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Магнитно-резонансная томография в дифференциальной диагностике первичных внемозговых опухолей: обзор радиомических исследований

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АННОТАЦИЯ

Обоснование. Анализ данных магнитно-резонансной томографии является основным методом для предоперационной дифференциальной диагностики первичных внемозговых опухолей. Однако точное их разграничение только на основе визуальной оценки этих данных может быть затруднительно.

Радиомика — это количественный подход к анализу данных медицинских изображений, позволяющий выявить взаимосвязь данных визуализации с фенотипическими и генотипическими особенностями опухолей.

Ранее в ряде аналитических публикаций проводилось обобщение результатов исследований, посвящённых дифференциальной диагностике первичных внемозговых опухолей на основе принципов радиомики. Быстрое накопление новых клинических примеров и увеличение количества исследований по данной проблеме обуславливают необходимость их дальнейшего анализа и систематизации, что и послужило основанием для выполнения настоящей работы.

Цель — систематизировать существующие данные о возможностях радиомики для дифференциальной диагностики первичных внемозговых опухолей.

Материалы и методы. Проведены поиск и анализ публикаций на русском и английском языках за последние пять лет. Поиск осуществлялся в системах PubMed/Medline, Google Scholar и eLibrary. В окончательный анализ включено 19 публикаций, касающихся дифференциальной диагностики первичных внемозговых опухолей, в которых были приведены радиомические признаки, использованные для дифференциальной диагностики новообразований.

Результаты. Во всех исследованиях было показано наличие взаимосвязи между радиомическими параметрами (текстурными и гистограммными) и типом опухоли. Эффективность дифференциальной диагностики опухолей радиомическими моделями превосходила эффективность классификации новообразований рентгенологами.

Наиболее часто использовались следующие алгоритмы для создания математичесиких моделей классификации опухолей на основе радиомических параметров: метод опорных векторов, логистическая регрессия, случайный лес. Методы опорных векторов и логистической регрессии продемонстрировали лучшие и более стабильные результаты.

Заключение. Использование концепции радиомики показывает многообещающие результаты в дифференциальной диагностике первичных внемозговых опухолей. Дальнейшее развитие этого направления требует стандартизации как методов сегментации, так и набора признаков, а также эффективного метода математического моделирования.

Ключевые слова: первичные внемозговые опухоли; магнитно-резонансная томография; менингиомы; радиомика; информационные технологии.

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Magnetic resonance imaging for the differential diagnosis of primary extra-axial brain tumors: a review of radiomic studies

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ABSTRACT

BACKGROUND: The analysis of magnetic resonance imaging data is considered the main method for the preoperative differential diagnosis of primary extra-axial tumors. However, the exact distinction of different primary extra-axial tumors based only on visual rating can be challenging. Radiomics is a quantitative method of analyzing medical image data, which allows us to understand and observe the connection between visual data and phenotypic and genotypic features of tumors. Earlier, several publications presented generalized results of research aimed at the differential diagnosis of primary extra-axial tumors based on the principles of radiomics. Fast accumulation of new clinical cases and increasing of the amounts of research on these cases demonstrate the need for their further analysis and systematization, which has led to this review.

AIM: To conduct a systematic analysis of existing data on radiomics potential for the differential diagnosis of primary extra-axial tumors.

MATERIALS AND METHODS: The search for publications over the past 5 years in Russian and English was conducted in PubMed/Medline, Google Scholar, and eLibrary databases. The final analysis included 19 papers on the differential diagnosis of extra-axial tumors. The included publications provided radiomic features used for the differential diagnosis of neoplasms.

RESULTS: All studies demonstrated the existence of a connection between radiomic parameters (textural and histogram) and tumor type. The effectiveness of tumor differential diagnostics with radiomic models exceeded the neoplasm classification made by radiologists. The most frequently used algorithms for creating mathematical models of tumor classification based on radiomic parameters were the reference vector method, logistic regression, and random forest.

CONCLUSION: The use of the radiomic concept shows promising results in the differential diagnosis of primary extra-axial tumors. Further development in this area demands the standardization of both the segmentation method and the set of features and an effective method of mathematics modeling.

