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Radiomics-Guided Prediction of Histopathological Aggressiveness and Margin Status in Solid Organ Malignancies: A Comprehensive Systematic Review Study

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Abstract

Background: Radiomics-guided imaging has become a promising non-invasive strategy to assess tumour biology characteristics in solid organ malignancies. Microvascular invasion, tumor grade, Ki-67 expression, Gleason Grade Group, ISUP grade, extracapsular extension, and margin status are all significant features that can be used to determine the aggressiveness of the condition, but are only confirmed after biopsy or surgery. The current study aims to summarize the evidence of the use of radiomics for the prediction of the histopathological aggressiveness and margin-related outcome in solid organ cancers. **Methodology:** This systematic review followed PRISMA 2020 guidelines. PubMed, Scopus, Web of Science, and Google Scholar databases were used to search for publications from January 2019 until February 2026. Studies that used full-text were included, and they were original studies using either CT, MRI, PET/CT, or ultrasound-based radiomics or machine-learning models. Eligible studies provided a prediction of pathological aggressiveness, margin status, or survival-related outcomes. Only articles reporting the results of a study with relevant outcomes were included. The certainty of evidence was estimated with GRADE and the risk of bias with QUADAS-2 and PROBAST. **Results:** 16 studies were included in the analysis from 512 records identified. The studies included in this were HCC, prostate cancer, renal cell cancer, PDA, and PNET. Predictive value of radiomics models was promising for the prediction of microvascular invasion, histological grade, ISUP/Fuhrman grade, Gleason Grade Group, Ki-67 expression, EXT, PSM, RS, and survival outcomes. The level of certainty was low to moderate, and the scores of most studies were medium. **Conclusion**: Radiomics-guided models could facilitate non-invasive prediction of tumor aggressiveness and margin-related outcomes, but need to be validated in a prospective multicentre study and standardized radiomics workflows prior to their routine use in clinical practice.

Keywords: Radiomics; Neoplasms; Diagnostic Imaging; Artificial Intelligence; Machine Learning; Neoplasm Grading

Introduction

The biological behaviour of solid organ malignancies is frequently unpredictable, and the clinical examination and visual imaging are insufficient to enable a complete prediction of the biological behaviour of the tumour, which makes solid organ malignancies a significant health burden in the global context. Features that are important in assessing aggressiveness, potential for recurrence, and treatment planning through histopathological evaluation include microvascular invasion, lymphovascular invasion, tumour grade, expression of Ki-67, extra-capsular extension, and surgical margin status [2,3]. These features, however, are typically confirmed following biopsy or surgical resection and do not have much clinical value before surgery [4].

Radiomics is a non-invasive imaging technique that generates high-dimensional quantitative features from the images that are routinely acquired by CT, MRI, or ultrasound [5]. These characteristics may be due to tumour heterogeneity, enhancement patterns, the texture of the tumour, and the presence of peritumoral changes, which are not obvious on traditional radiological interpretation [6]. In recent years, the capability of radiomics and machine-learning models in predicting microvascular invasion in hepatocellular carcinoma has been seen [7]. Furthermore, the Gleason grade and extracapsular extension in prostate cancer [8], and tumour grade or margin status in pancreatic malignancies have been demonstrated [9]. The rationale for this systematic review is the growing use of radiomics to predict tumour aggressiveness and margin-related outcomes before surgery. However, current evidence is scattered across different cancers, imaging modalities, prediction targets, and validation methods. A systematic synthesis is therefore needed to clarify the reliability, methodological quality, and clinical usefulness of radiomics-guided prediction models.

The study aims to evaluate the evidence of radiomics-based prediction of the intra-operative margin status and histopathology aggressiveness of solid organ malignancies. It will provide a summary of study characteristics, radiomics methods, prediction targets, key findings, and risk of bias in order to clarify the potential role of radiomics in precision diagnostics and in the pre-operative oncological decision-making.

Methodology

The PRISMA 2020 framework was used to ensure methodological transparency, regularity, and reproducibility throughout the review process in this systematic review [10].

