Journal of
Cardiology & Cardiovascular
Surgery

Original Article

DOI: 10.51271/JCCVS-0069

Preoperative risk stratification of pulmonary nodules in cardiovascular practice: development of a CT-based logistic regression model

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Cite this article: Ayhan Albayrak G. Preoperative risk stratification of pulmonary nodules in cardiovascular practice: development of a CT-based logistic regression model. *J Cardiol Cardiovasc Surg.* 2026;4(1):6-13. doi:10.51271/JCCVS-0069

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Received: 14/01/2026 ◆ **Accepted**: 23/02/2026 ◆ **Published**: 28/03/2026

ABSTRACT

Aims: Accurate risk stratification of pulmonary nodules incidentally detected during cardiovascular imaging is essential for guiding preoperative evaluation and cardiothoracic decision-making. This study aimed to identify independent predictors of pulmonary nodule malignancy and to develop a logistic regression–based risk scoring model, comparing its diagnostic performance with the Brock model.

Methods: This retrospective study included 125 patients with pulmonary nodules who underwent histopathological evaluation between January 2019 and December 2023. Patients were classified as benign (n=64) or malignant (n=61). Clinical characteristics and radiological parameters obtained from computed tomography and positron emission tomography/computed tomography were recorded. Univariable and multivariable logistic regression analyses were performed to identify independent predictors of malignancy. A weighted risk score was constructed based on regression coefficients. Discriminative performance was assessed using receiver operating characteristic curve analysis and compared with the Brock model using the DeLong test. A p value <0.05 was considered statistically significant.

Results: Multivariable analysis identified computed tomography nodule size, irregular margins, and pleural-based localization as independent predictors of malignancy (p<0.05). The proposed risk model demonstrated excellent discrimination with an area under the curve of 0.989 (95% confidence interval: 0.978–1.000), significantly superior to the Brock model (area under the curve=0.819; 95% confidence interval: 0.743–0.891; p<0.001). At the optimal cutoff value, sensitivity was 90.0% and specificity was 98.4%.

Conclusion: The developed logistic regression–based risk model provides a highly accurate tool for malignancy prediction in pulmonary nodules encountered during cardiovascular evaluation. Integration of this model into preoperative cardiovascular workflows may enhance multidisciplinary decision-making and reduce unnecessary invasive procedures.

Keywords: Risk assessment, cardiovascular imaging, thoracic surgery, neoplasm staging, diagnostic imaging

INTRODUCTION

Incidental pulmonary nodules are frequently identified during thoracic imaging performed for cardiovascular evaluation and preoperative assessment. Accurate differentiation between benign and malignant nodules is critical in cardiothoracic practice, as inappropriate management may result in unnecessary surgical procedures or delayed oncologic intervention.[1] Pulmonary nodules are increasingly detected with the widespread use of thoracic computed tomography (CT), both in lung cancer screening programs and as incidental findings during imaging performed for other clinical indications. Meta-analyses conducted in recent years indicate that pulmonary nodules are identified in approximately one-quarter to one-third of chest CT examinations, the majority of which are benign; however, a clinically significant proportion represents malignant or premalignant lesions, highlighting the critical importance of accurate early characterization. Early and reliable differentiation between benign and malignant nodules is essential, as it directly influences clinical decision-making, patient outcomes, and healthcare resource utilization. Although traditional radiological features—including nodule size, spiculated or irregular margins, and upper lobe location—remain important predictors of malignancy, reliance on individual imaging characteristics alone often provides insufficient diagnostic accuracy in routine clinical practice.[1]

Accurate differentiation between benign and malignant nodules is essential for guiding management decisions, including the need for surveillance imaging, positron emission tomography/computed tomography (PET/CT), or invasive diagnostics, and influences patient outcomes and healthcare utilization. Traditional CT morphological features—such as nodule size, margin characteristics (e.g., spiculation), density (solid vs subsolid), and lobar location—remain central to risk assessment in routine radiologic practice. However, individual radiological features alone often lack sufficient specificity and reproducibility to reliably distinguish malignant from benign nodules across diverse clinical contexts.[2]

CT-based radiomics has emerged as a noninvasive approach for more comprehensive characterization of pulmonary nodules beyond conventional visual assessment. Meta-analytic evidence demonstrates that radiomics-based models achieve high pooled diagnostic performance for malignancy prediction, with reported area under the curve (AUC) values of approximately 0.91, consistently outperforming traditional radiological evaluation in multiple studies.[3,4]

