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A systematic review of the predictive value of radiomics for nasopharyngeal carcinoma prognosis

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Abstract

Background: Radiomics has been widely used in the study of tumours, which has predictive and prognostic value in nasopharyngeal carcinoma (NPC). Therefore, we collected relevant literature to explore the role of current radiomics in predicting the prognosis of NPC.

Methods: We performed a systematic literature review and meta-analysis in accordance with the preferred reporting items in the systematic evaluation and meta-analysis guidelines. We included papers on radiomics published before May 5, 2024, to evaluate the predictive ability of radiomics for the prognosis of NPC. The methodological quality of the included articles was evaluated using the radiomics quality score. The area under the curve (AUC), combined sensitivity and combined specificity were used to evaluate the ability of radiomics models to predict the prognosis of NPC.

Results: A total of 20 studies met the inclusion criteria for the current systematic review, and 13 papers were included in the meta-analysis. The radiomics quality score ranged from 7 to 20 (maximum score: 36). The diagnostic test forest plots showed that the diagnostic OR of radiology was 11.04 (95% CI: 5.11–23.87), while the ORs for sensitivity and 1-specificity were 0.75 (95% CI: 0.73–0.78) and 0.74 (95% CI: 0.72–0.76), respectively. It cannot be determined whether the combined model was superior to the radiomics model for predicting the prognosis of NPC. It is unclear whether the fact that the radiomics model was composed of features extracted from MRI is due to CT. The AUC of PFS was larger than that of disease-free survival ($P < .05$). The overall AUC value is 0.8265.

Conclusion: This study summarized all the studies that examined the predictive value of radiomics for NPC prognosis. Based on the summarized AUC values, as well as sensitivity and 1-specificity, it can be concluded that radiomics has good performance in predicting the prognosis of NPC. Radiomics models have certain advantages in predicting the effectiveness of PFS compared to predicting disease-free survival. It cannot be determined whether the combination model is superior to the radiomics model in predicting NPC prognosis, nor can it be determined whether imaging methods have differences in predictive ability. The findings confirmed and provided further evidence supporting the effectiveness of radiomics for the prediction of cancer prognosis.

Abbreviations: AI = artificial intelligence, AUC = the area under the curve, CD = critical distance, CEA = cost–benefit analysis, CIs = confidence intervals, DCA = decision curve analysis, DFS = disease-free survival, EBV = Epstein–Barr virus, FN = false-negative, FP = false-positive, LASSO = least absolute screening and selection operator, NPC = nasopharyngeal carcinoma, ORs = odds ratios, PFS = progression-free survival, PRISMA = the preferred reporting items for systematic reviews and meta-analyses, QUADAS-2 = the quality assessment of diagnostic accuracy studies, Rad-Score = the radiology score, REML = the restricted maximum likelihood method, ROC = receiver operating characteristic, ROIs = regions of interest, RQS = the radiomics quality score, SEN = sensitivity, SEs = standard errors, SPE = 1-specificity, SROC = the summary receiver operating characteristic, TN = true negative, TP = true positive, UFS = univariant feature selection.

Keywords: meta-analysis, nasopharyngeal carcinoma, radiomics, systematic analysis

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All data generated or analyzed during this study are included in this published article [and its supplementary information files].

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1. Introduction

Nasopharyngeal carcinoma (NPC) is 1 of the most common EBV (Epstein–Barr virus)-related epithelial carcinomas and is highly prevalent in southern China and Southeast Asia. Its etiology is mainly related to EBV infection, and its occurrence is also related to chemical environmental factors and genetics. At present, radiotherapy is the main treatment for NPC. Synchronous radiochemotherapy, induction chemotherapy, and immunotherapy are also being developed.[1] Researchers are currently focusing on how to better predict the prognosis of nasopharyngeal carcinoma and how to provide more appropriate and reasonable treatment to patients with nasopharyngeal carcinoma at different stages. Traditional TNM staging reflects the prognosis of NPC to a certain extent and plays a key role in clinical care, clinical trial qualification and stratification, research, health services, cancer registration activities, cancer control and policymaking.[2] EBV detection is usually used for NPC population screening, and it also shows excellent results in prognosis and distant recurrence detection.[3] Some scholars found that the lower the plasma EBV DNA test value, the higher the 5-year survival rate in the pretreatment test.[4]

In recent years, artificial intelligence (AI) has made substantial progress in the diagnosis of cancer. Additionally, AI-based cancer imaging is used for other clinical applications. AI's diagnostic performance continues to improve, even surpassing that of human experts.[5] Radiomics refers to researchers segmenting medical images by regions of interest (ROIs), extracting a large number of radiomics features through computer software, and screening out features with high specificity for diagnosing certain diseases or identifying related diseases to guide clinical work.[6] Radiomics is a method of combining AI with imaging data, which is used for disease prediction, response prediction to different treatment modes, identification of treatment-related changes, and discovery of imaging manifestations of phenotypic and genotypic characteristics related to prognosis.[7]

Radiological data analysis highly relies on the subjective interpretation of skilled radiologists. The quantitative data extracted by Radiomics has better objectivity and can serve as an auxiliary tool for physician opinions, thereby improving the accuracy of diagnosis and treatment. Radiomics has been widely used in the study of tumors, which has predictive and prognostic value in NPC.[6]Therefore, we collected relevant literature to explore the role of current radiomics in predicting the prognosis of NPC.