Keywords: primary extra-axial brain tumors; magnetic resonance imaging; meningiomas; radiomics; information technology.

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磁共振成像在原发性脑外肿瘤鉴别诊断中的应用：放射组学研究综述

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简评

论证。磁共振成像数据分析是术前原发性脑外肿瘤鉴别诊断的主要方法。然而，仅凭对这些数据的目测评估很难准确区分不同的原发性脑外肿瘤。

放射组学是一种分析医学影像数据的定量方法。其允许确定成像数据与肿瘤表型和基因型特征之间的关系。

此前，一些分析性出版物总结了根据放射组学原理对原发性脑外肿瘤进行鉴别诊断的研究结果。随着新临床病例的迅速积累和相关研究的不断增加，有必要对其进行进一步分析和系统化。这就是本研究的基础。

该研究的目的是系统整理有关放射组学在原发性脑外肿瘤鉴别诊断方面潜力的现有数据。

材料与方法。我们搜索并分析了过去五年中用俄语和英语发表的出版物。搜索是在PubMed/Medline、Google Scholar和eLibrary数据库中进行。最终分析包括19篇关于原发性脑外肿瘤鉴别诊断的出版物。这些出版物包括用于肿瘤鉴别诊断的放射组学特征。

结果。所有研究都表明了，放射组学参数（纹理的和直方图的）与肿瘤类型之间存在相关性。通过放射组学模型对肿瘤进行鉴别诊断的效率优于放射科医生对肿瘤进行分类的效率。为了创建肿瘤分类的模型，我们最常使用了以下算法：支持向量法、逻辑回归法和随机森林法。支持向量法和逻辑回归法显示出更好、更稳定的结果。

结论。放射组学概念在原发性脑外肿瘤鉴别诊断中的应用显示出良好效果。这一方向的进一步发展需要分割方法和特征集的标准化，以及有效的数学建模方法。

关键词：原发性脑外肿瘤；磁共振成像；脑膜瘤；放射组学；信息技术。

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BACKGROUND

Preoperative differential diagnosis of primary extra-axial brain tumors (PEABTs) is based on the analysis of magnetic resonance imaging (MRI) semiotics, which most commonly includes a standard set of weighted images (WI), such as T2-WI, T1-WI, FLAIR, diffusion-weighted imaging (DWI), and contrast-enhanced T1-WI (T1-CE) [1–3].

PEABTs include both benign and malignant neoplasms of the meninges (meningiomas and mesenchymal tumors) and cranial nerves (neurinomas) [4].

The MRI semiotics of PEABTs have been studied in detail and described in established guidelines; however, atypical MRI patterns can complicate the differential diagnosis of tumors based on visual assessment alone [5,6]. Incorrect tumor type determination can result in incorrect treatment [1,2,7,8]. The most common difficulties are differentiating meningiomas of various grades, distinguishing solitary fibrous tumors from meningiomas, and localizing PEABTs in cerebellopontine angles [9–12].

Radiomics is a quantitative approach to medical image analysis and aims to identify the relationship between the digital characteristics of a diagnostic image and phenotypic and genotypic characteristics of a tumor [13].

Radiomics involves extracting quantitative features from images to provide an objective description of an imaging phenotype and determine the relationship between radiomic and genetic, molecular, and clinical features of tumors [14]. To extract quantitative parameters from images, morphometric, histogram, and texture analysis of segmented areas of interest is performed. Histogram and texture features reflect structural features not detectable visually [15]. In radiomics studies, various mathematical modeling and deep learning methods are used. The resulting differential diagnostic and prognostic models should be validated using an independent sample. Radiomics may be a powerful tool in clinical decision-making [16]. Figure 1 shows the steps of radiomic analysis.

Some analytical publications have summarized previous studies on radiomics-based differential diagnosis of PEABTs [13, 17]. The rapid accumulation of new clinical cases and increase in the number of studies related to this problem require further analysis and systematization, and thus, is the basis of the present study.