Furthermore, integration of radiomic features with epidemiological and clinical variables significantly enhances model discrimination, supporting the development of multimodal risk assessment frameworks. In parallel, PET/CT-based prediction models that combine metabolic activity with morphological parameters provide improved diagnostic accuracy compared with PET metrics alone, underscoring the added value of hybrid imaging approaches.[5] Nevertheless, substantial heterogeneity in study design, imaging protocols, and feature extraction methods highlights the need for standardized validation and model refinement. Additionally, the performance of established clinical prediction tools, such as the Brock model, demonstrates variable AUC values across different populations and nodule subtypes, reinforcing the necessity for external validation in diverse clinical cohorts.[6]

Recent advances in deep learning–based imaging analysis have shown promise in pulmonary nodule risk stratification. Approaches employing convolutional neural networks have demonstrated superior classification performance compared with traditional multiparametric statistical models across different clinical subgroups, supporting their potential role in enhancing diagnostic accuracy and facilitating integration into clinical workflows. However, challenges related to model generalizability, external validation, and interpretability remain significant barriers to widespread clinical implementation.[7]

Several prediction models have been proposed to estimate malignancy risk in pulmonary nodules, including the Brock model; however, their performance may vary across different populations and clinical settings. A comprehensive evaluation of clinical and radiological predictors, together with the development of practical risk scoring systems, may enhance individualized risk assessment and help reduce unnecessary invasive procedures.[8] Therefore, this study aimed to identify independent clinical and radiological determinants of pulmonary nodule malignancy, to develop a novel logistic regression–based risk scoring model applicable in cardiovascular clinical practice, and to compare its diagnostic performance with the established Brock model.

METHODS

Ethics

This study has been approved by the Ethics Committee of Şişli Hamidiye Etfal Training and Research Hospital (Date: 29.11.2022, Decision number: 2195). All procedures were carried out in accordance with the ethical rules and the principles of the Declaration of Helsinki.

Study Design and Population

This retrospective cohort study included 125 consecutive adult patients (≥18 years) with pulmonary nodules who underwent histopathological evaluation between January 2021 and December 2022 at a tertiary care center with cardiovascular and cardiothoracic services. Patients with at least one pulmonary nodule detected on thoracic CT were eligible for inclusion. Inclusion criteria required the availability of diagnostic-quality thoracic CT imaging and definitive histopathological confirmation. Patients with incomplete clinical data, inadequate imaging quality, or inconclusive pathology results were excluded. Based on histopathological findings, patients were classified into two groups: benign nodules (n=64) and malignant nodules (n=61).

All eligible patients who met the predefined inclusion and exclusion criteria during the study period were included consecutively to minimize potential selection bias. Only patients with histopathologically confirmed diagnoses were analyzed to ensure diagnostic accuracy and avoid outcome misclassification. Patients whose pulmonary nodules were managed solely with radiological surveillance without tissue confirmation were not included in the final analysis.

The logistic regression model was developed using the entire study cohort. Due to the relatively limited sample size, no formal internal validation procedure (such as bootstrapping or split-sample validation) was performed. Therefore, the reported performance metrics reflect apparent model performance within the derivation dataset.

Data Collection

Demographic and clinical data, including age, sex, smoking history, and family history of lung cancer, were obtained retrospectively from electronic medical records. Radiological characteristics were recorded from thoracic CT and PET/CT images.

Radiological Evaluation

All CT and PET/CT examinations were reviewed by experienced thoracic radiologists blinded to the histopathological outcomes. Recorded radiological variables included nodule size, density (solid or part-solid), margin characteristics (regular or irregular), presence of air bronchogram, calcification, cavitation, pleural-based location, upper lobe localization, number of nodules (single vs. multiple), presence of emphysema, and maximum standardized uptake value (SUVmax) on PET/CT. An SUVmax value >2.5 was considered positive for increased metabolic activity. Pulmonary nodules were evaluated in accordance with current international guidelines, and when multiple nodules were present, the most suspicious or largest nodule was selected for analysis.