2. Materials and methods

2.1. Study protocol

2.1.1. Eligibility criteria. *Inclusion criteria*. Patients with histologically confirmed nNPC, First MRI or CT images before treatment were available, Clinical data were available.

Exclusion criteria. Incomplete imaging or clinical data, loss to follow-up, history of anticancer treatment before radiography scans.

2.1.2. Information source. Four databases (Web of Science, PubMed, Embase, and Cochrane Library) were screened to select relevant articles published before May 5, 2024.

2.1.3. Search strategy. The retrieval form of "subject words + free words" was adopted. The keyword was: nasopharyngeal carcinoma. The free words were as follows: nasopharyngeal carcinomas, nasopharyngeal carcinoma, carcinoma, nasopharyngeal, carcinomas, nasopharyngeal, and radiomics. The retrieval strategy for PubMed was as follows:: (((("Nasopharyngeal Carcinoma" [Mesh]) OR ((((Nasopharyngeal Carcinomas [Title/Abstract]) OR (Nasopharyngeal carcinoma [Title/Abstract])) OR (Carcinoma, Nasopharyngeal [Title/Abstract])) OR (Carcinomas, Nasopharyngeal [Title/Abstract])))) AND (Radiomics [Title/Abstract])) AND (sensitivity* [Title/Abstract] OR sensitivity and specificity [MeSH Terms] OR (predictive [Title/Abstract] AND value* [Title/Abstract]) OR predictive value of tests [MeSH Term] OR accuracy* [Title/Abstract]).

2.1.4. Selection process. To further evaluate the relevant articles, we screened the full texts of the potentially eligible articles and excluded research on other aspects of radiomics (such as chemotherapy, inflammation, and staging). In the process of extracting data, we also excluded articles with irrelevant and incomplete data. The reference lists of the included articles were also reviewed to identify additional eligible studies. The types of images included in our study included MRI and CT images.

2.1.5. Data collection process. Two independent researchers screened the titles and abstracts of each article for potential inclusion in the current review. Reviews and other article types that did not meet the inclusion criteria were excluded.

This study was conducted in accordance with the preferred reporting items for systematic reviews and meta-analyses (PRISMA) guidelines.[8] This article does not require ethical approval as the data collected in the article are all from publicly available research.

2.2. Data collection

Extraction of basic information. We extracted the following data: article type, disease type, examination method, data source, tumor segmentation method, radiomics feature selection, ROI, etc.

Data extraction. The training set data were extracted, and the outcome indicators disease-free survival (DFS) and progression-free survival (PFS). For articles that provided cutoff values for the Radiology Score (Rad-score), we extracted sensitivity (SEN) and 1-specificity (SPE). For articles that provided The area under the curve (AUC), we extracted AUC values and their confidence intervals (CIs)/standard errors (SEs). For articles that provided receiver operating characteristic (ROC) curves, the GetData Graph Digitizer was used to extract pixel points on the curve, and 5 points were collected for each image.

2.3. Quality assessment

The radiomics quality score (RQS) was used to evaluate the methodological quality of qualified publications, and the quality assessment of diagnostic accuracy studies (QUADAS-2) was used to determine the risk of bias for each diagnostic experiments.[9,10]

The RQS assesses the quality of the survey methods by examining 16 items, such as image protocol quality, multiple segmentation, and phantom study on all scanners.[10] RQS assesses the quality of the survey methods by examining 16 items such as Image protocol quality, multiple segmentation, phantom study on all scanners.[10] Two experienced doctors independently rated the RQS of qualified articles. The QUADAS-2 assesses the risk of bias across different dimensions ("Patient Selection," "Index Test," "Reference Standard," and "Flow and Timing") and can be customized according to specific research questions. The risk of bias for each included study was determined by the QUADAS project of Review Manager 5.4 to evaluate the quality of diagnostic articles.[11]

2.4. Meta-analysis

A meta-analysis of the studies related to the prognosis of nasopharyngeal carcinoma was carried out. The data were retrieved by 2 independent reviewers. The internal effectiveness was

evaluated by the third reviewer. Only articles that provided the ROC curve, AUC index and their CIs were included in the meta-analysis. When there were multiple models in 1 article, we chose the best model. A suitable model was extracted based on subgroup analysis.