MATERIALS AND METHODS

A systematic review for the last 5 years was conducted according to PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses Protocols, 2009).

PubMed/MEDLINE, Google Scholar, and eLibrary databases were searched for scientific articles from the last 5 years using the following keywords: MRI, meningioma, neuroma, schwannoma, solitary fibrous tumor, radiomics, texture, МРТ, менингиома, невринома, шваннома, солитарная фиброзная опухоль, радиомика, текстура.

Articles with abstracts unrelated to the differential diagnosis of PEABTs were excluded, as well as those without a description in text of radiomic features in the differential diagnosis of tumors.

Finally, 19 publications were included in the review. Figure 2 shows the design of the current study.

Estimated parameters

As part of the systematic review, the following parameters were assessed in the selection of publications:

- Diagnostic task
- Number of patients

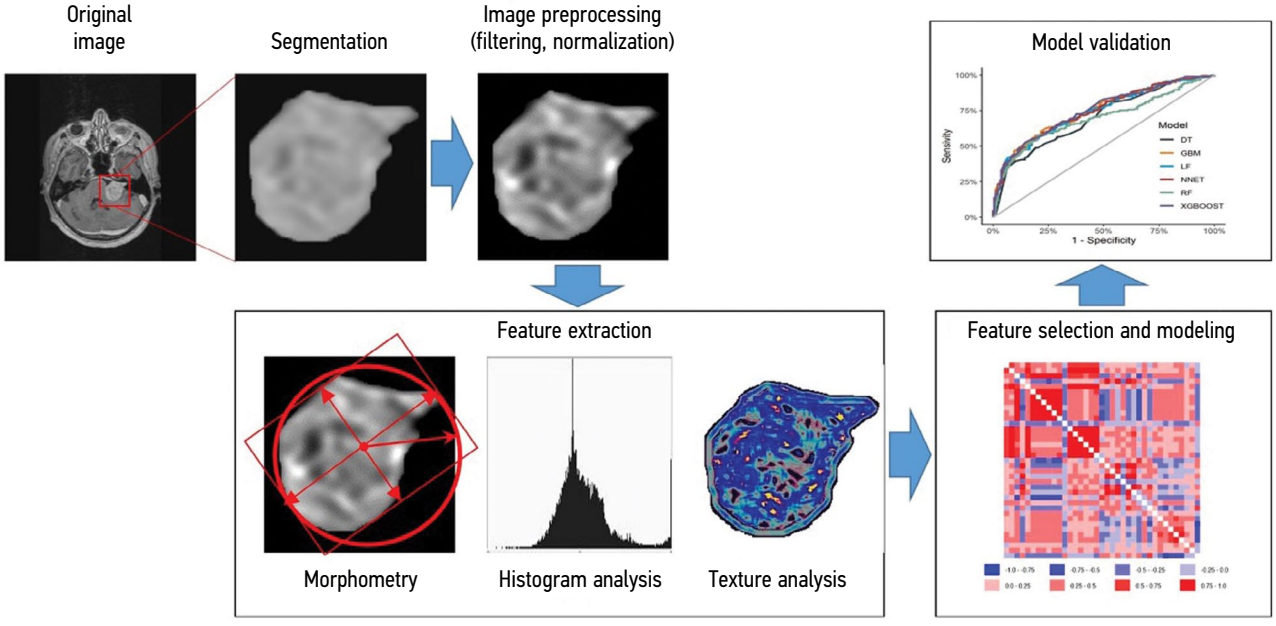

Fig. 1. Radiomic analysis stages.

