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Radiomics in thymic epithelial tumors: a scoping review of current status and advances

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Abstract

Background This scoping review aims to evaluate the current status and recent advances in the use of radiomics for the diagnosis, risk stratification, and staging of thymic epithelial tumors (TETs). The review also explores radiomics' potential in predicting the risk of myasthenia gravis (MG), an associated autoimmune condition in TETs patients.

Methods A comprehensive literature search was conducted using PubMed and Web of Science to identify studies published since 2012 on the application of radiomics in managing TETs. The studies were assessed for their methodologies, including imaging protocols, feature extraction techniques, and model performance metrics. The Radiomics Quality Score (RQS) was used to evaluate study quality.

Results A total of 23 studies, including 4701 patients, were analyzed. Radiomics-based models showed high accuracy in distinguishing TETs from other mediastinal masses, predicting risk subtypes, and improving the accuracy of TNM and Masaoka-Koga (MK) staging. Additionally, radiomics demonstrated potential in predicting the risk of MG in thymoma patients. However, all studies were retrospective, and only 6 studies included external validation, with an average RQS of 13.87, accounting for 38.52% of the maximum score.

Conclusion Radiomics shows great potential in advancing the diagnosis, risk stratification, and staging of TETs. However, its clinical implementation requires overcoming challenges in standardization, validation, and interpretability. Future research should focus on multi-center prospective studies, external validation, and integrating multi-modal imaging and molecular biomarkers to improve risk assessment and treatment strategies.

Keywords Thymic epithelial tumors, Radiomics, Diagnosis, Risk subtypes, TNM staging, Masaoka-Koga staging, Myasthenia gravis

Introduction

Thymic epithelial tumors (TETs) are the most common tumors found in the anterior mediastinum, originating from thymic epithelial cells [1]. Although relatively rare, these tumors pose a significant clinical challenge due to their wide range of biological behaviors, from slow-growing to highly aggressive [2]. Early and accurate diagnosis is essential for selecting the appropriate treatment and improving patient outcomes [3].

Diagnosing TETs typically involves a combination of imaging techniques, histopathological analysis, and clinical evaluation [4]. Common imaging methods like computed tomography (CT) and magnetic resonance imaging (MRI) are used to assess the tumor's presence,

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size, and extent [5, 6]. However, these conventional imaging techniques often struggle to differentiate between TETs subtypes and other mediastinal masses, such as thymic cysts and lymphomas [7, 8], making the need for more advanced diagnostic methods evident.

The World Health Organization classifies TETs into subtypes A, AB, B1, B2, and B3, based on the proportion of epithelial cells and lymphocytes [9, 10]. These subtypes vary in their malignancy risk and prognosis, with subtypes A, AB, and B1 generally associated with a lower malignancy risk, while B2 and B3 are considered high-risk [11]. Accurate identification of these subtypes is crucial for treatment planning, especially in determining whether patients may require only surgical intervention or more aggressive, multimodal therapies [12].

One of the essential components in managing TETs is staging, as it directly informs prognosis and treatment decisions [13]. The TNM staging system, which categorizes tumors based on tumor size (T), lymph node involvement (N), and distant metastasis (M), offers a comprehensive assessment of disease progression [14]. It helps in stratifying patients into different risk categories, guiding the use of surgery, radiation, or chemotherapy [15]. Radiomics has shown potential to improve the accuracy of TNM staging by providing precise tumor characteristics that go beyond traditional imaging interpretations [16]. Another widely used staging system is the Masaoka Koga (MK) staging system, which is based on the extent of local invasion and tumor spread [17]. This system divides TETs into four stages, with early-stage tumors (I-II) generally having a better prognosis and being amenable to surgical resection. In contrast, advanced-stage tumors (III-IV) often require more aggressive, multimodal treatments [18]. Radiomics could further refine MK staging by offering more detailed information on tumor invasion patterns and surrounding tissue involvement, allowing for better prediction of clinical outcomes [19].

Myasthenia gravis (MG) is a common autoimmune disorder associated with TETs, especially thymomas [20]. The presence of MG complicates the management of TETs, particularly in the perioperative period, where myasthenic crisis—a severe complication that can lead to respiratory failure—is a major concern [21]. Therefore, it is critical to assess the risk of MG in TETs patients prior to surgery to reduce postoperative complications and enhance patient outcomes.

