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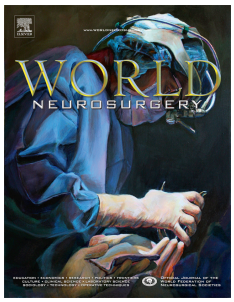

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MRI for predicting BI in meningiomas

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MRI Features for predicting brain invasion in meningiomas: A Systematic Review and Meta-Analysis

Abstract

PURPOSE: To systematically assess the MRI features of brain invasion (BI) in meningiomas and to evaluate the diagnostic performance of MRI for prediction of BI in meningiomas.

METHODS: A comprehensive search was conducted on Web of Science, PubMed, and EMBASE from January 1, 2016, to August 1, 2024, to confirm concerned eligible original articles. Data extracted from the articles included sample size, number of patients with BI or without BI, mean age, male/female ratio, authors, publication year, duration of patients, study design, strength (T) of magnet field, imaging sequences utilized, utilization of radiomics, and the reference standard methodology.

RESULTS: This systematic review included fourteen eligible articles investigating the MRI characteristics of BI in meningiomas. Meningiomas with BI exhibited higher volumes of peritumoral edema, irregular tumor shape, incomplete CSF cleft sign, heterogeneous contrast-enhancement, larger sizes, unclear tumor-brain interface, and lower mean ADC value. The meta-analysis involved twelve original studies, the summary area under the curve (AUC) of MRI for predicting BI in meningiomas was 0.91 (95% CI, 0.88–0.93, SE=0.0165, p=0.0185), with summary sensitivity and specificity of 0.85 (95% CI, 0.81–0.89, p<0.001)

and 0.83 (95% CI, 0.76-0.89, p<0.001), respectively. In subgroup analyses, those studies incorporated two or more sequences demonstrated superior sensitivity (0.86 vs. 0.82) and specificity (0.85 vs. 0.68) than these studies involved one sequence, especially, in the addition of ADC appears to further increase diagnostic performance, with the summary sensitivity was 0.89 and the summary specificity was 0.88. Studies with a sample size larger than 200 patients had higher sensitivity (0.86 vs 0.79) and specificity (0.85 vs 0.76). Researches contained the features from brain-to-tumor interface showed better sensitivity (0.89vs. 0.81) and DOR (44.3vs. 20.1), but similar specificity (0.84 vs 0.83). In addition, researches using radiomics showed better specificity (0.85 vs. 0.80) and DOR (34.8 vs. 28.9), but exhibited a lower sensitivity (0.83 vs. 0.91).

CONCLUSION: MRI demonstrated favorable diagnostic efficacy for prediction of BI in meningiomas. The diagnostic performance of MRI was notably influenced by the specific MR sequences employed, sample size, and the characteristics observed at the brain-tumor interface.

KEYWORDS: Meningioma, brain invasion (BI), MRI, tumor-brain interface.

MRI Features for predicting brain invasion in meningiomas: A Systematic Review and Meta-Analysis

1. Introduction

Brain invasion (BI) in meningiomas is characterized by tumor cells infiltrating the surrounding cerebral parenchyma in the absence of leptomeningeal structures [1, 2]. In 2016, BI was identified independent criterion for grade 2 meningioma in the World Health Organization (WHO) Classification of Tumors of the Central Nervous System (CNS) [3]. Although, some scholars have failed to establish a correlation between BI and meningioma prognosis[4], a classification that has been retained in the most recent 2021 edition [5]. BI of meningioma as a classification criterion for meningioma has been controversial. However, Li et al.[6] demonstrated a significant stratification of relapsed-free survival between grade 1 meningiomas and grade 1 meningiomas with BI in a study that included 1006 samples. In addition, Luo et al.[7] confirmed through retrospective analysis that compared with grade 1 meningiomas, grade 1 meningiomas complicated with brain invasion were more similar to grade 2 meningiomas in clinical manifestations and imaging features. As a result, they proposed the classification of, grade 1 meningiomas complicated with brain invasion as grade 2 meningiomas. Furthermore, BI has performed an important role in determining adjuvant radiotherapy and

trial inclusion[8-10]. Numerous, studies demonstrated BI as a stronger predictor for perioperative complication[11, 12], with the presence of BI increasing the risks of preoperative seizures and postoperative hemorrhage[13, 14]. Moreover, compared to non-invasive atypical meningiomas, BI showed a 3.5-fold increased incidence of tumor recurrence[15]. Considering the growing clinical significance, especially before surgery intervention, a comprehensive understanding of BI in meningiomas is imperative. This knowledge will significantly contribute to preoperative evaluations and the formulation of personalized treatment strategies for patients with meningiomas.

At present, the golden standard of BI in meningiomas relies on postoperative histopathological examination[16]. However, surgical biopsies may under-sample areas that have histological characteristics such as aggressiveness, potentially resulting in misdiagnosis of meningioma grade. The limitation of surgical sampling provides an opportunity for medical imaging. For CNS tumors, MRI is the most commonly used preoperative imaging method, offering a non-invasive and reproducible method to characterize the entire tumor and its interface with the brain. Identifying MRI features associated with tumor invasion can aid in directing biopsy placement. Therefore, the non-invasive and comprehensive assessment of meningioma BI by MRI before surgery may have great potential in clinical practice.

Several researchers have reported the MRI features and the diagnostic efficacy of MRI for the prediction of BI in meningiomas[17-20]. However, to our knowledge, a comprehensive systematic evaluation of MRI for predicting BI in meningiomas has not been conducted. Therefore, we aim to systematically assess the MRI features of BI in meningiomas and to evaluate the diagnostic efficacy of MRI for the prediction of BI in meningiomas.

2. Methods

This study was performed following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines[21].

2.1 Literature search

We conducted a comprehensive search on Web of Science, PubMed, and EMBASE from January 1, 2016, to August 1, 2024, to identify relevant original studies meeting the inclusion criteria. The search strategy utilized: ((((Magnetic Resonance Imaging) OR (MRI)) OR (MRI)) AND ((meningioma) OR (meningiomas))) AND ((brain invasion) OR (brain infiltration))). Besides, the bibliographies of the confirmed original articles were manually filtered to enlarge the search. The literature search was limited to publications in the English language.