Inclusion and Exclusion Criteria: The original research articles were included, especially those that assessed the performance of imaging or radiomics-based AI models for predicting aggressiveness or margin status for solid organ malignancies. Diagnostic, classification, and/or prognosis prediction-model studies using CT, MRI, or ultrasound-based radiomics were included. Studies that reported prediction of microvascular invasion, lymphovascular invasion, tumour grade, Fuhrman grade, ISUP grade, Gleason Grade Group, Ki-67 expression, extracapsular extension, resection margin status, recurrence-free survival, disease-free survival, or overall survival were deemed relevant and included. Full-text English-language articles with a DOI and information about journal issues were included. Studies that were narrative reviews, systematic reviews, meta-analyses, editorials, conference abstracts, case reports, letters to the editor, non-human studies, non-radiomics imaging studies, non-solid tumour studies, and articles that did not provide adequate methodological or outcome data were excluded. Studies that were not available in full text, did not have a DOI, or had unclear information about the bibliographic information were not included.

Data Sources: The literature search was conducted in the major databases (PubMed, Scopus, Web of Science, Google Scholar, and journal-specific repositories). Studies published from January 2019 to February 2026 were searched to include the latest evidence about the use of radiomics, machine learning, and predictive imaging in oncological pathology.

Search Strategy: A search strategy was developed using the Medical Subject Headings (MeSH) and free-text terms in the document that included those pertaining to radiomics, imaging, and solid organ malignancies, in addition to those dealing with the histopathological outcome. The keywords used were “radiomics”, “machine learning”, “artificial intelligence”, “computed tomography”, “magnetic resonance imaging”, “PET/CT”, “ultrasound”, “hepatocellular carcinoma”, “prostate cancer”, “renal cell carcinoma”, “pancreatic cancer”, “microvascular invasion”, “lymphovascular invasion”, “tumour grade”, “Ki-67”, “Gleason grade”, “ISUP grade”, “Fuhrman grade”, “extracapsular extension” and “positive surgical margin”. Boolean operators (AND, OR) were used to enhance the sensitivity and specificity of the searches. Hand searching of the reference lists of eligible studies was also conducted to find other relevant articles.

Study Selection: The procedure for the selection of the studies was carried out by using a multistep approach. The titles and abstracts were screened for irrelevant records. Secondly, full-text articles were screened to identify those that met the predetermined inclusion and exclusion criteria. All stages were done separately by two reviewers. Conflicts were resolved through discussion, but in cases where needed, by consulting a third reviewer.

Data Extraction: A structured data extraction form was used to extract data. The extracted variables consisted of the authors, year of publication, country, study design, sample size, type of cancer, patient population, imaging modality, radiomics approach, prediction target, and key findings. Other methodological information, including training and validation strategy, external validation, feature selection method, machine-learning algorithm, and reference standard, was also documented when available.

Outcome Measures: Radiomics-based prediction of histopathological aggressiveness and surgical margin-related outcomes were the main outcomes of interest. These were microvascular invasion, lymphovascular invasion, histological grade, Fuhrman grade, ISUP grade, Gleason Grade Group, Ki-67 expression, positive surgical margins, and resection margin status. When they were directly associated with a prediction model based on radiomics, such as prognostic outcomes such as recurrence-free survival, disease-free survival, and overall survival were also taken into account.

Quality Assessment: A modified version of the QUADAS-2 framework was used to do a risk of bias analysis of diagnostic or classification prediction studies and prospective diagnostic studies [11]. The risk of bias assessment of studies on prognostic prediction models was done with PROBAST [12]. The study design, the reference standard, the validation method, the reporting clarity of the study, the sample size, and external validation were used to categorize the judgments as low risk, moderate risk, or high risk. Certainty of evidence was measured by using the GRADE approach.