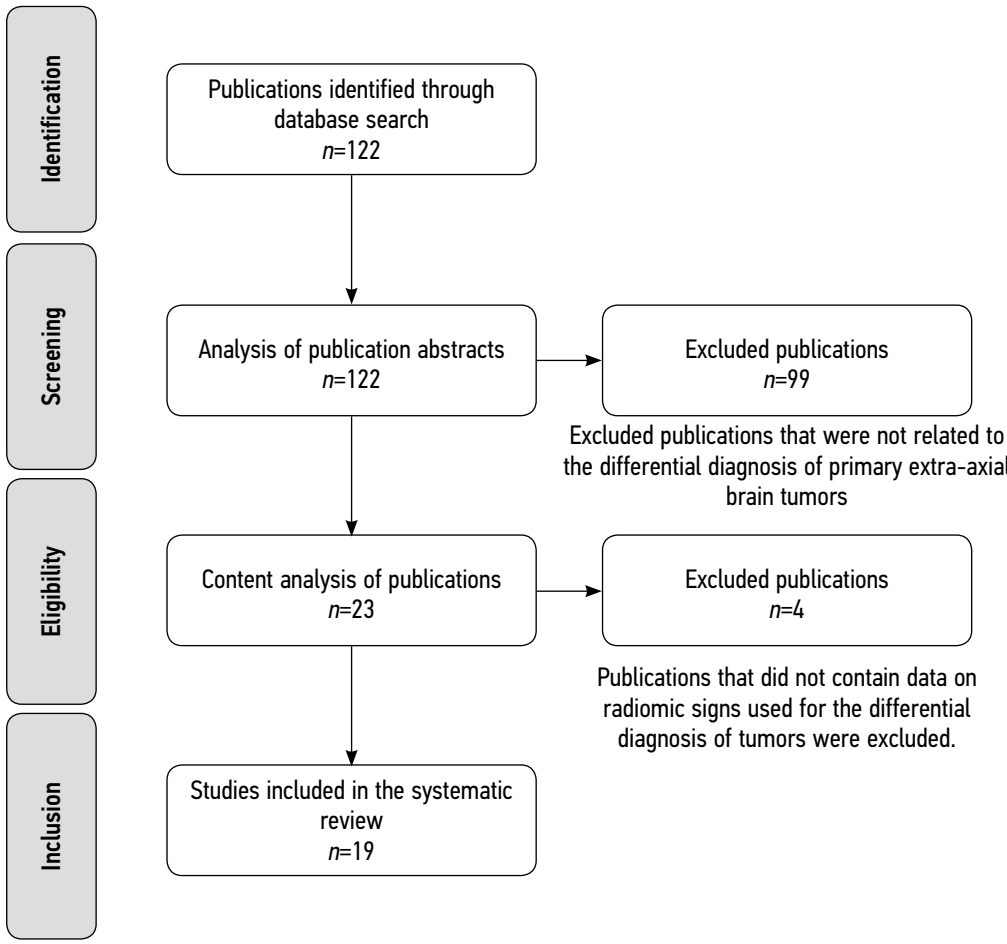

Fig. 2. Research design.

- Method of tumor segmentation
- WI types
- Significant differential diagnostic features
- Mathematical models used
- Validating the mathematical models used to classify tumors

This review included data from original clinical trials.

RESULTS

Several studies have investigated the effectiveness of radiomic features of MRI images in the differential diagnosis of PEABTs. In total, 121 studies published in the last 5 years were found in PubMed/MEDLINE and Google Scholar for the search query "meningioma or neuroma or schwannoma or solitary fibrous tumor) + (texture or radiomic) + MRI." For queries with different combinations of the words "MRI, meningioma, neuroma, schwannoma, solitary fibrous tumor, radiomics, and texture," only one publication was found in eLibrary. After analyzing the publications, 19 articles in English and Russian were included in the review.

Table 1 shows the characteristics of the selected articles according to research design.

DISCUSSION

Differential diagnosis

Twelve studies were found to have investigated the differential diagnosis of benign and malignant meningiomas. The differential diagnosis of meningiomas and solitary fibrous tumors was evaluated in four studies, and the differentiation between meningioma and hemangioma/craniopharyngioma/neurinoma was examined in one study.

Most studies have discussed a "binary" classification between two types of PEABTs [18,19,22-32,34,35]. Given the similar semiotics of all PEABTs, models capable of performing multiclass rather than binary classification between two prespecified tumor types have an advantage for clinical use. However, only four studies have distinguished between three or more types of PEABTs [20,21,33,36].