2.2 Inclusion criteria and Exclusion criteria

Studies were included based on the following criteria: 1) all patients with meningioma suffered operative treatment and were explicitly graded

by histopathological analysis; 2) MRI was performed before operative resection; 3) BI was confirmed by the pathological records or operative records which described apparent conglutination between the margin of the tumor and the brain parenchyma; 4) Original articles provided data necessary to establish a 2 x 2 table, including true-positive (TP), false-positive (FP), false-negative (FN), and true-negative (TN) values. Studies were excluded if they met the following criteria: 1) abstracts from conferences, reviews, letters, comments, or case reports/case series with fewer than 10 patients; 2) not focused on the application of MRI for predicting BI in meningiomas; and 3) overlapping patient cohorts in multiple studies.

2.3 Data extraction and quality assessment

The following data were extracted from the selected studies: sample size, number of patients with BI or without BI, mean age, male/female ratio, authors, publication year, duration of patients, study design, strength (T) of magnet field, imaging sequences utilized, utilization of radiomics, and the reference standard methodology. Two investigators independently extracted these data, resolving any discrepancies through discussion. The quality assessment of the involved studies applied the Quality Assessment of Diagnostic Accuracy Studies-2 (QUADAS-2)[22].

2.4 Statistical analysis

Statistical analysis was conducted using Stata SE 15.0 and Meta-Disc

1.4 software. 2×2 tables were reconstructed from the eligible studies to compute the sensitivities, specificities, positive likelihood ratios (PLR), negative likelihood ratios (NLR), and diagnostic odds ratios (DOR). The pooled sensitivity, specificity, PLR, NLR, DOR, and their 95% confidence intervals (95% CIs) were computed by a bivariate random effect model. An integrated hierarchical summary receiver operating characteristic (HSROC) map and the curve area under the HSROC curve (AUC) were applied to calculate the diagnostic efficiency of MRI for predicting BI in meningioma. Heterogeneity was assessed based on the following ways: (1) Cochran's Q test, with a *p*-value > 0.1 indicating no significant; (2) Higgins inconsistency index (I2) test, an I2 value higher than 50% indicated noteworthy heterogeneity. A Spearman correlation coefficient of less than 0.6 indicates the absence of a threshold effect. In Deeks' funnel plot asymmetry test, the *p*-value > 0.05 was considered the absence of publication bias. Subgroup analysis and sensitivity analysis were performed to seek out the factors for heterogeneity. The covariates of the subgroup covered: 1) magnet field strength; 2) methods of reference standard; 3) containing the features from the brain-to-tumor interface, in some studies of the included studies, the brain-to-tumor interface ROI refers to a boundary region which the script concurrently move the outline N mm inward and N mm outward generated a 2 × N mm extension of the tumor boundary; 4) study using radiomics; 5)

sample size; and 6) scanning sequences.

3. Results

3.1 Literature search

This study included fourteen eligible articles estimating the MRI features of BI in meningioma, involving a total of 7593 patients, were involved in this study. The process of literature selection is described in Figure 1.

3.2 Characteristics of included studies

Table 1 presents the characteristics of the studies and patients included in the analysis. All the studies were of retrospective nature. The sample size of the studies ranged from 55 to 1728. Among the fourteen included studies[17, 19, 20, 23-33], five utilized both pathology results and operative records as the reference standard for identifying BI in meningiomas[24 26, 27, 33, 34], while the remaining nine studies utilized only pathology result as the reference standard[17, 19, 20, 23, 25, 28, 29, 32, 35]. Two studies utilized 3.0T MRI scanner[32, 35],while eleven studies utilized 1.5T and 3.0T MRI scanners[17, 19, 20, 23, 24, 26-29, 33, 34], The magnetic field strength of the MRI scanner was not reported in one study [25]. All studies employed conventional MRI sequences, with three studies utilizing a single sequence, specifically T2WI or CE-T1WI,[25, 28, 35], and the remaining eleven studies incorporating two or more sequences, including T1WI, T2WI, DWI, FLAIR, CE-T1WI, ADC[17, 19, 20, 23, 24, 26, 27, 29, 32-34]. Among the included studies, eight employed the radiomics approach [17, 24, 26-28, 33-35], with six of

them including additional validation cohorts[23, 26-28, 33, 34]. In the eight radiomics researches, various classification models were classification performed, including random forest, logistic regression, Convolutional Neural Network, nomogram, and support vector machine. In twelve of the fourteen involved articles, the investigators were blinded to the BI status[17, 19, 20, 23, 24, 26-29, 32, 33, 35]; however, this information, was not reported in the remaining two studies[25, 34]. Three studies contained the information from brain-to-tumor interface[27, 28, 34].

3.3 Imaging Characteristics of Meningiomas with BI: A Systematic Review

Eight studies revealed that meningiomas with BI showed more peritumoral edema volume than meningiomas without BI(χ^2=246.970, p<0.001)[20, 25, 26, 28, 29, 32-34]. Additionally, four studies showed that irregular tumor shape was significantly more frequent in BI meningiomas(χ^2 =102.028, p<0.001)[19, 25, 26, 33]. Four studies demonstrated meningiomas with BI have unclear tumor-brain interface(χ^2=28.750, p<0.001) (li, luo, jiang, zhang2022). Three study indicated the sizes of meningiomas with BI were significantly larger than meningiomas without BI(χ^2=41.448 p<0.001) (jiang) [20, 26]. Two studies found that the incomplete CSF cleft sign was more frequent in meningiomas with BI(χ^2=21.274, p<0.001)[28, 29]. Heterogeneous contrast enhancement was revealed in BI meningiomas (χ^2=22.976, p<0.001)[19, 26]. Besides, on DWI, meningiomas with BI showed

lower mean ADC value than meningiomas without BI[20, 23, 31]. One study suggested in meningiomas with BI, features such as lobulated sign, vascular flow void, bone invasion, unclear tumor-brain boundary, finger-like protrusion, and mushroom sign were more familiar than in meningiomas without BI [20]. Furthermore, one study showed that meningiomas with BI were more commonly located in the anterior cranial fossa but less frequently found in the midline convexity. These BI-associated meningiomas exhibited higher rates of hyperostosis and a hypointense signal on T2-weighted imaging compared to meningiomas without BI [28]. Additionally, a rare finding that enlarged pial feeding artery was found in BI [29].