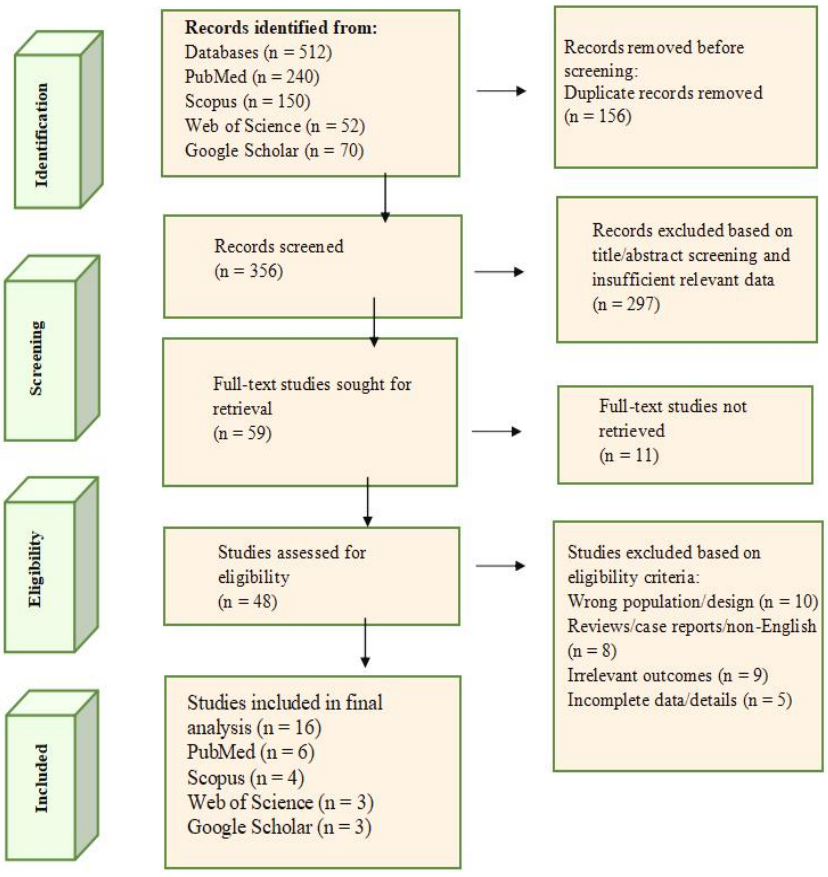

Figure 1: PRISMA flow diagram showing the identification, screening, eligibility assessment, and final inclusion of studies

Data Synthesis: Because of the significant heterogeneity in the types of cancer, imaging modality, segmentation method, radiomics feature extraction, machine-learning algorithms, validation method, and prediction target, no quantitative meta-analysis was conducted. Study characteristics, radiomics methodology, targets of the prediction, key findings, and patterns of risk of bias were analysed across the included studies.

Results

Initially, 512 articles were identified from four electronic databases: PubMed (n = 240), Scopus (n = 150), Web of Science (n = 52), and Google Scholar (n = 70). Duplicates were removed (n = 156), and 356 articles were screened by title and abstract, where 297 articles were excluded because they were irrelevant and/or lacked radiomics-related data. There were 59 articles for which the full texts were requested, and 11 were not found. The remaining 48 articles were evaluated for eligibility, and 32 were excluded due to various reasons such as reviews, case reports, conference abstracts, non-English articles, non-solid tumour studies, and studies without relevant histopathological or margin-related outcomes. In the end, 16 studies met all the eligibility criteria and were included in this systematic review (Figure 1).

The properties of the studies included are presented in Table 1. In the 16 studies, the main image modalities used for developing radiomics models included MRI, CT, PET/CT, and ultrasound, with the most common features utilized for prediction of histopathological markers of aggressiveness including MVI, tumour grade, ISUP grade, Gleason Grade Group, extra-capsular extension, and surgical margin status. Overall, the studies included in the review demonstrated the general application of radiomics in hepatocellular, prostate, renal, and pancreatic malignancies.

Table 1: Characteristics of included studies evaluating radiomics-guided prediction of histopathological aggressiveness and margin status in solid organ malignancies.

Author , Year Country	Study Design Sample Size	Cancer Type Study population	Imaging Modality	Radiomics Approach	Prediction Target	Key Findings
Chong et al., 2021[13] China	Retrospective single-centre study 356 HCC Patients (303 Male and 53 Female)	Solitary HCC ≤5 cm Pathologically confirmed patients of HCC who underwent preoperative MRI	Gadoxetate disodium–enhanced MRI including DWI, arterial, portal venous, and hepatobiliary phases	Multi-scale and multi-parametric MRI radiomics nomogram	MVI and recurrence-free survival	Radiomics score was the main independent predictor of MVI. The random forest radiomics nomogram showed strong preoperative prediction of MVI.
Xia et al., 2023[14] China	Retrospective multicentre study 918 patients with HCC	HCC Patients with pathologically proven HCC	Preoperative multiphase CT images	CT-based radiomics model using tumor and peritumor features/a hybrid model	MVI, early recurrence-free survival, overall survival, and MVI-associated gene expression	The hybrid CT-radiomics model showed the best performance for preoperative MVI prediction. It also stratified patients according to early recurrence-free survival and overall survival.
Mao et al., 2022[15] China	Retrospective study 122 HCC patients; 85 in the training set and 37 in the test set	HCC HCC patients with definite Edmondson-Steiner (E-S) grade classification from postoperative pathology and with complete Gd-EOB-DTPA-enhanced MRI	Gd-EOB-DTPA-enhanced MRI including arterial phase and hepatobiliary phase images	MRI-based radiomics using 242 features extracted from arterial and hepatobiliary phase images	Histological grade/differentiation of high-grade and low-grade HCC	Gd-EOB-DTPA-enhanced MRI radiomics combined with clinical parameters helped distinguish high-grade from low-grade HCC.
Zhang et al., 2019[16] China	Retrospective study 267 HCC patients; 194 in the training cohort and 73 in the validation cohort	HCC	Multimodal MRI, including triphasic dynamic contrast-enhanced MRI	Bi-regional MRI radiomics using features extracted from whole-tumor and peritumoral regions	Microvascular invasion	The bi-regional MRI radiomics nomogram effectively predicted MVI in HCC.
He et al., 2021[17] China	Retrospective study 459 Patients	PC Patients who underwent pelvic mpMRI and prostate biopsy at the First Affiliated Hospital of Suzhou University.	Multiparametric MRI, including T2WI and ADC	MRI-based radiomics signatures extracted from T2WI and ADC images	Benign/malignant prostate lesion discrimination, extracapsular extension	MRI-based radiomics models showed useful performance for distinguishing malignant prostate lesions