2.5. Statistical analysis

The random effects meta-analysis was carried out using the restricted maximum likelihood method (REML) to yield logarithmic odds ratios (ORs). For the articles in which the Rad-Score divided the truncation value, SEN and 1-SPE were extracted and converted into the true positive (TP) rate, true negative (TN) rate, false-positive (FP) rate, and false-negative (FN) rate. MetaDiSc 1.4 software was used to evaluate the threshold effect and draw the forest plot of the diagnostic experiment. For articles that provided ROC curves, the TP, FP, TN, and FN rates were fitted according to the extracted coordinate points, and the summary receiver operating characteristic (SROC) curve was drawn using MetaDiSc 1.4 software. Based on the extracted AUC value (C-index) and the confidence interval/standard error, MedCalc software was used to directly draw the forest map to evaluate the following aspects: the ability of the radiomics model to predict the prognosis of nasopharyngeal carcinoma, including the predictive value of the SEN/SPE, AUC/C-index, SROC; which model had better predictive ability when radiomics was used for MRI and CT; and which model had better predictive ability for DFS and PFS in radiomics.

R (version 4.0.5; https://cran.r-project.org/), MedCalc (https://www.medcalc.org/), GetData Graph Digitizer (version 2.26; http://www.getdata-graph-digitizer.com/), Review Manager (version 5.3), MetaDiSc (version 1.4; https://metadisc.software.informer.com/).

3. Results

3.1. Literature search

We preliminarily identified 114 relevant articles through the literature search. After eliminating duplicate publications, 53 articles remained. After screening titles and abstracts, 48 related articles remained for further analysis. Among them, there were 28 articles describing radiomics, nasopharyngeal carcinoma staging, chemotherapy, inflammation, etc, which were excluded. A total of 20 articles using a prediction model based on radiomics were ultimately included in this systematic review.[12–31] The outcome indicators of 5 articles were not detailed or it does not meet the requirements of this study.[14,21,28,30,31] The research

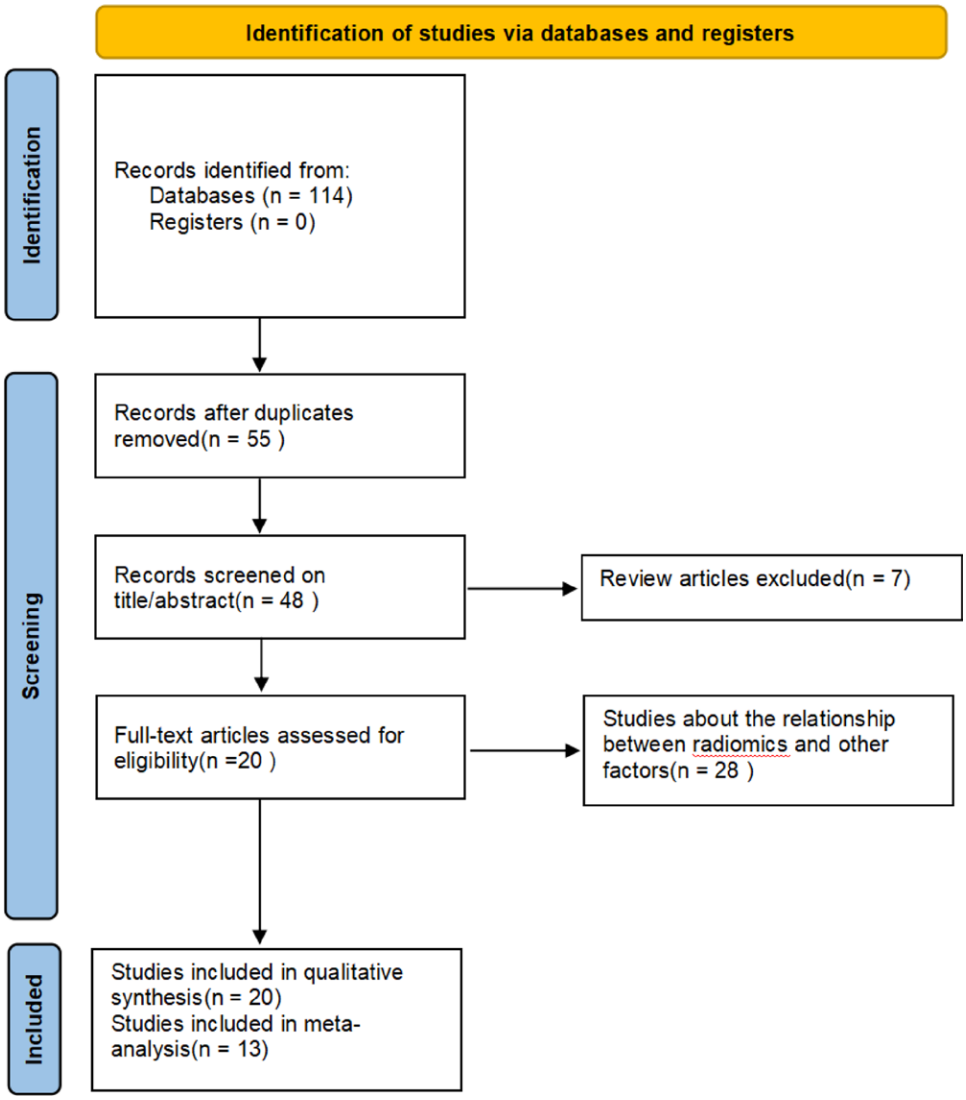

Figure 1. A schematic of the publication selection process.