3.4 Diagnostic Efficacy of MRI for Prediction of BI: A Meta-Analysis

Twelve studies[17, 19, 20, 23, 24, 26-28, 32-35], involving a total of contained 6449 patients, assessed the diagnostic efficacy of MRI for predicting BI in patients with meningiomas. The results of the quality assessment of these studies using the QUADAS-2 tool are depicted in Figure 2. The sensitivities of the individual involved articles were 0.69 to 0.93, while the specificities were 0.68 to 0.98. The Q test revealed that heterogeneity existed (Q=43.4, p<0.001) in the Twelve articles. Higgins I2 statistic demonstrated moderate heterogeneity in sensitivity (I2= 79.83%) and obvious heterogeneity in specificity (I2= 95.80%). The Spearman correlation coefficient was 0.018 (p = 0.957), indicating no threshold

effect. The pooled sensitivity was 0.85 (95% CI, 0.81–0.89, p<0.001), and the pooled specificity was 0.83 (95% CI, 0.76-0.89, p<0.001), Figure 3. The diagnostic odds ratio (DOR) was 29 (95% CI, 17-50, p<0.001). The area under the HSROC curve (AUC) was 0.91 (95% CI, 0.88–0.93, SE=0.0165, p=0.0185), Figure 4. Deeks funnel plot demonstrated that publication bias was not significant (p=0.42), as shown Figure 5.

To explore the reasons for heterogeneity, a meta-regression analysis and subgroup analysis were conducted. Among these potential covariates examined, magnetic field strength, utilization of radiomics, and the reference standard methodology, along with the inclusion of features from the brain-to-tumor interface, sample size of training group were found to be associated with the heterogeneity in sensitivity, MR sequence was found to be associated with the heterogeneity in sensitivity and specificity. Subgroup analysis demonstrated that MR sequences and sample size significantly affected the diagnostic efficacy of MRI in predicting BI (Table 2). When comparing to studies involving one sequence, those studies that incorporating two or more sequences demonstrated superior diagnostic performance, with a summary sensitivity of 0.86 and specificity of 0.85, especially, in the addition of ADC appears to further increase diagnostic performance, with the summary sensitivity was 0.89 (95% CI, 0.85-0.93, p=0.002, I2=84.3%) and the summary specificity was 0.88 (95% CI, 74% – 95%, p<0.001,

I2=98.6%). In the present meta-analysis, studies with a sample size larger than 200 patients had higher sensitivity (0.86 vs 0.79), specificity (0.85 vs 0.76), and DOR (37.8 vs. 9.9). Researches contained the features from brain-to-tumor interface showed better sensitivity (0.89vs. 0.81) and DOR (44.3vs. 20.1), but similar specificity (0.84 vs 0.83). Researches using radiomics showed better specificity (0.85 vs. 0.80) and DOR (34.8 vs. 28.9), but exhibited a lower sensitivity (0.83 vs. 0.91).

4. Discussion

Our study found that meningiomas with BI may exhibit characteristics such as increased peritumoral edema, irregular tumor shape, lower ADC values, indistinct tumor-brain boundary, absence of CSF cleft sign, presence of enlarged pial feeding arteries, and heterogeneous contrast enhancement. The study underscored the significance of peritumoral edema volume as a crucial imaging predictor of BI in meningiomas[25, 27]. This observation could be attributed to several factors, including the absence of an intact arachnoid surface at the interface between the tumor and brain parenchyma, damaged pial artery supply, and decreased vascular endothelial growth factor (VEGF) expression[36, 37]. However, it is important to acknowledge that benign meningiomas without BI often exhibit peritumoral brain edema due to compressive ischemia, mechanical venous obstruction, and increased hydrostatic pressure within the tumor. Although Adeli et al. [25]have proposed a specific cut-off value

for the volume of peritumoral edema (3.64 ccm), further extensive validation of these conventional imaging features is warranted. Additionally, the determination of a definitive cut-off value for peritumoral edema volume should be confirmed in the further studies. Based on these MRI features, multidisciplinary teams can develop patient-specific surgical plans, enabling complete resection of the lesion while the preserving as much normal surrounding brain tissue as possible. Simultaneously, these MRI features can help in stratifying meningioma patients into different risk categories for BI. Patients with high-risk features should undergo intensified postoperative surveillance to reduce the perioperative complications, such as hemorrhage. Furthermore, a preliminary estimate of BI can be made based on the MRI features of meningiomas in advance, guide specimen sampling, improve the accuracy of the pathological diagnosis of brain invasion. This could help patients receive timely adjuvant therapy after surgery, thereby improving overall outcomes.

The current study demonstrated that MRI exhibited a favorable diagnostic efficacy (AUC=0.91) in noninvasively predicting BI in meningiomas. The pooled sensitivity was 0.85 (95% CI, 0.81–0.89), and the pooled specificity was 0.83(95% CI, 0.76-0.89). This meta-analysis demonstrated that the studies that contained the features from the brain-to-tumor interface showed a better diagnostic performance than those

studies that only focused on mass features. This improvement could be linked to the behavior of malignant central nervous system tumors, such as glioblastoma, which typically grow invasively and infiltrate surrounding tissues. The actual tumor boundaries may extend beyond what is visible macroscopically by several millimeters [38]. Similarly, in invasive meningiomas, infiltrative and cluster-like invasion patterns may not be easily detected using conventional medical imaging techniques[16]. Joo et al.[27] and Li et al.[28] utilized AFNI/Skimage for the automated segmentation of the brain-to-tumor interface ROI, employing a morphology approach where the boundary was expanded internally and externally to create a brain-to-tumor area of 10 mm thickness. In the study by Xiao et al.[34], each patient had four brain-to-tumor areas with widths of 10, 8, 6, and 4 mm. They stated that brain-tumor interface MRI features with a boundary width of 8 mm showed the best diagnostic performance. However, the incorporation of the brain-to-tumor interface ROI is limited in current studies, underscoring the need for further investigations to validate these findings and determine optimal widths of the brain-to-tumor interface.