Zamboglou et al., 2019[18] Germany	Prospective study with retrospective validation cohort 60 patients; 20 prospectively enrolled patients and 40 patients in the validation cohort	PC Patients diagnosed with histologically confirmed primary prostatic adenocarcinoma, pre-treatment [68Ga]-PSMA-11 PET/CT imaging, and planned radical prostatectomy. .	[68Ga]-PSMA-11 PET/CT	PSMA PET-based radiomics using 133 radiomic features	Intraprostatic tumor discrimination, Gleason score characterization , and pelvic lymph node status	PSMA PET radiomic features differentiated prostate cancer from non-cancerous tissue and helped characterize aggressive disease by distinguishing Gleason score 7 from Gleason score ≥8 and nodal-positive from nodal-negative disease.
Qiao et al., 2023[19] China	Retrospective study 122 patients	PC Patients with pathologically proven prostate cancer who underwent preoperative MRI	Biparametric MRI comprising T2-weighted sequences, diffusion-weighted imaging, and apparent diffusion coefficient maps.	MR radiomics-based machine-learning models using radiomic features extracted from T2WI, DWI, and ADC images	Ki67 expression and Gleason Grade Group	Biparametric MRI radiomics-based machine-learning models showed potential for non-invasive prediction of Ki67 expression and Gleason Grade Group.
Yang et al., 2023[20] China	Retrospective study 392 prostate cancer patients	PC patients with pathologically confirmed PC	Prostate MRI	MRI-Based radiomics model combined with clinical parameters	Extracapsular extension	The combined MRI radiomics-clinical model showed satisfactory performance for predicting extracapsular extension in prostate cancer.
Pan et al., 2024[21] China	Retrospective study 89 patients with ccRCC(54 low-grade and 35 high-grade tumors)	ccRCC Patients with histopathologically proven ccRCC	Multimodal MRI including T1WI, T2WI, Dixon-MRI, BOLD-MRI, and SWI	Multimodal MRI radiomics combined with TC, cMRI, and fMRI texture features	Fuhrman grade/differentiation of low-grade and high-grade ccRCC	Multimodal MRI radiomics integrating TC, cMRI, and fMRI texture features was demonstrated as a useful quantitative method for effectively distinguishing .
Cheng et al., 2023[22] China	Retrospective study 147 patients(100 clear-cell RCC and 47 non-clear-cell RCC)	RCC Patients with renal cell carcinoma;	Preoperative enhanced CT, corticomedullary phase	CT-based radiomics model and nomogram	Pathological subtype discrimination: clear-cell RCC vs non-clear-cell RCC	CT-based radiomics models and the radiomics-clinical nomogram showed potential for non-invasive differentiation of ccRCC and non-ccRCC
Jiao et al., 2025[23] China	Retrospective study with external validation 503 patients	ccRCC Patients with ccRCC	Computed tomography urography, corticomedullary phase	CTU-based radiomics using PyRadiomics feature extraction	ISUP grading / histopathological grade of clear-cell renal cell carcinoma	CT urography-based radiomics and machine-learning models showed potential for non-invasive prediction of ISUP grade in ccRCC
Aymerich et al., 2025[24] Spain	Retrospective study 109 patients	ccRCC Patients with histopathologically confirmed ccRCC	Nephrographic-phase CT	CT-based radiomics model	ISUP grade / high-grade vs low-grade ccRCC	CT-based radiomics helped classify ISUP grade in ccRCC
Wang et al., 2024[25] USA and Italy	Retrospective multicentre study 89	Pancreatic ductal adenocarcinoma	Pre- and post-neoadjuvant therapy contrast-enhanced CT	Delta-radiomics model using 257 CT radiomic features	Resection margin status, overall survival, and disease-free survival	Delta-radiomics combined with clinical variables improved the prediction of resection margin