All CT and PET-CT images were reviewed by a single board-certified thoracic radiologist with substantial experience in thoracic imaging. The radiologist was aware of the clinical indication but blinded to the final histopathological diagnosis at the time of imaging evaluation. No independent second reading or formal interobserver agreement analysis was performed.

Brock Model Calculation

For each patient, the probability of malignancy was calculated using the Brock (Pan-Canadian Early Detection of Lung Cancer) model based on its original variables and coefficients. Brock scores were expressed as percentages and used for comparative performance analysis.

Statistical Analysis

The data analyses were performed using IBM Statistical Package for the Social Sciences (SPSS) for macOS, version 30.0 (IBM Corp., Armonk, NY, USA). The distribution of continuous variables was assessed using the Kolmogorov–Smirnov test, histogram inspection, and evaluation of skewness and kurtosis values (±2). Categorical variables were presented as counts and percentages [n (%)]. Continuous variables were expressed as mean±standard deviation for normally distributed data and as median (interquartile range, IQR) for non-normally distributed data. Comparisons between benign and malignant nodule groups were performed using Student's t-test for normally distributed continuous variables and the Mann–Whitney U test for non-normally distributed continuous variables. Categorical variables were compared using the Pearson chi-square test or Fisher's exact test, as appropriate.

Logistic regression analyses were conducted to identify factors associated with pulmonary nodule malignancy. Initially, univariate logistic regression analyses were performed for all variables. Variables with a p value <0.05 in univariate analysis, as well as those considered clinically relevant, were included in multivariate logistic regression analysis. Two separate logistic regression models were constructed.

Model A was designed to identify independent risk factors for malignancy by incorporating study-specific clinical and radiological variables. Based on the β coefficients obtained from the multivariate logistic regression analysis, a risk score model was developed to facilitate clinical applicability. Regression coefficients were scaled while preserving their relative magnitudes. Specifically, each β coefficient was divided by the smallest β coefficient in the model, and the resulting values were multiplied by 10 and rounded to the nearest integer to generate weighted scores. The total risk score was calculated by summing the individual scores for each variable, and individual malignancy probabilities were estimated using this total score. Model B was constructed using variables included in the Brock (Pan-Canadian Early Detection of Lung Cancer) model to evaluate the performance of the Brock model within the study population. Results of multivariate logistic regression analyses were reported as odds ratios (ORs) with 95% confidence intervals (CIs).

Predicted malignancy probabilities for Model A were obtained using the predicted probability outputs from the logistic regression analysis. Brock malignancy probabilities were calculated individually for each patient using the original coefficients defined in the PanCan model. The discriminative performance of the models was evaluated using ROC analysis, and the AUC was reported with 95% CIs. Differences between the AUCs of model A and the Brock model were compared using the DeLong method. A p value <0.05 was considered statistically significant for all analyses.

RESULTS

Of the 125 patients included in the study, 64 (51.2%) had benign nodules and 61 (48.8%) had malignant nodules. The mean age of patients in the malignant group was significantly higher than that of the benign group (66±13 vs. 59±15 years, p=0.011). No statistically significant differences were observed between the groups in terms of sex distribution or smoking history (p>0.05). From a radiological perspective, the presence of an air bronchogram was significantly more frequent in benign nodules (p=0.041). Malignant nodules were significantly larger in size on CT imaging compared with benign nodules (22.6±4.9 mm vs. 17.9±5.1 mm, p<0.001). In addition, CT attenuation values were significantly higher in malignant nodules than in benign nodules (p<0.001). Calcification was significantly more common in benign nodules (p<0.001). In contrast, pleural-based location, upper lobe localization, and irregular margin characteristics were observed significantly more frequently in malignant nodules (p<0.05). On PET/CT imaging, nodules with SUVmax >2.5 were significantly more prevalent in the malignant group (p<0.001). Furthermore, the Brock malignancy score was significantly higher in malignant nodules compared with benign nodules (44.0±17.3 vs. 23.4±13.5, p<0.001) (**Table 1**).