process of 2 articles does not conform to this study (using imaging data before and after treatment instead of single data prediction).[27,29]Therefore, our meta-analysis included 13 articles. Our PRISMA flowchart is shown in Figure 1, and the essential information of the included articles is shown in Table 1 (see Table 1, supplemental content, Supplemental Digital Content, http://links.lww.com/MD/N357, which illustrates the basic information).

3.2. Evaluation criteria for prognosis of NPC

The outcomes of interest in this study are DFS and PFS. PFS was defined as the time from the date of confirmation of the complete response to the date of the latest local recurrence, distant metastasis, death from any cause or the last follow-up. DFS is the time from the confirmation of complete remission of the disease to the recurrence of the disease or (for any reason) death.

3.3. Study evaluation

3.3.1. RQS scores. RQS scores range from 8 to 20 (maximum score: 36), as shown in Table 2. The highest percentage of RQS observed among the included studies was 55.6%. After the evaluation was completed by 2 reviewers, they reevaluated any differences until a consensus was reached. See supplementary materials for detailed scores (see Table 2, supplemental content, Supplemental Digital Content, http://links.lww.com/MD/N357, which illustrates the RQS Scoring rules, and see Table 3, supplemental content, Supplemental Digital Content, http://links.lww.com/MD/N357, which illustrates RQS scores of each study).

3.3.2. QUADAS-2. The risk of bias assessment based on the QUADAS-2 is shown in Figure 2. Regarding patient selection, most articles did not specify whether the selection of cases is continuous, and all articles neglected to use case control. Regarding the index test, all articles were interpreted with the outcome known, and the threshold was defined on the premise of knowing the outcome in the articles that defined the threshold, while the articles that did not define the threshold are not clear. Regarding the reference standard, the outcome was the gold standard of the evaluation (which can correctly distinguish the disease status), and the gold standard has nothing to do with the radiomics model to be evaluated. Regarding flow and timing, most of the articles reported no loss of follow-up. One article explained the situation leading to 1 patient being lost to follow-up, and the follow-up of 1 article was unknown.

3.3.3. Meta-analysis. For Rad-score literature with cutoff value (dividing patients into high and low risk), draw diagnostic test forest plots, as shown in Figure 3; for documents that provide AUC value, use AUC value to draw forest map, as shown in Figure 4; for the literature that provides ROC curve, use the fitting data to draw SROC curve, as shown in Figure 5 (see Table 4, supplemental content, Supplemental Digital Content, http://links.lww.com/MD/N357, which illustrates Bias assessment and funnel plots for each study).

The results of this study are as follows:

(1) The diagnostic test forest plots showed that the diagnostic OR of radiology was 11.04 (95% CI: 5.11–23.87), while the ORs for SEN and SPE were 0.75 (95% CI: 0.73–0.78) and 0.74 (95% CI: 0.72–0.76), respectively;
(2) The AUC indicating the predictive value of the combination of radiohistology and a clinical model for NPC prognosis was 0.827 (95% CI: 0.783–0.871). The AUC for the radiomics model was 0.773 (95%CI: 0.731–0.815). Because of the overlap of CIs, it cannot be determined whether the combined model was superior to the radiomics model for predicting the prognosis of NPC. This finding may be due to insufficient sample size.
(3) The predicted AUC values of the radiomics features extracted from MRI and CT were 0.775 (95% CI: 0.715–0.836) and 0.863 (95% CI: 0.794–0.933), respectively. The CIs of the 2 models overlapped. Therefore, it is unclear whether the fact that the radiomics model was composed of features extracted from MRI is due to CT.
(4) When the radiomics model was used to predict the AUC of PFS and DFS, the total AUC was 0.875 (95% CI: 0.836–0.914) and 0.755 (95% CI: 0.726–0.785), respectively. The AUC of PFS was larger than that of DFS, and the CIs did not overlap. The difference was statistically

Table 1

Essential information.