	neoadjuvant-treated PDAC patients; 58 in the discovery cohort and 31 in the validation cohort					status and survival outcomes in neoadjuvant-treated pancreatic cancer patients
Zhu et al., 2024[26] China	Retrospective multicentre study 228 patients with NF-PNETs (115 in the training cohort and 113 in external testing cohorts)	Nonfunctioning pancreatic neuroendocrine tumors Patients with NF-PNETs undergoing MRI at 5 centers.	Non-contrast MRI, including T2-weighted imaging and apparent diffusion coefficient images	MRI-based radiomics model using features extracted from T2WI and ADC	Histologic grade/differentiation of grade 1 from grade 2/3 NF-PNETs	The fusion model that combines radiomics and radiological features provides a non-invasive tool for grading and risk stratification before surgery.
Javed et al., 2024[27] USA	Retrospective study 270 patients(201 in development cohort and 69 in internal validation cohort)	Nonfunctional pancreatic neuroendocrine tumors Patients who underwent resection for NF-PNETs	Pancreas-protocol contrast-enhanced CT including arterial and venous phases.	CT-derived radiomics signature using 2436 radiomic features	Pathologic tumor grade prediction of higher-grade NF-PNETs	The CT-derived radiomics signature showed good ability to predict tumor grade preoperatively and demonstrated higher sensitivity than EUS-FNA for identifying grade 2/3 lesions
Dong et al., 2023[28] China	Retrospective study 64 patients(44 in training cohort and 20 in validation cohort)	Pancreatic neuroendocrine tumors Patients with surgery and histopathologically confirmed pNETs;	B-mode ultrasound images	Ultrasound-based radiomics mode	Histopathological tumor grade / WHO grade 1 vs grade 2–3 pNETs based on Ki-67 index and mitotic activity	B-mode ultrasound radiomics showed potential for predicting histopathological grade and Ki-67-related tumor aggressiveness in pancreatic neuroendocrine tumors.

Abbreviations: *ADC, apparent diffusion coefficient; ccRCC, clear-cell renal cell carcinoma; cMRI, conventional magnetic resonance imaging; CT, computed tomography; CTU, computed tomography urography; DCE-MRI, dynamic contrast-enhanced magnetic resonance imaging; DFS, disease-free survival; DWI, diffusion-weighted imaging; ECE, extracapsular extension; E-S grade, Edmondson-Steiner grade; EUS-FNA, endoscopic ultrasound-guided fine-needle aspiration; fMRI, functional magnetic resonance imaging; Gd-EOB-DTPA, gadolinium-ethoxybenzyl-diethylenetriamine pentaacetic acid; ISUP, International Society of Urological Pathology; Ki-67, proliferation index marker Ki-67; MVI, microvascular invasion; MRI, magnetic resonance imaging; mpMRI, multiparametric magnetic resonance imaging; NF-PNETs, nonfunctioning pancreatic neuroendocrine tumors; OS, overall survival; pNETs, pancreatic neuroendocrine tumors; PSMA, prostate-specific membrane antigen; RCC, renal cell carcinoma; RFS, recurrence-free survival; SHAP, Shapley additive explanations; SWI, susceptibility-weighted imaging; WHO, World Health Organization.*

The 16 studies selected for this systematic review are summarized in Table 1 below to show the main characteristics of the studies. The studies included four main groups of solid organ malignancies: hepatocellular, prostate, renal cell, and pancreatic tumors. The majority of the studies were retrospective, and they utilized radiomics models derived from MRI, CT, PET/CT, or ultrasound imaging. These primary prediction targets included microvascular invasion, tumour grade, ISUP grade, Fuhrman grade, Gleason Grade Group, Ki-67 expression, extracapsular extension, positive surgical margins, resection margin status, and survival-related outcomes. The table illustrates that, overall, radiomics has been extensively studied as a non-invasive method to predict the histopathological aggressiveness and margin-related outcomes prior to treatment or surgery. The risk of bias assessment of studies on diagnostic/classification radiomics prediction was shown in Table 2 based on an adapted QUADAS-2 framework. The overall risk of bias was moderate in most studies, primarily because the studies were retrospective, the sample size was small, blinding was not clearly reported, and external validation was not reported. The level of detection and reporting bias was generally low, as most studies relied on histopathology or surgical pathology as the standard of reference, and outcomes were reported explicitly in these studies, including model development. The overall risk in studies with external or multicentre validation was lower, whereas the overall risk in Dong et al. (2023[28] was high because of its very small validation cohort. Overall, the certainty of evidence after GRADE assessment was rated as low to moderate, with a primary reason being retrospective designs, methodological heterogeneity, limited external validation, and heterogeneity of imaging modalities and prediction targets.