Table 1. Distribution of clinical, demographic, and radiological characteristics of patients with pulmonary nodules

Variables	Total	Benign (n=64)	Malignant (n=61)	p value
Sex				0.112
Male	73 (58.4)	33 (51.6)	40 (65.6)	
Female	52 (41.6)	31 (48.4)	21 (34.4)	
Age (years)	62±15	59±15	66±13	0.011
Smoking history (smoker)	74 (59.2)	35 (54.7)	39 (63.9)	0.293
Air bronchogram	67 (53.6)	40 (62.5)	27 (44.3)	0.041
CT size (mm)	20.2±5.5	17.9±5.1	22.6±4.9	<0.001
CT density (HU)	39 (24–70)	31.5 (16.5–43)	63 (37–86)	<0.001
Family history of lung cancer	24 (19.2)	15 (23.4)	9 (14.8)	0.218
Number of nodules				0.571
Single nodule	83 (66.4)	41 (64.1)	42 (68.9)	
Multiple nodules	42 (33.6)	23 (35.9)	19 (31.1)	
Calcification	35 (28.0)	1 (1.6)	34 (55.7)	<0.001
Cavitation	26 (20.8)	9 (14.1)	17 (27.9)	0.057
Pleural location				<0.001
Pleural-based	61 (48.8)	6 (9.4)	55 (90.2)	
Non–pleural-based	64 (51.2)	58 (90.6)	6 (9.8)	
Upper lobe location	40 (32.3)	13 (20.3)	27 (45.0)	0.003
Emphysema	26 (21.0)	12 (18.8)	14 (23.3)	0.531
Margin characteristics				<0.001
Smooth	57 (45.6)	51 (79.7)	6 (9.8)	
Irregular	68 (54.4)	13 (20.3)	55 (90.2)	
PET SUVmax				<0.001
Negative	65 (52.0)	51 (79.7)	14 (23.0)	
>2.5	60 (48)	13 (20.3)	47 (77)	
Nodule type				<0.001
Solid	85 (68)	28 (43.8)	57 (93.4)	
Part-solid	40 (32)	36 (56.3)	4 (6.6)	
Brock score (%)	33.4±18.6	23.4±13.5	44±17.3	<0.001

Data are presented as number and percentage [n (%)] for categorical variables and as mean±standard deviation or median (interquartile range, IQR) for continuous variables, CT: Computed tomography, HU: Hounsfield unit, PET: Positron emission tomography, SUVmax: Maximum standardized uptake value

In univariate analysis, age, CT nodule size, PET SUVmax >2.5, irregular margin characteristics, pleural-based location, and upper lobe localization were significantly associated with malignancy (p<0.05). In multivariate logistic regression analysis, CT nodule size (OR=1.236, 95% CI: 1.015-1.504; p=0.035), irregular margin characteristics (OR=90.005, 95% CI: 7.236-1119.562; p<0.001), and pleural-based location (OR=111.605, 95% CI: 10.683-1165.88; p<0.001) remained independent predictors of malignancy. Age and upper lobe localization lost statistical significance after adjustment for other variables (**Table 2**).

Based on the variables found to be independently associated with malignancy in multivariate analysis (model A), a final weighted risk score model was developed (**Table 3**). Regression coefficients were transformed into weighted scores to facilitate clinical applicability, and total scores ranged 0 to 32.

The linear predictor (LP) equation was defined as: LP=−6.896+0.380×(total score). As the total score increased, the estimated probability of pulmonary nodule malignancy increased markedly. The estimated probabilities of malignancy were derived from the underlying logistic regression model and subsequently mapped to predefined total score intervals (0–4: <5%; 5–9: 10–25%; 10–14: 25–50%; 15–19: 50–75%; ≥20: ≥85%). These probability thresholds were established to provide a clinically interpretable framework for risk stratification and management decision-making (**Table 4**).

Table 3. Predictor variables and weighted scoring system derived from the multivariable logistic regression model

Variable	Criteria	Points
Age	+1 point per 10-year increase	1
Nodule size (CT)	+1 point per 5 mm increase	1
PET SUVmax ≥2.5	Yes	4
Irregular margin	Yes	12
Pleural-based localization	Yes	12
Upper lobe location	Yes	2
Total score range		0–32

CT: Computed tomography, PET: Positron emission tomography, SUVmax: Maximum standardized uptake value, Total score was calculated by summing the weighted points assigned to each predictor variable.

Table 4. Total score–based risk stratification and corresponding malignancy probabilities

Total score	Estimated probability of malignancy
0–4	<5%
5–9	10–25%
10–14	25–50%
15–19	50–75%
≥20	≥85%

The estimated probabilities of malignancy were derived from the underlying logistic regression model and subsequently mapped to predefined total score intervals (0–4: <5%; 5–9: 10–25%; 10–14: 25–50%; 15–19: 50–75%; ≥20: ≥85%). These probability thresholds were established to provide a clinically interpretable framework for risk stratification and management decision-making.