Assessments incorporating two or more MRI sequences, particularly ADC images, demonstrated markedly enhanced diagnostic performance in contrast to those utilizing only a single sequence, in the subgroup analysis. T2 images are more effective at measuring edema and are

typically used on water-rich tissue [39]. T2-FLAIR images can effectively suppress the high signal from free water and enhance lesion. T1C images are not only typically used to represent tumor boundary and blood flow but can also be used to assess the level of tumor invasiveness[40]. DWI and ADC images provide information on the diffusion of water molecules within tissues, and help in delineating the boundaries and extent of tumors. As a result, multisequence models may be more sensitive in display details about tumors and have a higher diagnostic capacity than use a single sequence alone. Despite the heterogeneity, in multi-sequence study, in the addition of ADC appears to further increase diagnostic performance, with the summary sensitivity was 0.89 (95% CI, 0.85-0.93, p=0.002, I2=84.3%) and the summary specificity was 0.88 (95% CI, 74% – 95%, p<0.001, I2=98.6%). Therefore, we cautiously recommend a variety of imaging sequences including ADC for the detection BI in meningiomas. Moreover, in the current meta-analysis, studies involving patients less than 200 had lower diagnostic performance than studies performed with a larger sample (≥200). A larger sample size enhances the statistical power of diagnostic tests, stabilizes the estimation of sensitivity and specificity, and narrows the confidence intervals, thereby improving diagnostic efficacy. Consequently, it is imperative to maximize the sample size in diagnostic trials to enhance the accuracy and reliability of the diagnosis.

The present meta-analysis involved 7 studies that assessed the diagnostic performance of radiomics methods in predicting BI in meningiomas, with a summary sensitivity of 0.83(95% CI, 0.80–0.87) and a summary specificity of 0.85(95% CI, 0.78–0.92). Radiomics can extract numerous parameters from tumors and related regions, containing intensity texture and geometric features that are typically challenging to discern on conventional imaging and imperceptible to the human eyes[41]. Currently, radiomics methods are widely used in predicting molecular and biological behavior characteristics of CNS tumors[42-45], often exhibiting superior diagnostic performance compared to traditional methodologies. Furthermore, Xiao et al.[34] and Joo et al.[27] have demonstrated that the inclusion of radiomics features alongside peritumoral edema volume results in enhanced diagnostic performance for distinguishing meningiomas with BI when compared to models based solely on edema volume. However, our analysis of studies incorporating radiomics methods revealed higher DOR and specificity, albeit with lower pooled sensitivity compared to other investigations. This discrepancy may be attributed to the data-driven nature of radiomics methods, which heavily relies on data quality. The lack of standardized protocols across institutions introduces variability, that encompass imaging protocols, feature extraction, feature selection, and classification models. This is a significant challenge and limitation in the field of

radiomics. Hence, more large sample size, multi-center studies are required to explore the most suitable MRI sequences, radiomics features and machine learning algorithms. Furthermore, Overfitting is a prevalent issue in radiomics, wherein models exhibit high performance on training data but demonstrate limited generalizability to slightly different scenarios, unless trained on a highly diverse dataset [46]. To mitigate this problem, it is recommended to employ strategies such as increasing sample size, utilizing cross-validation, and incorporating multiple imaging methods in the training cohort. Additionally, the inclusion of a separate test cohort is essential to ensure the diagnostic efficacy in the training cohort[47, 48].

This meta-analysis revealed substantial heterogeneity in the sensitivity (I2 =79.83%) and specificity (I2 =96.9%). While the meta-regression and subgroup analysis provided insights into some sources of heterogeneity, some other reasons of the heterogeneity had not been found. In our meta-analysis, seven studies took pathology as the reference standard, whereas the remaining five studies utilized both pathology and operative records as reference standards. It has been noted that a significant proportion of surgical specimens may be deemed unassessable pathologically [49, 50], potentially contributing to the substantial heterogeneity observed in sensitivity and specificity estimates. However, it is difficult to obtain extensive tumor-brain interface specimen tissue during surgical resection.

Besides, the utilization of cavity ultrasonic aspirators intra-operative is an additional reason for the heterogeneous assessment of BI. The establishment of standardized criteria for surgical sampling and neuropathological analyses related to BI remains a subject of debate. Consequently, BI in meningiomas may not be consistently identified solely through histopathological examination. It is imperative to establish a noninvasive, efficient, and reliable method for detecting BI. To discern whether a meningioma has infiltrated the surrounding brain tissue, the development of imaging standardization protocols for BI should be guided by established pathological evidence.

Limitations

It is noteworthy that this study is subject to a few limitations. First of all, a variety of MR sequences was applied to predict BI in meningiomas in the included studies, resulting in varying levels of heterogeneity in sensitivity and specificity. To conquer the heterogeneity, meta-regression and subgroup analysis, were implemented. Secondly, while meningioma is a prevalent brain tumor, this systematic review only encompassed 14 original articles, and the meta-analysis included 12 studies involving a total of 6449 patients. In the future, more research including larger sample sizes from various centers are required. Thirdly, it is essential to note that all the studies included in this analysis were retrospective in

nature. Moreover, there was variation in the standardization of MRI characteristics across the included studies. Establishing criteria for MRI acquisition, processing, and image analysis is crucial for the effective utilization of MRI as a reliable predictor for BI in meningiomas.