Comparison of the effectiveness of tumor classification by visual assessment and models based on mri semiotics or radiomic parameters

Two studies have compared the effectiveness of tumor classification between radiologists and radiomics models [20,30]. In these studies, the tumor type was determined by a radiologist based on the MRI image, without mathematical

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Table 1. Diagnostic tasks of radiomic analysis for the differential diagnosis of primary extra-axial brain tumors

1	2	3	4	5	6	7	8
Authors	**Types of tumors**	**Number of patients**	**Segmentation**	**The most informative signs**	**Method of modeling**	**Validation (number; %)**	**Diagnostic information content**
Y.W. Park et al. 2019 [18]	Mb/Mm	136	SA	T1-CE (Histo, GLCM, GLRLM) ADC (Histo, GLCM, GLRLM)	RF, SVM	58; 42.6%	The best model (SVM): AUC 0,86; Acc 89,7%; Sn 75%; Sp 93.5% Other models: AUC 0.74–0.85
K.R. Laukamp et al. 2019 [19]							
Y. Lu et al. 2019 [20]	Gr 1/2/3	152	Man	ADC (Histo, GLCM, GLRLM, AU, Wav)	DT	46; 30.2%	Radiomics model: Acc, 79.51% Model (semiotics + clinical data): Acc, 62.96% Classification by radiologists: Acc, 61%–62%
C. Chen et al. 2019 [21]	Gr 1/2/3	150	Man	Shape T1-CE (GLCM, GLRLM, GLSZM)	LDA, SVM	30; 20%	The best model (LDA): Acc, 75.6% Other models: 57.6%–73.3%
Y. Zhu et al. 2019 [22]	Mb/Mm	181	Man	Shape T1-CE (GLCM, GLRLM, GLSZM)	SVM	82; 45.3%	The best model: AUC, 0.811; Sn, 76.9%; Sp, 89.8%
O. Morin et al. 2019 [23]	Mb/Mm	303	NA	Shape T1-CE (Histo, Wav GLCM, GLRLM, GLSZM)	RF	85; 28.1%	Semiotics model: AUC, 0,68; Acc, 62% Radiomics model: AUC, 0,71; Acc, 65%
X. Li et al. 2019 [24]	Mb/Mm	90	Man	Shape T2-WI, T1-WI и T1-CE (Histo)	LR	28; 31.1%	Models of individual weight types: AUC, 0.781–0.821
C. Ke et al. 2020 [25]	Mb/Mm	263	Man	T2-WI (GLCM, GLRLM, GLSZM) T1-WI (GLCM) T1-CE (GLRLM, GLSZM)	SVM	79; 30%	Models of individual weight types: AUC, 0.67–0.75; Acc, 68%–75%; Sn, 42%–74%; Sp, 67%–82% Models of weight combination: AUC, 0.83; Acc, 80%; Sn, 84%; Sp, 78%
J. Hu et al. 2020 [26]	Mb/Mm	316	SA	Shape T2-WI и T1-WI (Wav) T1-CE (Histo, GLSZM, Wav) ADC (Histo, GLCM, Wav) SWI (GLCM, Wav)	RF	NP	Model (semiotics + clinical data): AUC, 0,7 Model (T2-WI + T1-WI + T1-CE): AUC, 0.78; Acc, 74%; Sn, 65.5%; Sp, 77.7% Model (T2-WI + T1-WI + T1-CE + ADC + SWI): AUC, 0.81; Acc, 78%; Sn, 66.7%; Sp, 83%
Y.W. Park et al. 2019 [18]	Mb/Mm	136	SA	T1-CE (Histo, GLCM, GLRLM) ADC (Histo, GLCM, GLRLM)	RF, SVM	58; 42.6%	The best model (SVM): AUC, 0.86; Acc, 89.7%; Sn, 75%; Sp, 93.5% Other models: AUC, 0.74–0.85
K.R. Laukamp et al. 2019 [19]	Mb/Mm	71	SA	Shape FLAIR (GLCM) ADC (GLSZM)	LR	NP	Models of weight types: AUC, 0.72–0.8 Models of weight combination: AUC, 0.91; Sn, 79%; Sp, 89%
H. Chu et al. 2021 [27]	Mb/Mm	98	SA	Shape T1-CE (Histo, GLCM, GLRLM, GLSZM)	LR	30; 30.6%	Radiomics model: AUC, 0.948; Acc, 92.9%; Sn, 91.7%; Sp, 100%
Y. Han et al. 2021 [28]	Mb/Mm	131	NA	Shape T1 FLAIR (Histo, GLRLM, GLSZM)	LR, RF, SVM, KNN, DT, and XGB	27; 20.6%	Model T1 FLAIR: AUC, 0.956; Sn, 87%; Sp, 92% Models of weight combination: AUC, 0.922; Sn, 87%; Sp, 93%