In univariate analysis, age, CT nodule size, upper lobe localization, and irregular margin characteristics were significantly associated with malignancy (p<0.05) (**Table 5**). However, in multivariate analysis, only CT nodule size and irregular margin characteristics remained independent predictors of malignancy (p<0.001). Sex, family history of lung cancer, presence of emphysema, and number of nodules were not independently associated with malignancy (p>0.05).

The proposed model demonstrated excellent discriminative performance for predicting pulmonary nodule malignancy, with an AUC of 0.989 (95% CI: 0.978–1.000; p<0.001). In contrast, the Brock model showed a lower discriminative performance, with an AUC of 0.819 (95% CI: 0.743–0.891; p<0.001). The difference between the two models was statistically significant (p<0.001) (**Table 6, Figure**). The sensitivity and specificity of the proposed model were 90.0% and 98.4%, respectively, whereas the Brock model demonstrated a sensitivity of 65.6% and a specificity of 87.5%.

Internal validation was performed using both split-sample (70% training, 30% testing) and bootstrap resampling

Table 2. Univariate and multivariate logistic regression analysis of factors associated with pulmonary nodule malignancy (model A)

Variables	Univariate analysis		Multivariate analysis	
	OR (95% CI)	p value	OR (95% CI)	p value
Age (years)	1.033 (1.007–1.060)	0.014	1.039 (0.974–1.108)	0.242
CT size (mm)	1.192 (1.104–1.288)	<0.001	1.236 (1.015–1.504)	0.035
PET SUVmax				
Negative	Reference	–	Reference	–
>2.5	13.170 (5.615–30.894)	<0.001	5.341 (0.872–32.712)	0.070
Margin characteristics				
Smooth	Reference	–	Reference	–
Irregular	35.962 (12.715–101.709)	<0.001	90.005 (7.236–1119.562)	<0.001
Pleural location				
Non–pleural-based	Reference	–	Reference	–
Pleural-based	88.611 (26.952–291.329)	<0.001	111.605 (10.683–1165.880)	<0.001
Upper lobe location				
No	Reference	–	Reference	–
Yes	3.210 (1.452–7.097)	0.004	1.964 (0.299–12.909)	0.482

Odds ratios (ORs) with 95% confidence intervals (CIs) were estimated using logistic regression analysis. Variables with p<0.10 in univariate analysis were entered into the multivariate model (model A). p-value <0.05 was considered statistically significant. CT: Computed tomography, PET: Positron emission tomography, SUVmax: Maximum standardized uptake value

Table 5. Logistic regression analysis of factors predicting pulmonary nodule malignancy according to the Brock model variables (model B)

Variables	Univariate analysis		Multivariate analysis	
	OR (95% CI)	p value	OR (95% CI)	p value
Age (years)	1.033 (1.007–1.060)	0.014	1.031 (0.991–1.072)	0.135
CT size (mm)	1.192 (1.104–1.288)	<0.001	1.252 (1.100–1.425)	<0.001
Sex				
Male	Reference	–	Reference	–
Female	0.559 (0.272–1.149)	0.114	1.753 (0.465–6.605)	0.407
Upper lobe location				
No	Reference	–	Reference	–
Yes	3.210 (1.452–7.097)	0.004	4.395 (0.653–29.580)	0.128
Margin characteristics				
Regular	Reference	–	Reference	–
Irregular	35.962 (12.715–101.709)	<0.001	79.399 (16.038–393.079)	<0.001
Family history of lung cancer				
No	Reference	–	Reference	–
Yes	0.565 (0.227–1.410)	0.221	0.525 (0.106–2.594)	0.429
Emphysema				
No	Reference	–	Reference	–
Yes	1.319 (0.554–3.139)	0.532	0.263 (0.058–1.183)	0.082
Number of nodules				
Single nodule	Reference	–	Reference	–
Multiple nodules	0.806 (0.383–1.698)	0.571	0.310 (0.053–1.812)	0.194