Conclusion

MRI was testified a good diagnostic efficacy for the prediction of BI in meningioma. The diagnostic efficacy was influenced by factors such as the MR sequences, sample size, and features from the brain-to-tumor interface. Future studies focusing on the application of MRI for BI prediction are warranted to further investigate the diagnostic efficacy of radiomics methods. It is advised to consider employing larger sample sizes, using multi-MR sequences analysis involving ADC images etc, integrating characteristics from both the brain-to-tumor interface and tumor parenchyma in the analysis of BI in meningiomas.

Declaration of conflicting interest

The authors declare that there is no conflict of interest.

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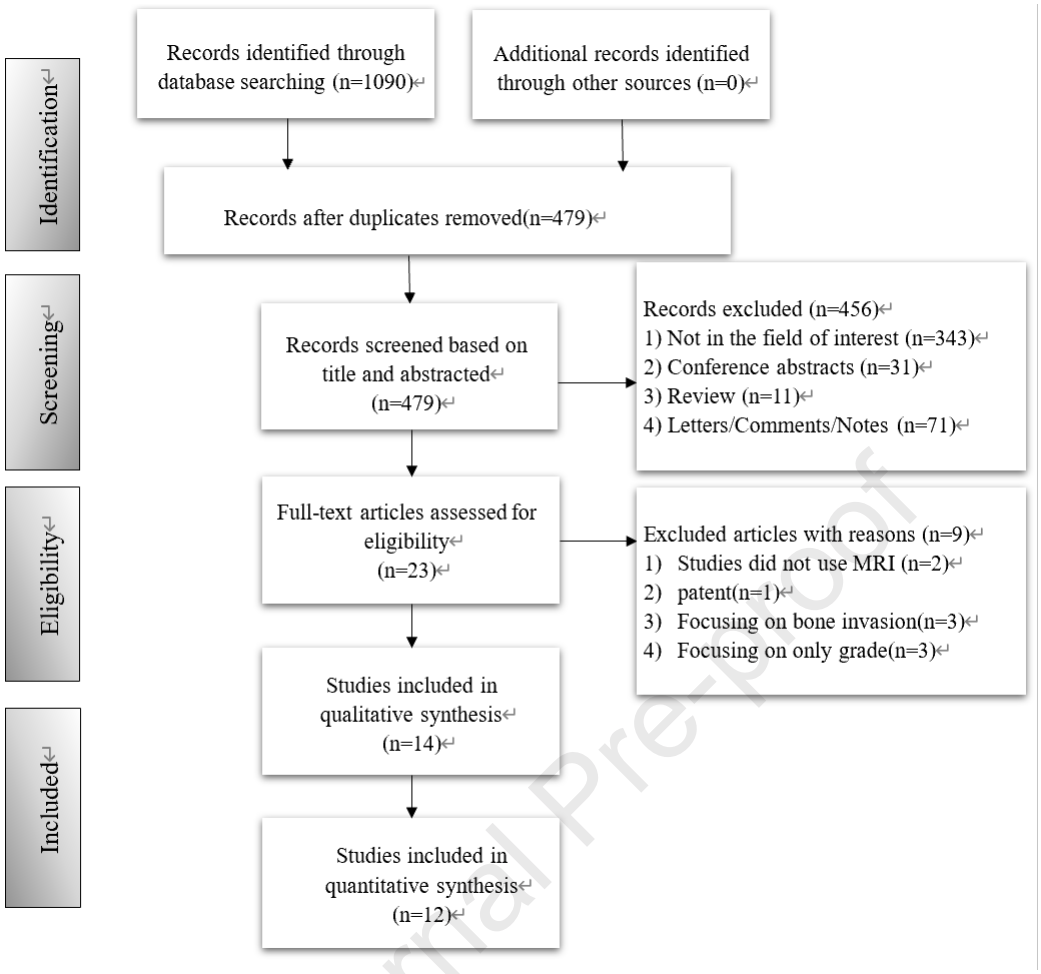
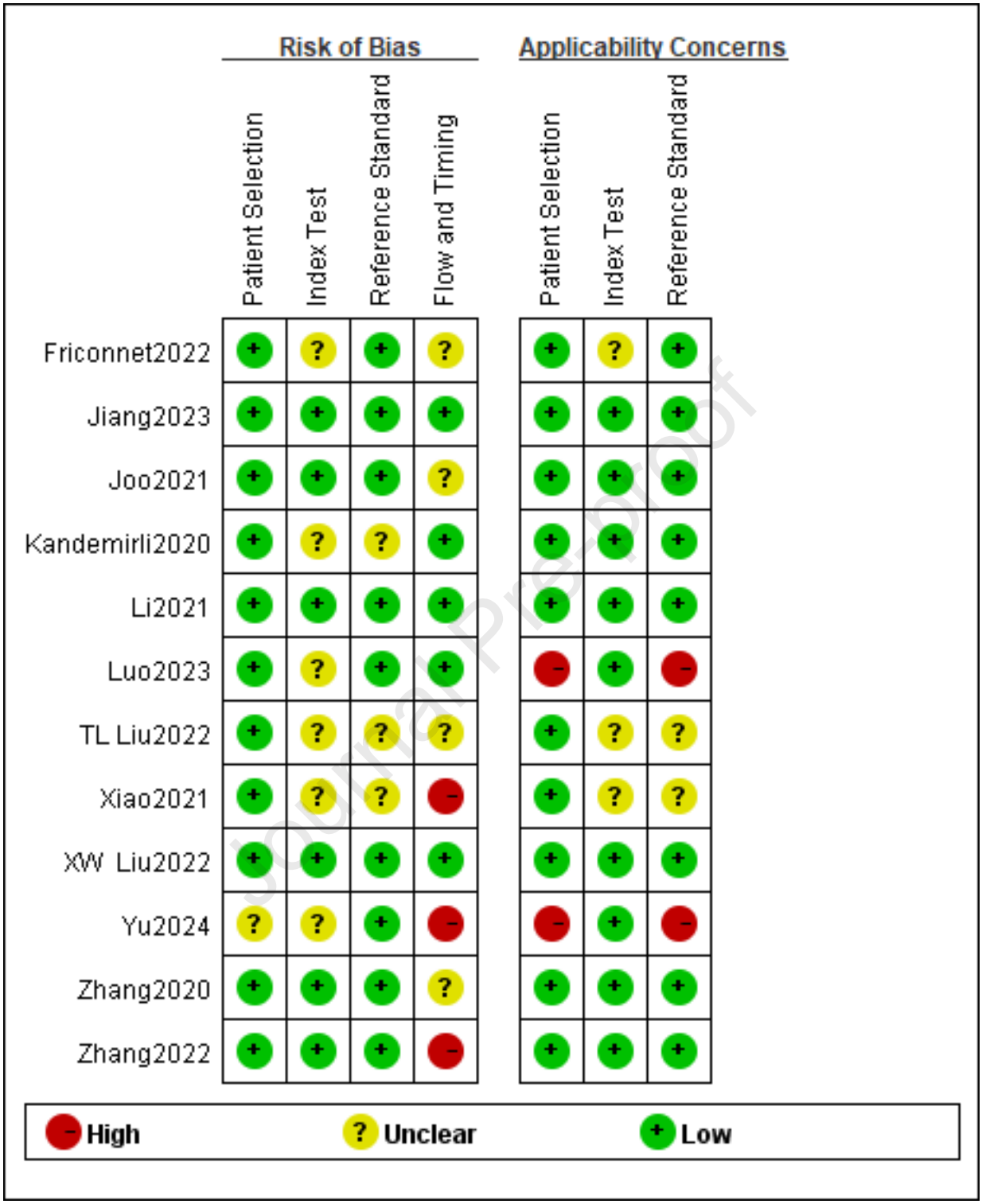
Study no.	Author (year of publication)	No. of total patients	No. of patients with brain invasion	No. of patients with non-brain invasion	Mean age (years)	Male:female	Duration of patients	Study design	Blinding to reference standard	Method of reference standard	Magnetic field strength (T)	Scanning sequence	**Radiomics (classification model)**	**Validation method**	**ROI contain brain-to-tumor interface**
1	Friconnet et al (2022)	101	13	88	60.2	34:67	2012-2019	Retrospective	Yes	Pathology	1.5T/3.0T	T1WI, CE-T1WI	**No**	/	**N**
2	Jiang et al (2023)	675	108	567	50.8	210:465	2006-2022	Retrospective	Yes	Pathology	1.5T/3.0T	T1WI, T2WI, CE-T1WI, ADC	**No**	/	**N**
