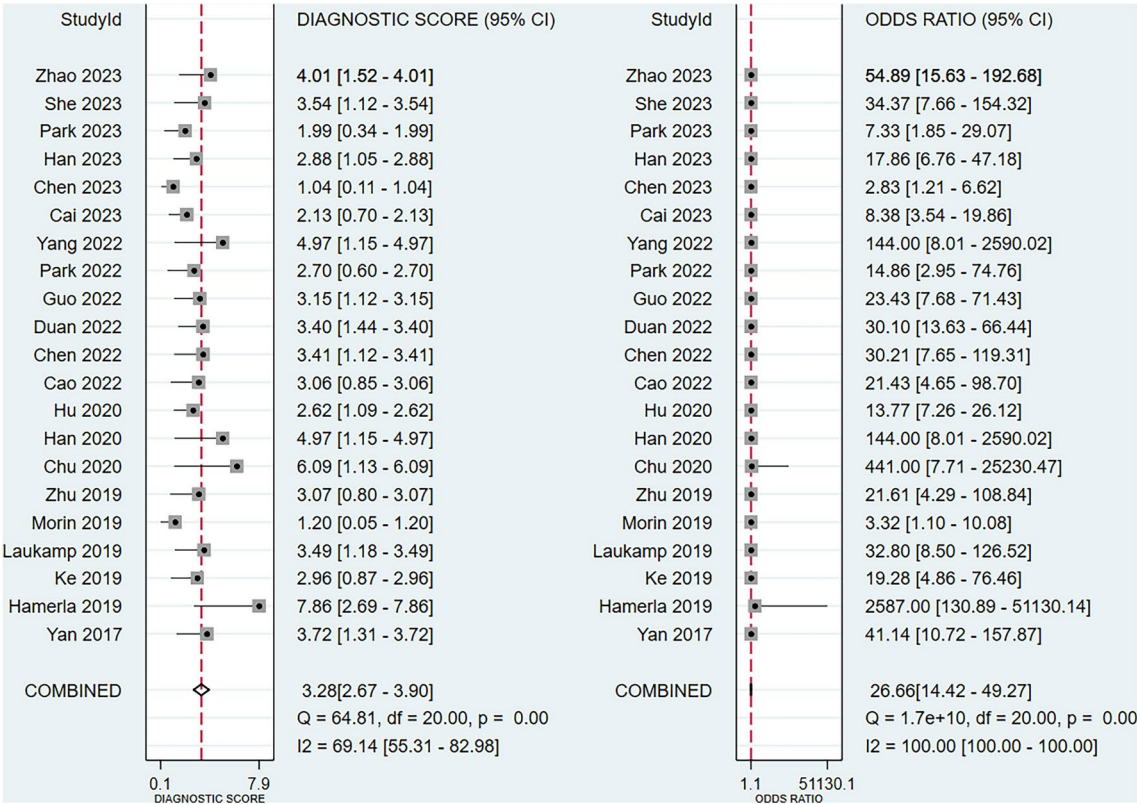


Fig. 6. Forest plot of the DOR of magnetic resonance imaging radiomics for the diagnosis of Meningiomas. Diagnostic odds ratio.

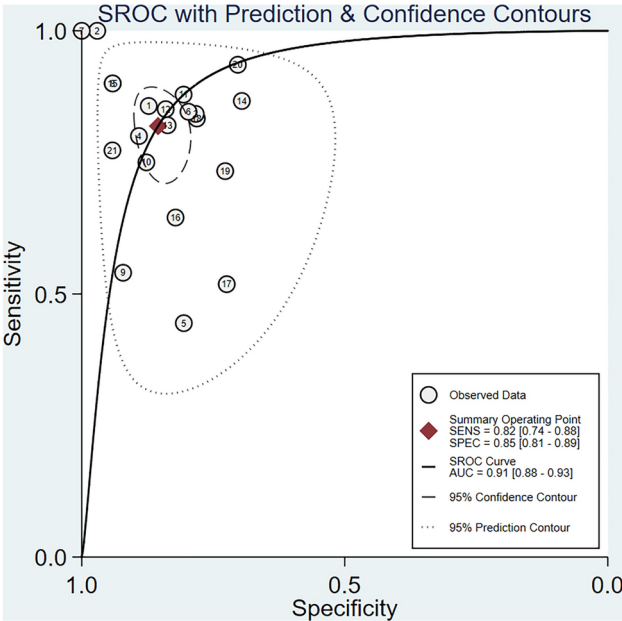


Fig. 7. SROC curve of magnetic resonance imaging radiomics for the diagnosis of Meningiomas. SROC summary receiver operating characteristic, SENS sensitivity, SPEC specificity, AUC area under the curve.