Author, yr	Study Type	Cancer	ROI	Imaging	Training set	Test set	External Validation
Bao (2022)[12]	Retrospective cohort study	NPC	GTV	MRI	119	52	0
Bao (2021)[13]	Retrospective cohort study	NPC	CTV	MRI	159	40	0
Intarak et al (2022)[15]	Retrospective cohort study	NPC	GTV	CT	157	40	0
Dmytriw et al (2022)[14]	Retrospective cohort study	NPC	GTV	CT	60	0	0
Kang (2021)[16]	Retrospective cohort study	NPC	GTVnx, ln	MRI	476	119	0
Mao (2019)[17]	Retrospective cohort study	NPC	GTV	MRI	79	0	0
Ming (2019)[18]	Retrospective cohort study	NPC	GTV	MRI	200	103	0
Peng et al (2019)[19]	Retrospective cohort study	NPC	CTV	CT	470	237	0
Shen (2020)[20]	Retrospective cohort study	NPC	GTV	MRI	230	97	0
Xie et al (2020)[21]	Retrospective cohort study	NPC	GTV	CT	125	41	182
Yan et al (2021)[22]	Retrospective cohort study	NPC	GTV	CT	218	93	0
Yang et al (2019)[23]	Retrospective cohort study	NPC	GTVnx, ln	MRI	149	75	0
Zhang (2017)[24]	Retrospective cohort study	NPC	CTV	MRI	80	33	0
Zhong et al (2020)[25]	Retrospective cohort study	NPC	GTV	MRI	447	191	0
Zhu et al (2021)[26]	Retrospective cohort study	NPC	GTVnx	CT	109	47	0
Xu et al (2023)[30]	Retrospective cohort study	NPC	GTV	CT/MRI	88	44	0
Sun (2023)[27]	Retrospective cohort study	NPC	GTV	MRI	80	40	0
Long et al (2023)[31]	Retrospective cohort study	NPC	GTV	PET-CT	138	34	0
Xi et al (2024)[28]	Retrospective cohort study	NPC	GTVnx	MRI	313	0	0
Dang et al (2024)[29]	Retrospective cohort study	NPC	GTV	MRI	180	46	0

CT = computed tomography, CTV = gross target volume, GTV = gross target volume, GTVln = gross tumor volume in the metastatic lymph nodes, GTVnx = gross tumor volume in the nasopharynx, MRI = magnetic resonance imaging.

significant, indicating that the radiomics model was superior for predicting the effectiveness of PFS.

(5) The SROC curve shows that the combined AUC value is 0.8265, which indicates that the radiomics model has a good predictive effect for the prognosis of NPC.

Heterogeneity: according to the evaluation of threshold effect, the spearman correlation coefficient is 11, P value = .180, $P > .05$, and there is no obvious threshold effect. See the Supplementary Materials, Supplemental Digital Content, http://links.lww.com/MD/N357 for details; see the Supplementary Materials, Supplemental Digital Content, http://links.lww.com/MD/N357 for the heterogeneity at the beginning of the study. Due to the large heterogeneity, the random effect model is adopted; the funnel chart shows that in the discussion of the total effect and subgroup analysis, the risk of publication bias is high. See the Supplementary Materials, Supplemental Digital Content, http://links.lww.com/MD/N357 for details.

4. Discussion

Radiomics is a combination of AI and imaging data that has developed rapidly in recent years. The articles we included were published between 2017 and 2024, and over time, the methods adopted by the articles tended to show improvements. Generally, the literature on using radiomics to predict the prognosis of NPC is divided into several steps: selection and grouping of research objects, image acquisition and ROI region segmentation, extraction and selection of radiomics features, model construction and validation, statistical analysis and data summary.

Table 2

RQS score.

RQS scoring item	Details	Average
Image protocol quality	A research record is not available[17]	1
Multiple segmentations	A research record is not available[14]	0.93
Phantom study on all scanners	No research has been carried out	0
Imaging at multiple time points	All studies have collected this item	1
Feature reduction or adjustment for multiple testing	All studies have collected this item, 1 research record is not available[17]	2.8
Multivariable analysis with nonradiomics feature	Most of the studies also compared clinically relevant prediction methods, and 2 studies were not done[14,16]	0.8
Detect and discuss biological correlates	No research has been carried out	0
Cutoff analyses	Seven studies defined cutoff values[12,13,16–18,22,26]	0.47
Discrimination statistics	All studies have conducted AUC/C-index research, and 6 studies have adopted resampling method[12,13,22,23,25,26]	1.4
Calibration statistic	Eight studies reported calibration statistics[12,13,19,20,22,23,25,26]; 5 of them adopted the resampling method[12,13,22,23,25]	0.87
Prospective study registered in a trial database	No prospective study	0
Validation	All have been verified, 1 of which uses multicentre data[21]	2.13
Comparison to "gold standard"	Except for 2 studies, other studies were compared with clinical models[14,16]	1.6
Potential clinical utility	DCA curve was used in 4 studies[12,13,22,26]	0.53
Cost-effectiveness analysis	No research has been carried out	0
Open science and data	Except for the ROI segmentation method of the 2 studies is not clear, the rest provide open source data[14,26]	1.87
Total score (Maximum:36)		15.40

The inclusion criterion used in the studies reviewed herein was usually NPC confirmed by pathology without metastasis. Before treatment, an imaging scan was performed, and the standard treatment protocol was accepted. Patients were usually divided into a training set and a verification set. One article described external validation, while another article did not divide patients into groups.[17,21] For the ROI region segmentation, the GTV and CTV are the main parameters. Some studies used GTVnx and GTVln, but due to the insufficient number of studies, it is impossible to determine the difference between these parameters.