1	2	3	4	5	6	7	8
J. Zhang et al. 2022 [29]	Gr 1/2	242	Man	T2-WI (GLRLM, Wav) T1-CE (GLSZM, Wav)	LR	73; 30.2%	Models of individual weight types: AUC, 0.67–0.717; Acc, 61.1%–69.4%; Sn, 60.7%–75%; Sp, 61.4%–65.9% Models of weight combination: AUC, 0.734; Acc, 72.2%; Sn, 67.9%; Sp, 75%
Differential diagnosis of meningiomas and solitary fibrous tumors							
X. Li et al. 2019 [30]	Mb/SFT	67	Man	FLAIR, DWI и T1-CE (GLRLM)	SVM	20; 29.9%	Model T1-CE: AUC, 0.90; Acc, 87.5% Classification by radiologists: AUC, up to 0.7; Acc, up to 77.3%
J. Dong et al. 2020 [31]	Mb/SFT	192	Man	T2-WI (GLCM, GLRLM, GLSZM) T1-WI (Histo, GLCM, GLSZM) T1-CE (Histo, GLCM, GLRLM)	LR	59; 30.7%	Models of individual weight types: AUC, 0.772–0.864; Acc, 69.5%–81.4%; Sn, 60%–73.3%; Sp, 79.3%–89.7% Models of weight combination: AUC, 0.939; Acc, 83.1; Sn, 90%; Sp, 75.9%
Y. Fan et al. 2022 [32]	Mb/SFT	220	NA	Semiotics T2-WI (Histo, GLCM, GLRLM) T1-CE (GLRLM)	SVM, LR	73; 33.2%	Models of individual weight types: AUC, 0.75–0.85; Acc, 69.9%–72.6%; Sn, 68.5%–98%; Sp, 13.6%–87.5% Models of weight combination: AUC, 0.9; Acc, 82.2%; Sn, 79.6%; Sp, 87.5% Model (clinical data + semiotics): AUC, 0.79; Acc, 76.7%; Sn, 79.6%; Sp, 70.8%
J. Wei et al. 2022 [33]	Gr 1–3/ SFT	292	Man	T2-WI (Histo, GLCM, GLRLM, GLSZM, NGTDM, Wav) T1-WI (GLCM, Wav, GLRLM) T1-CE (GLCM, Wav, GLSZM)	LR, DT, RF, and SVM	88; 30.1%	Model (clinical data + semiotics): AUC, 0.766; Acc, 65.9%; Sn, 67.4%; Sp, 64.3% Models of individual weight types: AUC, 0.731–0.818; Acc, 64.8%–71.6%; Sn, 63%–89.1%; Sp, 52.4%–66.7% Models of weight combination: AUC, 0.902; Acc, 81.8%; Sn, 89.1%; Sp, 73.8%
Differential diagnosis of meningiomas from other PEABTs							
Z. Tian et al. 2020 [34]	M/C	127	Man	Semiotics T2-WI (Histo) T1-CE (Histo, GLCM)	LR	NP	Model AUC T1-CE: 0.776
C. Wang et al. 2022 [35]	M/H	96	Man	Shape T2-WI, T1-CE и ADC (Histo, Wav) T1-WI (Histo, GLSZM, GLRLM, Wav) DWI (GLCM, Wav)	KNN, LR, RF, SVM, XGB, and DT	19; 20%	Classification by radiologists: AUC, 0.545–0.756 Semiotics model: AUC, 0.805 The best model (ADC, SVM): AUC, 0.95 Other radiomics models: AUC, 0.73–0.94
Yevvgeniy N. Surovtsev et al. 2023 [36]	Mb/Mm/H	66	A	T2-WI (GLCM, GLRLM, Wav) T1-WI (GLCM Wav) FLAIR (Wav) ADC (GLCM, GLRLM) T1-CE (Histo)	LDA	27; 40.9%	Semiotics model: AUC, 0.78; Sn, 50%–83.3%; Sp, 75%–81% Radiomics model: AUC, 0.86; Sn, 83.3%–100%; Sp, 91.7%–100%