3	Joo et al (2021)	604	117	487	55.7	173:431	2012-2017	Retrospective	Yes	Pathology+ operation record	1.5T/3.0T	T1WI, T2WI, CE-T1WI, FLAIR	**Yes(random forest)**	**Yes(validation)**	**Y**
4	Kandemirli et al (2020)	108	56	52	NR	NR	2010-2019	Retrospective	Yes	Pathology	1.5T/3.0T	CE-T1WI	**Yes(random forest)**	**no**	**N**
5	Li et al (2021)	284	173	111	56.8	108:176	2011-2020	Retrospective	Yes	Pathology	1.5T/3.0T	T1WI, T2WI, CE-T1WI,	**Yes(logistic regression)**	**Yes(validation)**	**Y**
6	TL Liu et al (2022)	800	62	738	61.3	204:596	2016-2021	Retrospective	Yes	Pathology	3.0T	CE-T1WI, FLAIR, ADC	**Yes(Convolutional Neural Network)**	**no**	**N**
7	Xiao et al (2021)	719	154	565	53.3	176:543	2012-2020	Retrospective	NR	Pathology+ operation record	1.5T/3.0T	T1WI, CE-T1WI, FLAIR	**Yes(random forest and logistic regression)**	**Yes(validation)**	**Y**
8	XW Liu et al (2022)	55	25	30	54.1	21:34	2020-2022	Retrospective	Yes	Pathology	3.0T	CE-T1WI	**No**	/	**N**
9	Zhang et al (2020)	1728	335	1393	51.9	414:1314	2010-2019	Retrospective	Yes	Pathology+ operation record	1.5T/3.0T	T2WI, CE-T1WI	**Yes(support vector machine)**	**Yes(validation)**	**N**
10	Zhang et al (2022)	658	81	577	52.2	136:522	2010-2020	Retrospective	Yes	Pathology+ operation record	1.5T/3.0T	T1WI, T2WI, CE-T1WI	**Yes(logistic regression)**	**Yes(validation)**	**N**
11	Ong et al (2020)	100	60	40	60.4	37:63	2005-2016	Retrospective	Yes	Pathology	1.5T/3.0T	T1WI, T2WI, DWI, FLAIR, CE-T1WI	**No**	/	/
12	Adeli et al (2018)	617	24	593	59.0	176:441	NR	NR	NR	Pathology	NR	T2WI	**No**	/	/
13	Luo et al (2023)	675	108	567	50.8	210:465	2006-2022	Retrospective	Yes	Pathology	1.5T/3.0T	T1WI, T2WI,ADC, FLAIR, CE-	**NO**		