In addition to the prediction of radiomics itself, clinically related models have gradually been integrated into the radiomics model, such as TNM staging, EBV DNA copy number, and LDH content. The addition of these models has improved the ability to predict cancer prognoses, but it is difficult to perform further analysis due to the large differences between nonradiomics models. For outcome indicators, although DFS and PFS are discussed separately in this paper and some results have been obtained, it is difficult to unify the observation time of DFS and PFS in different articles, which is often reported in months and usually ranges from 1 year to 5 years. MRI and CT have different sequences, and the characteristics of these sequences may be different, which needs further discussion and research. Two articles combined imaging data before and after treatment to predict disease prognosis, which is a new approach.[27,29] However, their data has significant heterogeneity compared to other articles, so only a systematic review was conducted.

Both the AUC and C-index are manifestations of the effectiveness of predictive diagnostic experiments. The C-index is an extension of the AUC, and the AUC is a special case of the C-index. The C-index for the binary classification model is equivalent to the AUC. Therefore, we will generalize the AUC and C-index.

Different articles have different descriptions of the selection of radiation features, but they generally include shape features, first-order intensity features, texture features, grayscale features and wavelet-based features. Texture features are adopted by most studies. The screening of radioactive characteristics usually involves least absolute screening and selection operator (LASSO) regression. In addition, RFE based on SVR in Python, univariant feature selection (UFS), and the Pearson correlation analysis are also used.[16,20,21] The optimal method for this process has yet to be identified.

The included literature used the Rad-Score to predict DFS, PFS and other outcome indicators and evaluated the calibration and optimization of the model through a series of methods. For example, some studies have adopted nomograms to integrate the predictive effects of radiology and other variables on disease prognosis. By combining radiomics and other variables, the effect of the whole model increased.[12,19,20,22,23,25–27,29,30] The following calibration curve evaluates the predictive ability of Nomoto. Critical distance (CD) diagram of the performance ranking of different resampling technologies obtained by the Nemenyi test.[21] Decision curve analysis (DCA) is used to derive the net income of the model at different probabilities and draw a curve to determine the threshold range of probability and the size of income, thus improving the practicability of the model.[30,32]

In terms of data statistics, the outcome is survival data. The included articles performed correlation analysis between radiology and prognosis, performed COX regression analysis, drew ROC curves, and obtained AUC values and CIs. Some articles also divided patients into high-risk and low-risk groups based on the Rad-Score and then calculated parameters such as specificity and sensitivity.

Figure 2. Bias assessment chart.

Cost–benefit analysis (CEA) can help decision-makers understand the additional cost of introducing a new technology, which plays an important role in middle- and low-income countries.[33] NPC usually occurs in Southeast Asia, and CEA is more important, but the current included studies did not perform such analyses.

Recently, many articles have examined the application of radiomics in NPC. These articles further support the use of radiomics to predict the prognosis of NPC, including the prediction of radiation temporal lobe injury, the side effects of chemotherapy, lymph node metastasis, distant metastasis, recurrence and inflammation.[34–38] Additionally, relevant