Odds ratios (ORs) and 95% confidence intervals (CIs) were calculated using logistic regression analysis. Reference categories are indicated. A p value < 0.05 was considered statistically significant. CT: Computed tomography

Table 6. ROC analysis results of the proposed model and the Brock model for predicting pulmonary nodule malignancy

Model	AUC (95% CI)	p value	Sensitivity (%)	Specificity (%)
Brock model	0.819 (0.743–0.891)	<0.001	65.6	87.5
Proposed logistic regression model	0.989 (0.978–1.000)	<0.001	90.0	98.4

AUC indicates area under the receiver operating characteristic (ROC) curve; AUC: Area under the curve, CI: Confidence interval. Sensitivity and specificity were calculated at the optimal cut-off values determined by ROC analysis. The diagnostic performance of the proposed model and the Brock model was evaluated using ROC curve analysis.

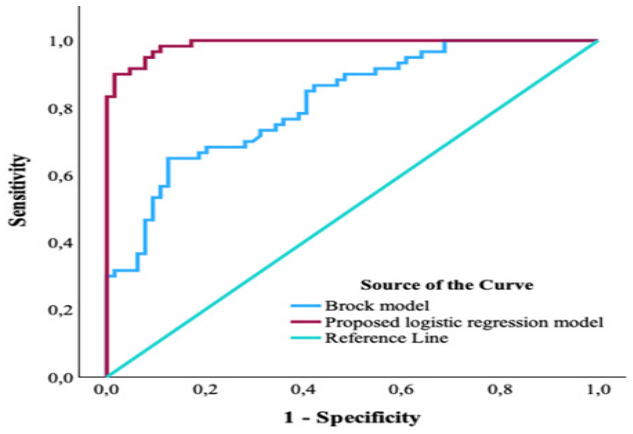

Figure. Comparison of ROC curves of the proposed logistic regression model and the Brock model for predicting pulmonary nodule malignancy
ROC: Receiver operating characteristic

(1000 iterations). The model demonstrated consistently high discriminative performance in the development cohort (AUC=0.989). In split-sample validation, the AUC remained high (0.972). The optimism-corrected AUC after bootstrap was 0.983, indicating minimal overfitting. Nevertheless, external validation in an independent cohort is required before clinical implementation (**Table 7**).

Table 7. Internal validation and optimism-corrected performance of model A

Performance measure	AUC
Development cohort (entire dataset)	0.989
Split-sample validation (70% training–30% testing)	0.972
Optimism-corrected AUC (bootstrap, 1000 resamples)	0.983

Internal validation included split-sample (70/30) and bootstrap (1000 iterations) analyses. The optimism-corrected AUC (0.983) indicated minimal overfitting and good model stability. AUC: Area under the curve

DISCUSSION

In this retrospective study, we developed a clinically applicable logistic regression–based risk model to predict pulmonary nodule malignancy and compared its diagnostic performance with the Brock model within a cardiovascular clinical context. The proposed model demonstrated excellent discriminative ability, significantly outperforming the Brock model, with an AUC of 0.989 versus 0.819. Our findings indicate that specific radiological characteristics—particularly nodule size, margin irregularity, and pleural-based localization—are strong independent predictors of malignancy.

Accurate risk stratification is especially important in patients undergoing cardiovascular evaluation and cardiothoracic surgical assessment, as incidentally detected pulmonary nodules may influence surgical planning, timing of intervention, and perioperative management strategies. Inadequate assessment may lead either to unnecessary invasive thoracic procedures or to delays in appropriate oncologic referral. The integration of a validated and practical risk scoring model into cardiovascular preoperative workflows may therefore enhance multidisciplinary decision-making, optimize patient selection for invasive procedures, and improve overall clinical management.

The high discriminative performance observed in this study may reflect the inclusion of strong radiological predictors such as nodule size, irregular margins, and pleural-based location. Nodule size remains one of the most robust predictors of malignancy in pulmonary nodules. In our study, malignant nodules were significantly larger than benign nodules, and nodule size remained an independent risk factor in multivariate analysis. This finding is consistent with current international guidelines and prior studies, which emphasize increasing malignancy risk with increasing nodule diameter.[9,10] Similarly, large population-based studies have demonstrated that nodule growth and size are key determinants in malignancy risk stratification.[11]

Margin characteristics emerged as one of the strongest predictors in our model. Irregular or spiculated margins were significantly more frequent in malignant nodules and demonstrated a very high OR in multivariate analysis. Irregular margins reflect invasive tumor growth and desmoplastic reaction and have been consistently associated with malignancy in prior radiological and pathological studies.[9-12] Our results reinforce the central role of detailed morphologic assessment in pulmonary nodule evaluation.