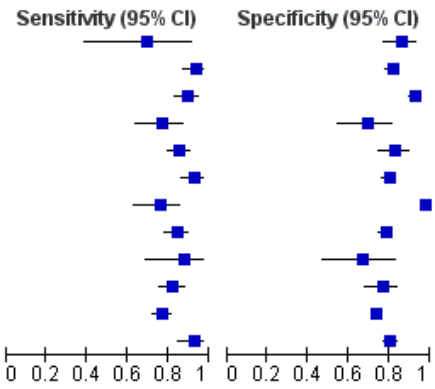
												T1WI			
14	Yu (2024)	469	262	207	52.5	206:263	2016-2022	Retrospective	Yes	Pathology+ operation record	1.5T/3.0T	FLAIR,T2WI, CE-T1WI	**Yes(logistic regression)**	**Yes(validation)**	**N**

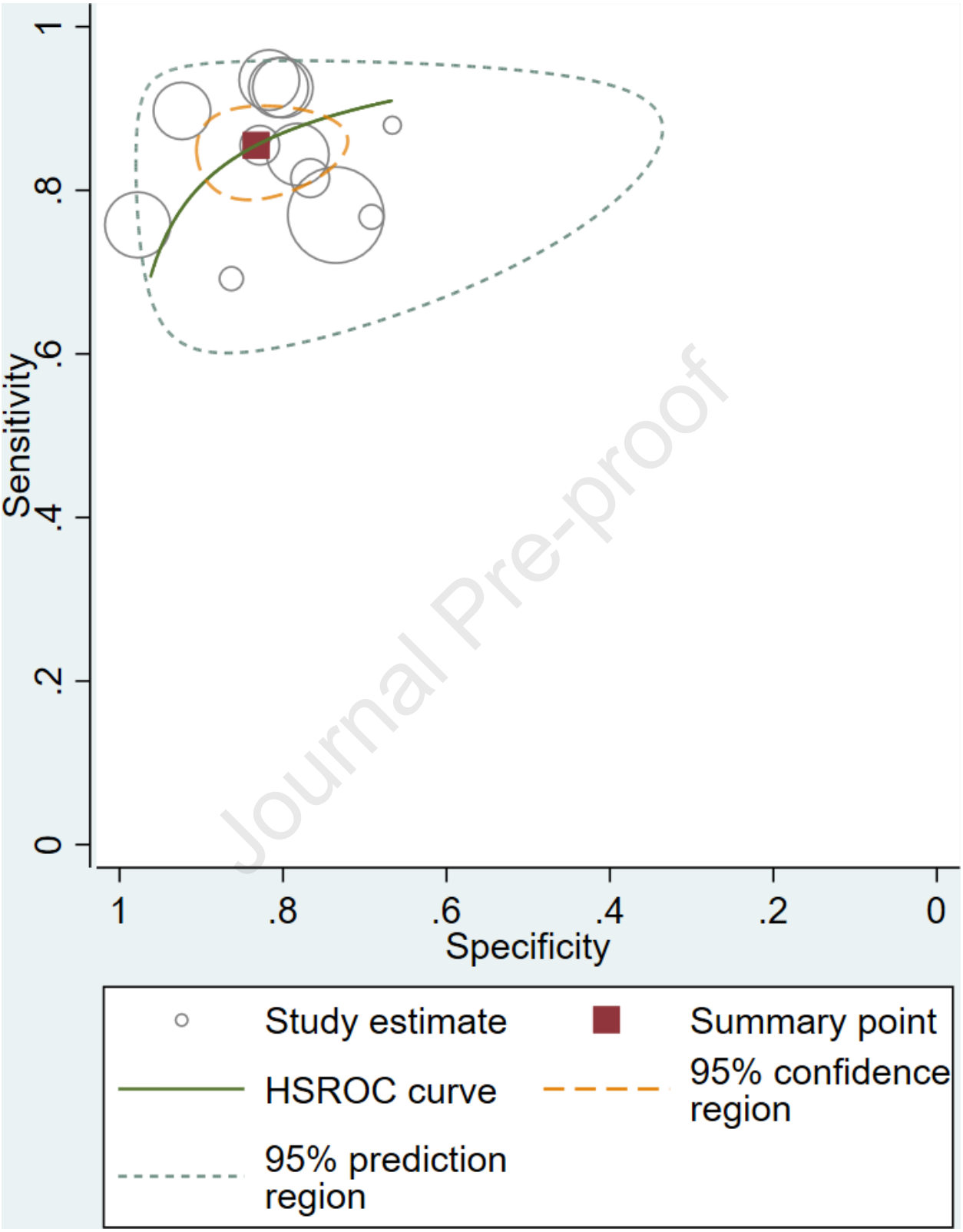
Analysis	No. of studies	Pooled sensitivity		*p*	Pooled specificity		*p*	Pooled DOR		*p*
		Value(95%CI)	I^2(%)	value	Value(95%CI)	I^2(%)	value	Value(95%CI)	I^2(%)	value
Magnet field strength(T)				0.01			0.92			0.003
3 T	2	0.81(0.68-0.94)	42.9		0.92(0.83-1.00)	97.1		49.0(4.6-523.9)	88.4	
1.5 and 3.0T	10	0.86(0.82-0.90)	78.5		0.82(0.74-0.90)	91		26.0(14.6-46.3)	88.3	
Radiomics				<0.001			0.56			<0.001
yes	8	0.83(0.80-0.87)	69.4		0.85(0.78-0.92)	97.7		34.8(8.7-82.9)	92.0	
no	4	0.91(0.86-0.96)	53.1		0.80(0.68-0.92)	47.8		28.0(13.6-57.5)	50.6	
Sample size of training group				<0.001			<0.001			<0.001
≥200	9	0.86(0.82-0.90)	79.7		0.85(0.80-0.91)	97.3		37.8(19.0-73.7)	91.8	
< 200	3	0.79(0.67-0.91)	10.2		0.76(0.59-0.93)	75.5		9.9(5.2-18.9)	0	
MR Sequence				<0.001			<0.001			<0.001
one sequence	2	0.82(0.69-0.94)	32.1		0.68(0.45-0.92)	0		8.9(4.3-18.5)	0	
two or more sequences	10	0.86(0.80-0.90)	78.0		0.85(0.80-0.91)	97		35.8(16.5-77.5)	90.8	
Containing the features from brain-to-tumor interface				<0.001			0.15			0.001
yes	5	0.89(0.85-0.93)	52.7		0.84(0.73-0.93)	91.7		44.3(23.0-85.6)	79.1	
no	7	0.81(0.76-0.86)	67.2		0.83(0.74-0.91)	97.7		20.1(9.2-46.6)	89.4	
Methods of reference standard				<0.001			0.15			<0.001
pathology+ operation record	5	0.85(0.80-0.91)	78.8		0.82(0.71-0.92)	95.6		26.0(11.2-60.0)	92.2	
pathology	7	0.86(0.80-0.91)	71.7		0.85(0.77-0.92)	96.4		31.7(14.8-68.0)	81.3	