Table 2: Risk of bias(ROB) assessment for diagnostic/classification prediction studies using adapted QUADAS-2

Author & Year	Selection Bias	Performance Bias	Detection Bias	Attrition Bias	Reporting Bias	Other Bias	Overall Risk
Mao et al., 2022[15]	Moderate (Small retrospective sample)	Moderate (Blinding not stated)	Low (Pathology reference clear)	Low (Train-test split clear)	Low (Models fully reported)	Moderate (No external validation)	Moderate (Some validation limits)

Zhang et al., 2019[16]	Moderate (Retrospective patient cohort)	Moderate (Blinding not stated)	Low (Pathologic MVI reference)	Low (Validation cohort included)	Low (Nomogram clearly reported)	Moderate (Single-country dataset)	Moderate (Limited external validity)
He et al., 2021[17]	Moderate (Retrospective hospital cohort)	Moderate (Blinding not stated)	Low (Pathology/biopsy reference)	Low (Training-testing split clear)	Low (Models clearly reported)	Moderate (No external validation)	Moderate (Validation limitation present)
Qiao et al., 2023[19]	Moderate (Small retrospective cohort)	Moderate (Blinding not stated)	Low (Pathologic PCa confirmed)	Low (Complete cohort analyzed)	Low (Algorithms clearly reported)	Moderate (Single-centre sample)	Moderate (Generalizability limited)
Yang et al., 2023[20]	Moderate (Retrospective single setting)	Moderate (Blinding not stated)	Low (Pathologic PC confirmed)	Low (Train-validation split clear)	Low (Nomogram clearly reported)	Moderate (No external validation)	Moderate (External testing absent)
Pan et al., 2024[21]	Moderate (Small retrospective cohort)	Moderate (Blinding not stated)	Low (Histopathology reference clear)	Low (Cross-validation performed)	Low (Models clearly reported)	Moderate (Limited sample size)	Moderate (Sample-size concern)
Cheng et al., 2023[22]	Moderate (Retrospective single-centre cohort)	Moderate (Blinding not stated)	Low (Pathologic subtype reference)	Low (Train-validation split clear)	Low (Performance fully reported)	Moderate (Borderline topic relevance)	Moderate (Scope partly indirect)
Jiao et al., 2025[23]	Low (Large cohort included)	Low (External validation used)	Low (Pathologic ISUP reference)	Low (Training-testing defined)	Low (SHAP results reported)	Low (External validation present)	Low (Robust validation present)
Aymerich et al., 2025[24]	Moderate (Small retrospective cohort)	Low (Cross-validation performed)	Low (Histopathology reference clear)	Low (Complete cohort analyzed)	Low (SHAP results reported)	Moderate (No external validation)	Moderate (External validation absent)
Zhu et al., 2024[26]	Low (Five-centre cohort used)	Low (External testing cohort)	Low (Histologic grade reference)	Low (Training-testing clear)	Low (Models clearly reported)	Low (Multicentre validation present)	Low (Strong validation design)
Javed et al., 2024[27]	Moderate (Retrospective surgical cohort)	Moderate (Internal validation only)	Low (Surgical pathology reference)	Low (Validation cohort included)	Low (Comparison clearly reported)	Moderate (No external validation)	Moderate (External testing absent)
Dong et al., 2023[28]	Moderate (Small retrospective cohort)	Moderate (Blinding not stated)	Low (WHO grading reference)	Low (Validation cohort included)	Low (Model outcomes reported)	High (Very small validation)	High (Small validation concern)

The traffic-light plot illustrates the risk of bias for seven diagnostic/classification studies using the QUADAS-2 framework (Figure 2). It highlights that while most studies had a low risk of bias in domains like the reference standard and reporting, many faced moderate risks due to limitations such as small sample sizes and a lack of external validation. Overall, the risk of bias was moderate.