Pleural-based localization was another independent predictor of malignancy in our cohort. Malignant nodules were significantly more likely to be pleural-based compared with benign lesions. This finding may be related to the propensity of certain lung cancers, particularly adenocarcinomas, to arise in peripheral lung regions adjacent to the pleura.[10,11] Previous imaging studies have also highlighted pleural contact as a feature associated with increased malignancy risk.[10]

Functional imaging with PET/CT provided additional discriminatory value. Nodules with SUVmax values greater than 2.5 were significantly more frequent in the malignant group, consistent with previous reports demonstrating increased glucose metabolism in malignant pulmonary lesions.[11] From a practical clinical perspective, patients classified as low risk may be managed with structured radiological follow-up, intermediate-risk patients may benefit from further functional imaging such as PET/CT, whereas high-risk patients should be considered for prompt invasive diagnostic evaluation or surgical referral.

Beyond its diagnostic accuracy, the proposed risk score may have particular relevance in cardiovascular surgery and preoperative assessment settings, where incidental pulmonary nodules are frequently detected during routine thoracic imaging. In such scenarios, accurate malignancy risk stratification is essential to optimize perioperative planning, avoid unnecessary delays in cardiac or vascular procedures, and prevent unwarranted invasive interventions. By providing a structured and quantitative risk estimate, the model may support multidisciplinary decision-making and contribute to safer and more individualized preoperative management strategies.

Although PET SUVmax demonstrated a strong association with malignancy in univariate analysis, it did not remain independently significant in the multivariable model. This finding may be explained by shared predictive information with other structural radiological variables, particularly nodule size and morphological characteristics, which are closely related to metabolic activity. In diagnostic cohorts enriched with clinically suspicious nodules, the incremental predictive contribution of SUVmax may diminish once strong anatomical predictors are included in the model. Importantly, the lack of independent statistical significance does not imply absence of clinical value; rather, it suggests that metabolic information provided by PET may partially overlap with morphological risk features captured by CT-based variables.[12,13]

Upper lobe localization was significantly associated with malignancy in univariate analysis but lost statistical significance after adjustment for other variables. This observation aligns with prior studies suggesting that upper lobe predominance is associated with lung cancer risk, particularly in smokers, but may be confounded by other radiological features when multivariate models are applied.[14,15]

The Brock model, originally developed in a low-risk lung cancer screening population, demonstrated lower discriminative performance in our cohort. This result was expected, as our study population consisted of patients with clinically suspicious nodules who underwent histopathological evaluation, rather than asymptomatic individuals detected through screening programs.[16,17] Screening-based models may underestimate malignancy risk when applied to higher-risk diagnostic populations.[16,18]

Although the proposed model demonstrated excellent discriminative performance with a high AUC value (0.989), this result should be interpreted with caution. The single-center design and relatively limited sample size may increase the risk of sample-specific overfitting. To mitigate this concern, internal validation using bootstrap resampling was performed, which supported the stability and robustness of the model estimates. Nevertheless, despite favorable internal validation results, external validation in independent and multicenter cohorts is essential to confirm the generalizability and reproducibility of the model across diverse patient populations before routine clinical implementation. Similar observations have been reported in diagnostic cohort-based prediction models.[17]

The proposed scoring system provides a transparent and quantitative framework for malignancy risk estimation that can be readily implemented in daily clinical workflow. Each predictor identified in the multivariable model is assigned

a weighted score proportional to its regression coefficient, allowing straightforward bedside calculation. Age contributes 1 point per 10-year increase, CT size contributes 1 point per 5-mm increase, PET SUVmax ≥2.5 adds 4 points, upper lobe location adds 2 points, while irregular margins and pleural-based localization—being the strongest predictors—contribute 12 points each. The total score ranges from 0 to 32 and is incorporated into the logistic equation (LP= −6.896+0.380×total score) to derive the estimated probability of malignancy.