Note. Abbreviations:
Tumors: Mb, benign meningiomas (grade 1); Mm, malignant meningiomas (grades 2 and 3); M, meningiomas without grade; N, neurinomas; C, craniopharyngiomas; H, hemangiomas; SFT, solitary fibrous tumors; Gr, grade
Segmentation: Man, manual; SA, semiautomatic; A, automatic
Features: ADC, apparent diffusion coefficient; SWI, susceptibility weighted imaging; Histo, histogram; GLCM, gray level co-occurrence matrix; GLRLM, gray level run length matrix; GLSZM, gray level size zone matrix; NGTDM, gray-tone difference matrix; AU, autoregressive model; Wav, wavelet
Mathematical modeling methods: LR, logistic regression; NB, naive Bayes classifier; SVM, support vector machine; TC, text categorization; KNN, K-nearest neighbors method; DT, decision tree; RF, random forest; LDA, linear discriminant analysis; XGB, extreme gradient boost; MLP, multilayer perceptron
Test information parameters: Acc, accuracy; Sn, sensitivity; Sp, specificity; AUC, area under the curve
Other: NP, not performed; NA, not available

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modeling based on visual features. The use of radiomics models was advantageous, with an accuracy of 10%–17%.

Five studies have compared the accuracy of tumor classification between models based on MRI semiotics and radiomics features [20,23,32,33,36]. In these studies, the visual semiotic features were systematized and stratified. Based on these features, mathematical models may be developed.

The use of mathematical semiotic models for tumor classification may be more advantageous over the radiologist's opinion because a radiologist's differential diagnosis is largely based on experience and subjective. Moreover, systematizing and integrating the evaluation of MRI semiotic features increases their information value.

Differentiating tumors using models based on radiomic parameters was significantly superior to classifying tumors by radiologists, and their information value was higher than that of semiotic models.

The most valuable studies are those that compare the information value of radiomics models with the results of visual assessment of MRI semiotics. Furthermore, the ability to automate image analysis for computer decision support systems remains an advantage of the radiomics approach.

Patient sample size and model validation

Most studies have included relatively small numbers of patients:

- <100 patients: 6 publications [19,24,27,30,35,36],
- 100–200 patients: 7 publications [18,20-22,28,31,34],
- 200–300 patients: 4 publications [25,29,32,33],
- >300 patients: 2 publications [23,26].

Larger samples are typical for differential diagnosis studies of meningiomas. The small sample size may be because of the unequal prevalence of the different types of PEABTs. Most PEABTs (> 80%) are benign meningiomas, and other tumors are rare [4], making it challenging to select a large patient population.

Validation was completed in 84.2% of the trials. In most studies, the validated group comprised approximately one-third of the total enrolled patients. Note that the clinical significance of differential diagnostic models is reduced by the lack of testing of model performance on the validation set.

Tumor segmentation

Segmenting the tumor is the first and fundamental step in radiomics analysis [14]. To avoid distortion of radiomic features and ensure reproducibility of results, the segmentation technique should accurately distinguish neoplastic tissue from brain matter and peripheral edema.

Most PEABTs are characterized by a marked increase in MRI signal intensity on T1-WI after contrast administration, whereas the isointense and hypointense MRI signals of adjacent structures are preserved [9]. This feature is the basis for the sharp difference in brightness between the contrasted tumor and adjacent structures and accuracy of tumor margin visualization. Most studies included in the review (63.2%) have performed segmentation specifically on contrast-enhanced T1-WI [18,21-28,30,33,36].