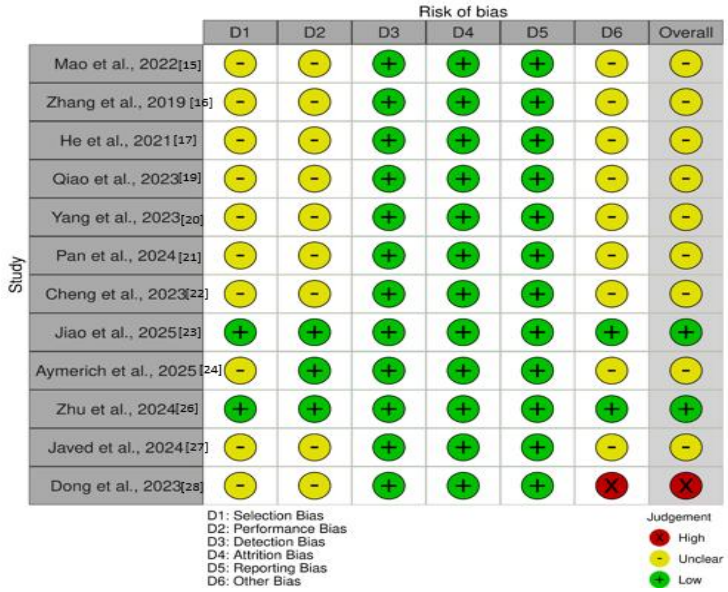

Figure 2: ROB traffic-light plot for diagnostic/classification prediction studies assessed using the adapted QUADAS-2 framework.

Table 3 shows the results of the ROB analysis for prognostic prediction-model studies based on the PROBAST framework. Because of the lack of external validation, the use of a single centre and a retrospective study design, the overall risk was moderate for Chong et al., 2021[13] The

multicentre design, clearly defined cohorts, and internal/external testing and complete outcome reporting are factors which demonstrated low overall risk as shown by Xia et al., 2023[14] A moderate overall risk was found in Wang et al., 2024[25] but with caution due to the small number of centres involved in the validation that may affect the stability and generalizability of the prognostic model.

Table 3: Risk of bias assessment for prognostic prediction-model studies using PROBAST

Author & Year	Selection Bias	Performance Bias	Detection Bias	Attrition Bias	Reporting Bias	Other Bias	Overall Risk
Chong et al., 2021[13]	Moderate (Retrospective single-centre cohort)	Moderate (Predictor blinding unclear)	Low (Pathologic MVI reference)	Low (Validation cohort included)	Low (Nomogram clearly reported)	Moderate (No external validation)	Moderate (External validation absent)
Xia et al., 2023[14]	Low (Multicentre cohort used)	Low (Internal/external testing)	Low (Pathologic reference standard)	Low (Cohorts clearly defined)	Low (Outcomes fully reported)	Low (External validation present)	Low (Robust validation design)
Wang et al., 2024[25]	Low (Multicentre cohort used)	Low (External validation included)	Low (Pathologic RMS reference)	Low (Discovery-validation clear)	Low (Survival outcomes reported)	Moderate (Small validation cohort)	Moderate (Validation sample limited)

The figure 3 presents a traffic-light plot assessing the risk of bias for a prognostic prediction model study. The analysis shows that the included study had low bias in key areas like participant selection and outcome determination but was rated with a moderate overall risk.

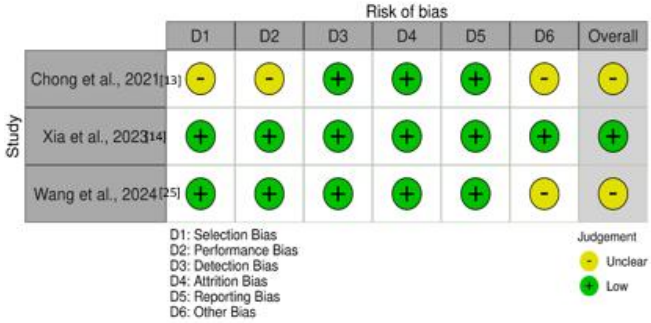

Figure 3: Risk of bias traffic-light plot for prognostic prediction-model studies assessed using the PROBAST framework.

The ROB analysis of the prospective diagnostic accuracy/prediction study has been summarized as a table (Table 4) based on the QUADAS-2 checklist. Zamboglou et al., 2019[18] demonstrated low selection bias, as the primary cohort was prospectively enrolled, and low detection bias was seen due to the use of the histological reference standard. The reporting and attrition bias were also low, since the methodology was well described and a validation cohort was used. But the overall risk assessment was considered moderate because of manual segmentation and the small sample size of prospective participants, which could affect the reproducibility and generalizability.