For clinical usability, total scores were stratified into actionable risk categories: 0–4 (<5% risk), 5-9 (10-25%), 10-14 (25-50%), 15-19 (50-75%), and ≥20 (≥85% risk). This categorization enables immediate risk-adapted management decisions. For example, a patient accumulating ≥20 points—corresponding to an estimated malignancy probability of ≥85%—can be confidently prioritized for early invasive diagnostic procedures and cardiothoracic surgical evaluation, supported by the model's high specificity (98.4%). Conversely, patients with scores ≤4 (<5% risk) may be safely managed with structured radiological surveillance. By translating multivariable regression output into an intuitive point-based system with clearly defined probability thresholds, the model bridges statistical prediction and real-world clinical decision-making.

The observed performance differences between the proposed model and the Brock model should be interpreted in the context of underlying population characteristics. The Brock model was developed in a lung cancer screening cohort, where disease prevalence is relatively low and nodules are often smaller and incidentally detected.[18] In contrast, the present study was conducted in a diagnostic cohort enriched with histopathologically confirmed cases, resulting in a higher pretest probability of malignancy and a broader representation of clinically suspicious nodules. Such differences in case-mix, prevalence, and spectrum of disease are well known to influence model discrimination and calibration. Models developed in screening populations may exhibit attenuated performance when applied to diagnostic cohorts, and vice versa, highlighting issues of model transportability. Therefore, the superior discriminative performance observed in our cohort likely reflects both tailored predictor selection and the specific clinical context in which the model was derived. External validation in diverse clinical settings, including screening populations, will be essential to assess generalizability and transportability.[19,20]

Accurate preoperative assessment is a cornerstone of cardiothoracic surgical planning. Previous studies have demonstrated that inadequate risk stratification may increase perioperative morbidity and delay appropriate oncologic treatment.[21-23] In this context, integrating a validated radiological risk score into cardiovascular surgical workflows may improve patient selection and optimize perioperative outcomes.

Limitations

Several limitations should be acknowledged. First, the retrospective and single-center design may limit the external validity and generalizability of the findings. Although consecutive patient inclusion was applied to reduce selection bias, the study population consisted exclusively of histopathologically confirmed cases. Patients managed conservatively with radiological follow-up were not included, which may restrict applicability to lower-risk nodules encountered in routine screening or incidental detection settings. Therefore, a degree of selection bias cannot be entirely excluded.

Second, the relatively limited sample size and absence of internal validation procedures, such as bootstrapping or split-sample validation, should be considered when interpreting the excellent discriminative performance of the model (AUC=0.989). Although the high AUC likely reflects the use of histopathology as a reference standard, the clinically selected diagnostic cohort, and the inclusion of radiological variables with strong effect sizes—particularly irregular margins and pleural-based localization—the possibility of optimism bias or overfitting cannot be completely excluded.

Third, radiological assessments were performed by a single experienced thoracic radiologist. While this ensured consistency in image interpretation, interobserver variability was not evaluated. Consequently, the reproducibility of radiological feature assessment across different observers remains uncertain.

Taken together, these factors underscore the need for prospective, multicenter studies with larger and more heterogeneous populations, as well as formal internal and external validation, to confirm the robustness, calibration, transportability, and clinical utility of the proposed risk model.

CONCLUSION

As a result, this study demonstrates that CT nodule size, irregular margin characteristics, and pleural-based localization are strong and independent predictors of pulmonary nodule malignancy. The proposed CT-based logistic regression–derived weighted risk score model showed superior diagnostic performance compared with the Brock model. Implementation of this practical and tailored prediction tool in cardiovascular and cardiothoracic clinical practice may enhance multidisciplinary decision-making, improve diagnostic accuracy, reduce unnecessary invasive procedures, and optimize perioperative patient management.

ETHICAL DECLARATIONS

Ethics Committee Approval

This study has been approved by the Ethics Committee of Şişli Hamidiye Etfal Training and Research Hospital (Date: 29.11.2022, Decision number: 2195).

Informed Consent

As this was a retrospective study, formal written informed consent was not required and was therefore not obtained.

Peer Review Process

This manuscript was subject to external peer review.

Conflict of Interest

The author declare no conflicts of interest related to this study.

Financial Disclosure

The author received no financial support for the conduct or publication of this research.

Author Contributions

The author is solely responsible for the conception, design, data collection, analysis, interpretation, and writing of the manuscript.

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