The segmentation method affects the final simulation result. The automatic and semiautomatic methods have a higher reproducibility than the manual methods in the determination of tumor boundaries [37]. In the presented studies, less preferred manual segmentation was most common [18-20,22,23,27-29,31-33]. Only five studies have used automated or semiautomated methods [18,19,26,27,36].

Significant radiomic features

A feature of radiomics studies is the presence of a sufficiently large initial set of parameters, and the most informative parameters are selected to solve the problem. Histogram and texture parameters of tumors are the most informative radiomic features for the differential diagnosis of PEABTs.

The power of radiomics models for the differential diagnosis of PEABTs is increased by expanding the set of radiomic parameters to include different WI types. Seven studies have compared models based on the radiomic parameters of one WI type with models that included the features of different WI types [19,25,28,29,31-33]. In six of these studies, the advantage of the latter was demonstrated based on a comparison of the information values of the tests [19,25,29,31-33]. One study has revealed the poor results of weight combination models [28].

In comparing the two combined models, Hu et al. [26] have shown that a model containing an extended spectrum of weights (T2-WI, T1-WI, T1-CE, apparent diffusion coefficient [ADC] map, susceptibility weighted imaging [SWI]) was slightly superior to a model based on T2-WI, T1-WI, and T1-CE.

The advantage of models using several types of weights is their ability to reflect different aspects of the tumor. For example, T2-WI and T1-WI reflect the degree of hydration (amount of fluid) in the tumor, T1-CE reflects the permeability of the blood–brain barrier, DWI and ADC reflect the cellularity of the tumor, and SWI is sensitive to hemorrhage and fossilization. Therefore, integrating the parameters within the model allows a more complete representation of the morphological characteristics and better results.

The shape parameter values were limited. The information value of these parameters was evaluated in ten studies [21-23,26-28,31-33,35]. Shape parameters were informative in studies that have performed modeling based on one WI type [21-23,27,28,35]. Three studies [31-33] have shown that shape parameters are uninformative when constructing models that include multiple WI types. In a study by Hu et al. [26], shape parameters were informative and were included in the modeling; however, their proportion was not large compared with that of histogram and texture parameters (the model included 17 histogram and texture parameters and 3 morphometric parameters).

Mathematical modeling methods

In the presented studies, various mathematical modeling methods were used to create models. The most common algorithms were as follows:

- Support vector machine (SVM): 9 studies [18,21,22,25,28,30,32,33,35],
- Logistic regression (LR): 10 studies [19,24,27-29,31-35],
- Random forest (RF): 6 studies [18,23,26,28,33,35].

Three studies [18,28,33] have analyzed the results of tumor classification using models based on these methods and showed conflicting results. In a study by Park et al. [18] (RF and SVM) and in another by Wei et al. [33] (LR, RF, SVM), the methods showed a comparable level of information value. However, in a study by Han et al. [28], the results varied significantly according to the modeling technique (one of the information value parameters of the test, area under the curve (AUC), varied from 0.628 to 0.922), whereas the SVM showed more stable results.

Among all modeling methods, the best information value parameters were demonstrated by LR [27] and SVM [35], wherein the AUC was 0.95.

CONCLUSION

The use of radiomics approach shows promising results in the differential diagnosis of PEABTs. Additionally, clinical practice implementation requires greater methodological rigor in the conduct of radiomics studies, including mandatory validation, standardization of segmentation methods, determination of the required feature set, and more informed choice of mathematical modeling methods. The use of histograms and texture parameters of different WI types for further revealing the potential of radiomics in the differential detection of PEABTs appears favorable.

Prospective studies using automated segmentation methods and an expanded set of WI types and the development of radiomics models that allow multiclass differential diagnosis of PEABTs may lay the foundation for creating powerful tools for digital clinical decision support systems and can ensure optimal patient treatment selection.

ADDITIONAL INFORMATION

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