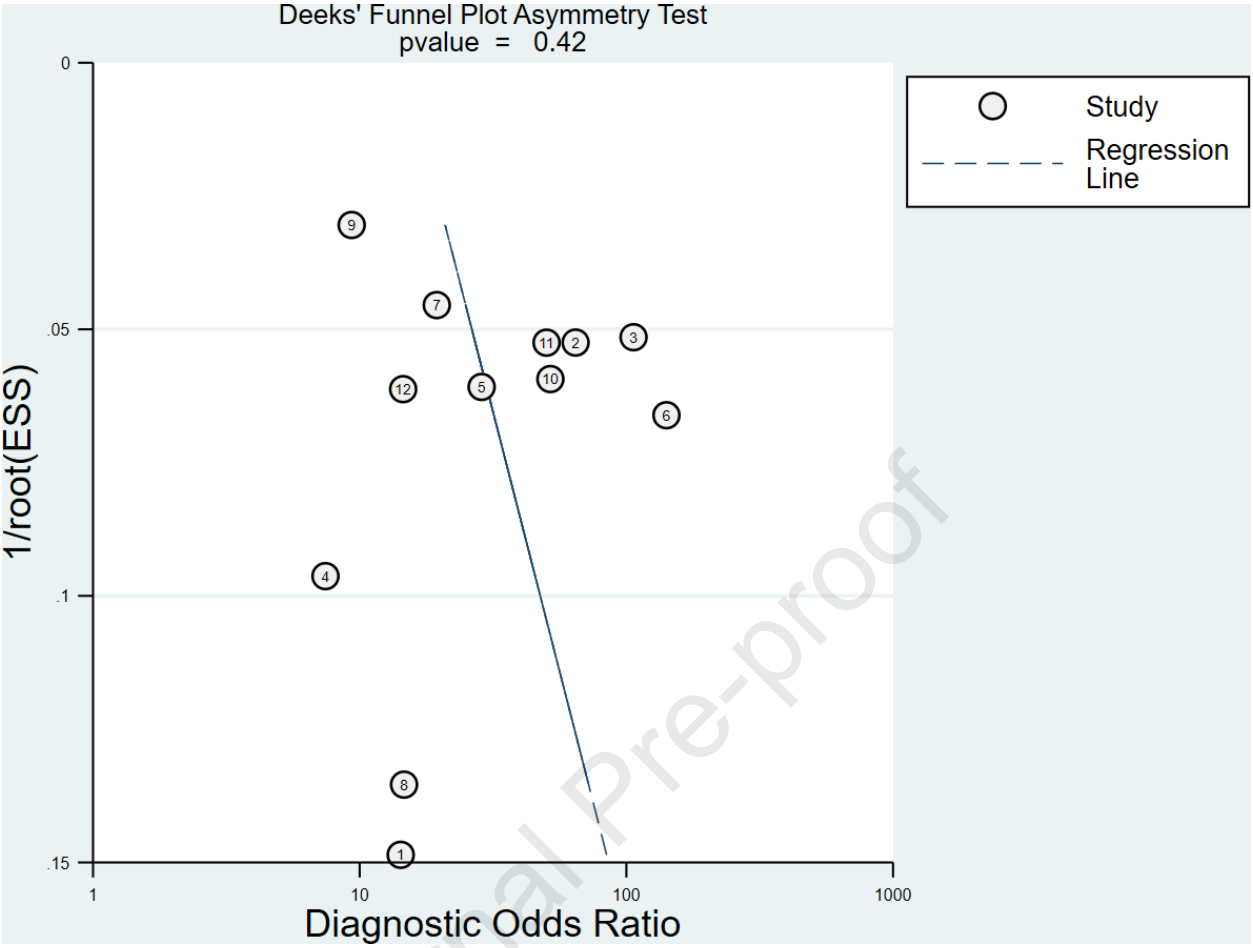




Study	TP	FP	FN	TN	Sensitivity (95% CI)	Specificity (95% CI)
Friconnet2022	9	12	4	76	0.69 [0.39, 0.91]	0.86 [0.77, 0.93]
Jiang2023	101	104	7	465	0.94 [0.87, 0.97]	0.82 [0.78, 0.85]
Joo2021	105	37	12	450	0.90 [0.83, 0.95]	0.92 [0.90, 0.95]
Kandemirli2020	43	16	13	36	0.77 [0.64, 0.87]	0.69 [0.55, 0.81]
Li2021	148	19	25	92	0.86 [0.79, 0.90]	0.83 [0.75, 0.89]
Luo 2023	100	113	8	454	0.93 [0.86, 0.97]	0.80 [0.77, 0.83]
TL Liu2022	47	16	15	722	0.76 [0.63, 0.86]	0.98 [0.97, 0.99]
Xiao2021	130	123	24	442	0.84 [0.78, 0.90]	0.78 [0.75, 0.82]
XW Liu2022	22	10	3	20	0.88 [0.69, 0.97]	0.67 [0.47, 0.83]
Yu 2024	128	27	28	89	0.82 [0.75, 0.88]	0.77 [0.68, 0.84]
Zhang2020	258	368	77	1025	0.77 [0.72, 0.81]	0.74 [0.71, 0.76]
Zhang2022	75	112	6	465	0.93 [0.85, 0.97]	0.81 [0.77, 0.84]







BI =brain invasion

MRI= magnetic resonance imaging

CSF= Cerebrospinal Fluid

AUC=the area under the curve

WHO =World Health Organization

CNS=central nervous system

PRISMA =Preferred Reporting Items for Systematic Reviews and Meta-Analyses

QUADAS-2=Quality Assessment of Diagnostic Accuracy Studies-2

HSROC =hierarchical summary receiver operating characteristic

Declaration of interest statement

We declare that we have no financial and personal relationships with other people or organizations that can inappropriately influence our work. there is no professional or other personal interest of any nature or kind in any product, service and/or company that could be construed as influencing the position presented in, or the review of, the manuscript entitled.