Table 4: ROB assessment for prospective diagnostic accuracy/prediction study using QUADAS-2

Author & Year	Selection Bias	Performance Bias	Detection Bias	Attrition Bias	Reporting Bias	Other Bias	Overall Risk
Zamboglou et al., 2019[18]	Low (Prospective primary cohort)	Moderate (Manual segmentation used)	Low (Histology reference standard)	Low (Validation cohort included)	Low (Methods fully described)	Moderate (Small prospective sample)	Moderate (Small sample concern)

The traffic-light plot summarizes the ROB assessment for a single prospective diagnostic accuracy study using the QUADAS-2 checklist (Figure 4). It confirms a low risk of bias for selection, detection, attrition, and reporting, while indicating a moderate overall risk.

Figure 4: ROB traffic-light plot for the prospective diagnostic accuracy/prediction study assessed using QUADAS-2.

Discussion

Radiomics models based on imaging have been found to have increasing promise in predicting histopathological aggressiveness and margin-related outcomes in solid organ malignancies. Studies included in the analysis included hepatocellular carcinoma, prostate cancer, renal cell carcinoma, and pancreatic tumors. Microvascular invasion, tumour grade, ISUP grade, Fuhrman grade, Gleason Grade Group, Ki-67 expression, extracapsular extension, positive surgical margins, resection margin status, and survival outcomes were the primary prediction targets. These results suggest that radiomics could provide quantitative biological information in addition to the information obtained from conventional visual imaging. MRI- and CT-based radiomics models were found useful to predict MVI and histological grade, which are closely related to recurrence and aggressive tumour behaviour, in HCC [29]. In pancreatic and renal tumors, radiomics was found to be associated with predicting the tumour grade and outcomes related to resection margins [30].

MVI is generally diagnosed post-surgery, but its pre-operative identification is important for resection planning, decision for transplantation, and for the classification of the risk of recurrence [31]. Multiparametric MRI and multiphase CT radiomics were reported to predict MVI in Chong et al., 2021[13]and could provide prognostic information related to the recurrence-free or overall survival in Xia et al., 2023[14,] which is similar to previous studies [32]. Mao et al., 2022[15] demonstrated that the MRI radiomics signature obtained with the help of a Gd-EOB-DTPA could distinguish between high-grade and low-grade HCC [33], and Zhang et al., 2019[16] revealed that bi-regional MRI radiomics, combining the tumour and peritumoral region, could enhance the prediction of MVI [34]. The results in this study suggest that radiomics may be able to reflect the tumour heterogeneity, peritumoral vascular alteration, and micro-invasive pattern, which may not be fully understood by conventional radiological analysis [35].

Radiomics was primarily used for predicting local invasion and pathological aggressiveness in prostate cancer [36]. MRI models helped predict extracapsular extension and positive surgical margins, which are critical for surgical planning and decisions of nerve-sparing [37]. PSMA PET also helped differentiate the intraprostatic tumour with increased Gleason score and nodal status as a radiomics application [38]. Biparametric MRI radiomics was also found to predict Ki-67 expression and Gleason Grade Group by Qiao et al., 2023[19,] which helped to differentiate indolent and aggressive disease. Conventional MRI might have limited sensitivity for the detection of microscopic extension, but radiomics can give quantitative texture and diffusion-based information, which is clinically relevant [39]. But this needs to be translated into practice and needs to be reproducible, scanner-independent, and validated in multiple centres. Multimodal MRI and CT-based radiomics were able to distinguish between low-grade and high-grade tumors using Fuhrman or ISUP grading systems in ccRCC [40].

Radiomics shows potential as a non-invasive decision support tool, but there is still a lack of evidence and methodological variability. Heterogeneity and variable methodological quality were the reasons for the low to moderate certainty of evidence in GRADE. Future research should focus on prospective multicentre studies, establishing a standardized radiomics workflow, reporting in a transparent manner, external validation, and assessing the clinical utility to establish reliability for the use of radiomics in personalized oncological decision-making.

Conclusion

The results of this systematic review support the use of radiomics-guided imaging models for predicting histopathological aggressiveness and margin-related outcomes in solid organ malignancies, with promising value. In all included studies, radiomics was used to predict microvascular invasion, tumour grade, ISUP grade, Gleason Grade Group, Ki-67 expression, extra-capsular extension, and resection margin status. All these results highlight the potential of radiomics in precision diagnostics and preoperative oncological planning. But it is important to note that future prospective, multi-centre studies with standardized work-flows and with external validation are needed before routine clinical implementation.

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