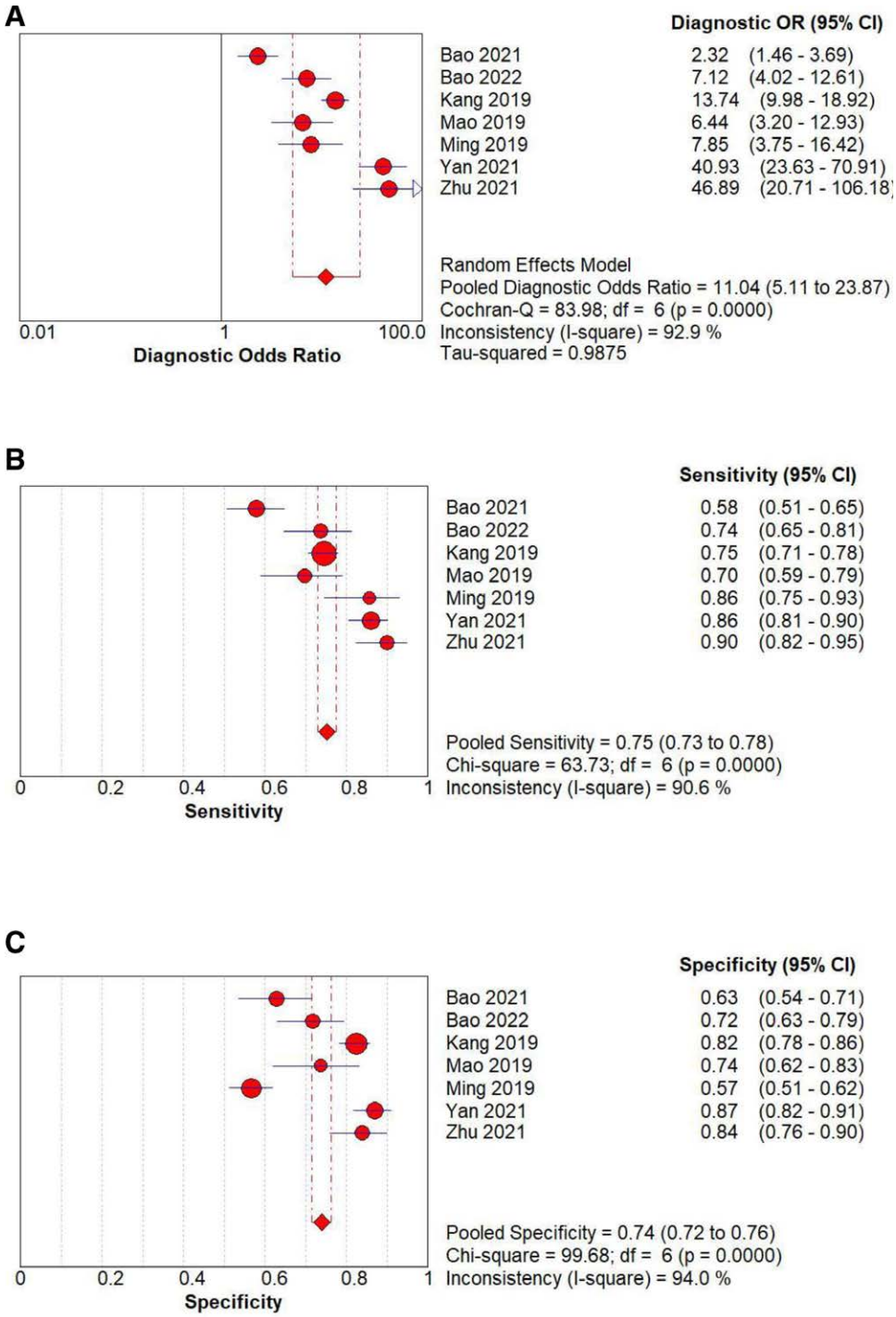

Figure 3. Forest plots.

systematic reviews have been published. A previous meta-analysis well described the ability of radiomics to predict the efficacy of neoadjuvant chemotherapy for treating nasopharyngeal carcinoma.[39] In conclusion, this article combines the SEN and SPE indicators and summarizes the AUC values (SROC). However, the article does not specify the specific outcome indicators included in the literature or whether there are differences between them, nor does it discuss the differences of imaging methods used (MRI&CT). This study clearly elaborates on the outcome indicators and their differences included in the literature and categorizes and discusses them. At the same time, it also summarizes and compares the imaging methods used in radiology. Although the final conclusion did not draw any differences between different imaging methods, it still provides some data reference for later research. An increasing number of studies are expected to confirm and improve the usefulness of radiomics.

5. Conclusion

This study summarized all the studies that examined the predictive value of radiomics for nasopharyngeal carcinoma prognosis, combined AUC values, constructed SROC curves, and evaluated