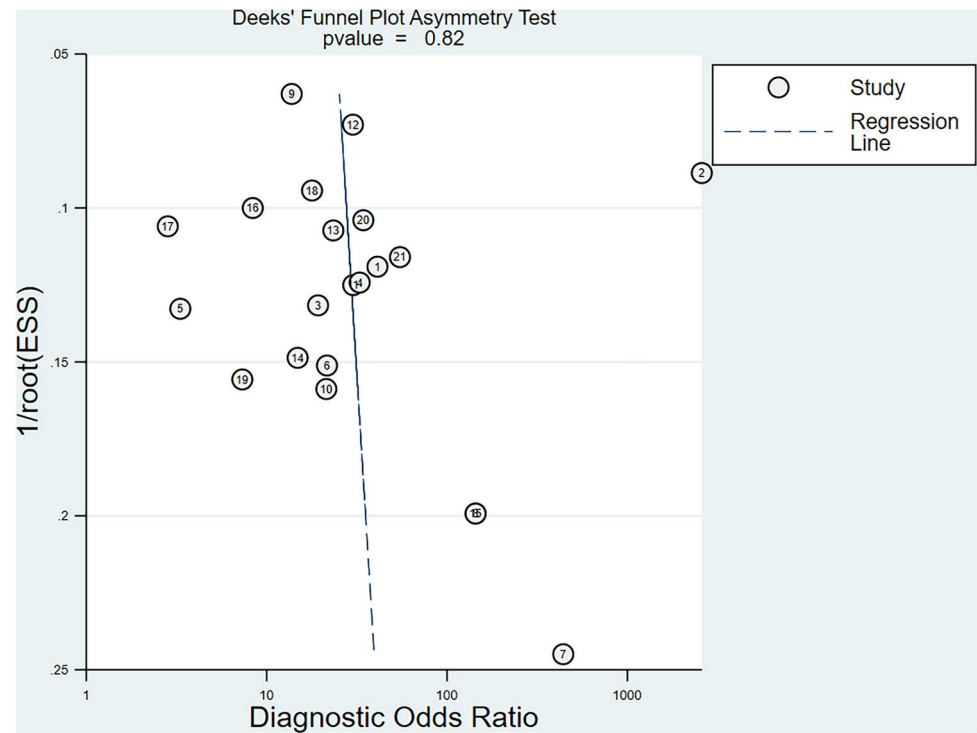


Fig. 8. Deeks’ funnel plot of magnetic resonance imaging radiomics for the diagnosis of Meningiomas. ESS effective sample size.

Subgroup	No. of studies	Sensitivity (95% CI)	Specificity (95% CI)	AUC (95% CI)	DLR+ (95% CI)	DLR– (95% CI)	DOR (95% CI)
Country							
China	16	0.80 (0.73–0.86)	0.85 (0.81–0.89)	0.90 (0.87–0.92)	5.36 (4.0–7.05)	0.23 (0.16–0.32)	23.22 (14.04–38.40)
Other	5	0.85 (0.53–0.97)	0.85 (0.71–0.93)	0.91 (0.88–0.93)	5.81 (2.36–14.32)	0.17 (0.04–0.77)	33.86 (3.37–340.56)
Modeling method							
Deep learning	4	0.80 (0.56–0.92)	0.79 (0.71–0.85)	0.924 (0.872–0.984)	3.82 (2.12–6.09)	0.25 (0.09–0.59)	15.17 (3.67–62.55)
Radiomics	12	0.83 (0.76–0.88)	0.83 (0.78–0.87)	0.90 (0.87–0.92)	4.81 (3.76–6.16)	0.21 (0.15–0.29)	23.04 (14.33–37.04)
Machine learning	5	0.80 (0.51–0.94)	0.91 (0.82–0.96)	0.94 (0.91–0.95)	8.78 (3.56–21.70)	0.22 (0.07–0.69)	40.65 (5.79–285.42)
Sample size							
> 100	9	0.82 (0.67–0.91)	0.86 (0.79–0.91)	0.91 (0.88–0.93)	6.06 (3.62–10.14)	0.21 (0.10–0.42)	29.25 (9.70–88.19)
< 100	12	0.81 (0.73–0.88)	0.83 (0.78–0.88)	0.89 (0.86–0.92)	4.92 (3.60–6.71)	0.22 (0.15–0.33)	22.05 (11.76–41.33)
MRI sequence							
Multi-parametric	15	0.81 (0.72–0.88)	0.85 (0.80–0.89)	0.90 (0.87–0.93)	5.49 (3.91–7.73)	0.22 (0.14–0.34)	25.23 (12.83–49.64)
Enhanced T1WI	6	0.85 (0.68–0.94)	0.86 (0.77–0.92)	0.92 (0.89–0.94)	6.03 (3.24–11.23)	0.17 (0.07–0.43)	35.71 (7.89–156.82)
Combine clinical factors							
Yes	4	0.83 (0.76–0.88)	0.88 (0.77–0.94)	0.84 (0.81–0.87)	6.79 (3.51–13.12)	0.19 (0.13–0.29)	34.94 (14.72–82.90)
No	17	0.82 (0.72–0.89)	0.85 (0.80–0.89)	0.90 (0.87–0.93)	5.45 (3.90–7.62)	0.21 (0.13–0.34)	26.16 (12.48–54.83)

Table 2. Heterogeneity analysis results included in the study.

Data availability

Some or all data, models, or code generated or used during the study are available from the corresponding author by request.

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Author contributions

Guarantor of integrity of the entire study: YK; study concepts and design: SX; literature research: SZ; statistical analysis: SZ; manuscript preparation: SX and SZ; manuscript editing: YK. Particularly, SX and SZ are co-first authors of the article because they contributed to the work equally.

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Competing interests

The authors declare no competing interests.

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