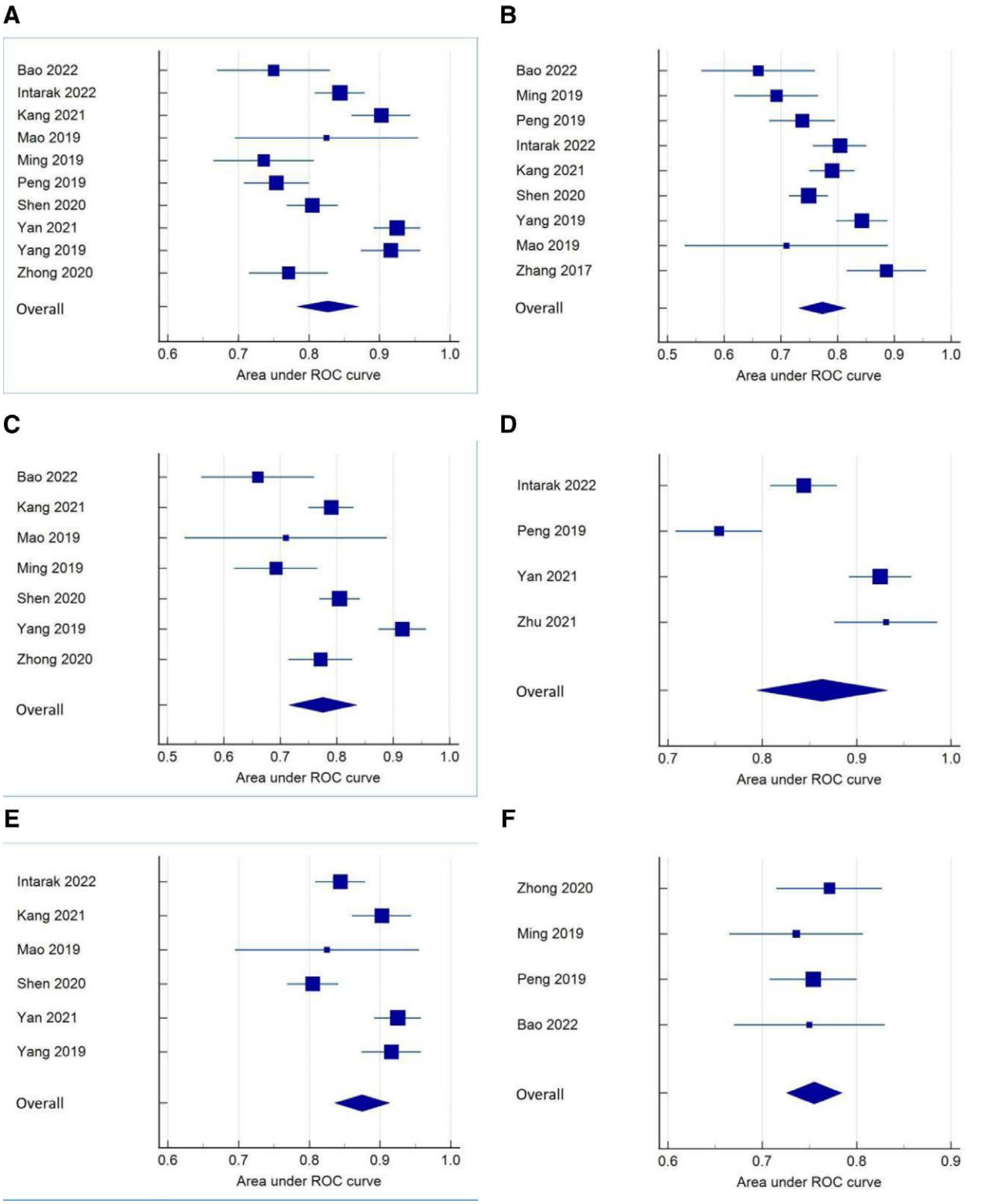

Figure 4. AUC merged forest plots. AUC = the area under the curve.

the studies with the RQS score and the QUADAS-2. Radiomics models have certain advantages in predicting the effectiveness of PFS compared to predicting DFS. It cannot be determined whether the combination model is superior to the radiomics model in predicting NPC prognosis, nor can it be determined whether imaging methods have differences in predictive ability. The findings confirmed and provided further evidence supporting the effectiveness of radiomics for the prediction of cancer prognosis.

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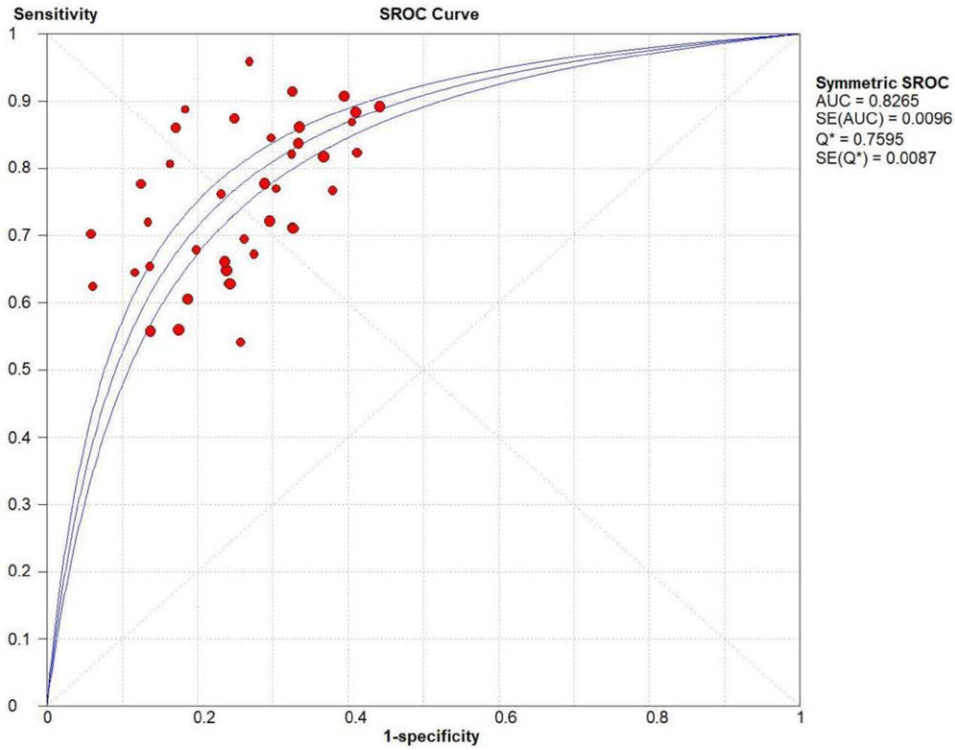

Figure 5. Combined SROC curve. SROC = the summary receiver operating characteristic.

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