Radiomics, an emerging field in oncology, has shown promise in extracting high-dimensional data from medical images that can provide insights into tumor heterogeneity and other clinically relevant features [22]. This non-invasive approach has potential in improving the diagnosis, risk stratification, and staging of TETs, as well as in predicting associated conditions like MG. Through radiomics analysis, clinicians may gain a better understanding of the biological characteristics of TETs, paving the way for more personalized and effective treatment strategies.

This scoping review aims to summarize the current status and recent advances in the use of radiomics in the management of TETs, focusing on its applications in diagnosis, predicting histological risk subtypes, staging based on the TNM and MK systems, and assessing the risk of MG.

Materials and methods

Literature search strategy

This scoping review, which involved only publicly available data, did not require ethical approval. A comprehensive literature search was conducted using PubMed and Web of Science's advanced search to identify studies on the application of radiomics in managing TETs, with a focus on diagnosis, risk subtypes, TNM and Masaoka Koga staging, and MG risk. Keywords such as "thymic epithelial tumors," "thymoma," "radiomics," and "radiomic" were used. Boolean operators ("AND" and "OR") combined the keywords, and filters restricted the search to articles published from 2012 onward, as radiomics only emerged as a field in 2012.

Inclusion and exclusion criteria

Studies were included if they met the following criteria: (1) Original research articles that applied radiomics to the diagnosis, risk subtype prediction, TNM staging, MK staging, or MG risk assessment in patients with TETs. (2) Studies utilizing imaging modalities such as CT, MRI, or PET/CT to extract radiomics features. (3) provided sufficient methodological detail to evaluate the robustness of the radiomics approach. Exclusion criteria included studies not related to radiomics, non-original research (e.g., reviews, editorials), and studies lacking a focus on diagnosis, risk stratification, staging, or MG assessment.

Data extraction and radiomics workflow

Data were extracted from each study, including study design (predominantly retrospective), sample size, reference standards (e.g., pathology, imaging), data sources (single or multi-institution), and outcomes related to diagnosis, risk subtype prediction, TNM staging, MK staging, and MG risk assessment.

The radiomics workflow was comprehensively reviewed, including imaging modalities (e.g., CECT, PET/CT, MRI), software tools like PyRadiomics and ITK-SNAP were commonly employed, preprocessing techniques such as normalization and manual 3D segmentation. Feature selection and modeling methods

varied across studies. The optimal models used for analysis included logistic regression (LR), Support Vector Machine (SVM), random forest (RF) models, and other algorithms, with validation methods such as internal and external cross-validation. Performance metrics, such as the area under the curve (AUC), were systematically recorded.

Evaluation of study quality

The quality of the included studies was assessed using the Radiomics Quality Score (RQS) framework, which evaluates several key aspects [23]. These include image protocol quality (scored from 0 to 2), the use of multiple segmentations (0 or 1), and the implementation of phantom studies (0 or 1) to assess reproducibility. Feature reduction techniques were also considered (scored from -3 to 3), alongside the use of multiple time points (0 or 1), non radiomics features (0 or 1), biological correlates (0 or 1), and cutoff analysis (0 or 1). Discrimination statistics (0 to 2) and calibration statistics (0 to 2) were assessed to evaluate the model's performance and predictive accuracy. Studies were also evaluated based on the presence of a prospective study design (0 to 7), external validation (scored from -5 to 5), and clinical application (0 to 2). Additionally, the inclusion of a gold standard (0 to 2), cost-effectiveness analysis (0 or 1), and open science principles (0 to 4) were considered. The total RQS allowed for categorization of the studies, helping to identify those that provided high-quality evidence with the potential to inform clinical practice. Detailed scoring criteria is available at Supplementary.

The RQS assessment was independently conducted by two senior radiologists (Dr. X.W. and Dr. P.H.), both of whom have extensive experience in radiomics-based research and systematic reviews. In cases of disagreement, a third evaluator (Dr. W.D.) was consulted to resolve any discrepancies. This evaluation process ensured the reliability and consistency of the quality assessment.

Results

Literature search and data collection

We retrieved a total of 104 papers from PubMed (51) and Web of Science (53), which were then screened based on titles and abstracts. After eliminating 50 duplicates, 54 articles were evaluated in full text. Of these, 23 studies met the inclusion criteria and were included in the final analysis (Fig. 1). Key findings from Supplementary Table S1, including study characteristics such as sample size, study design, data sources, and conclusions.

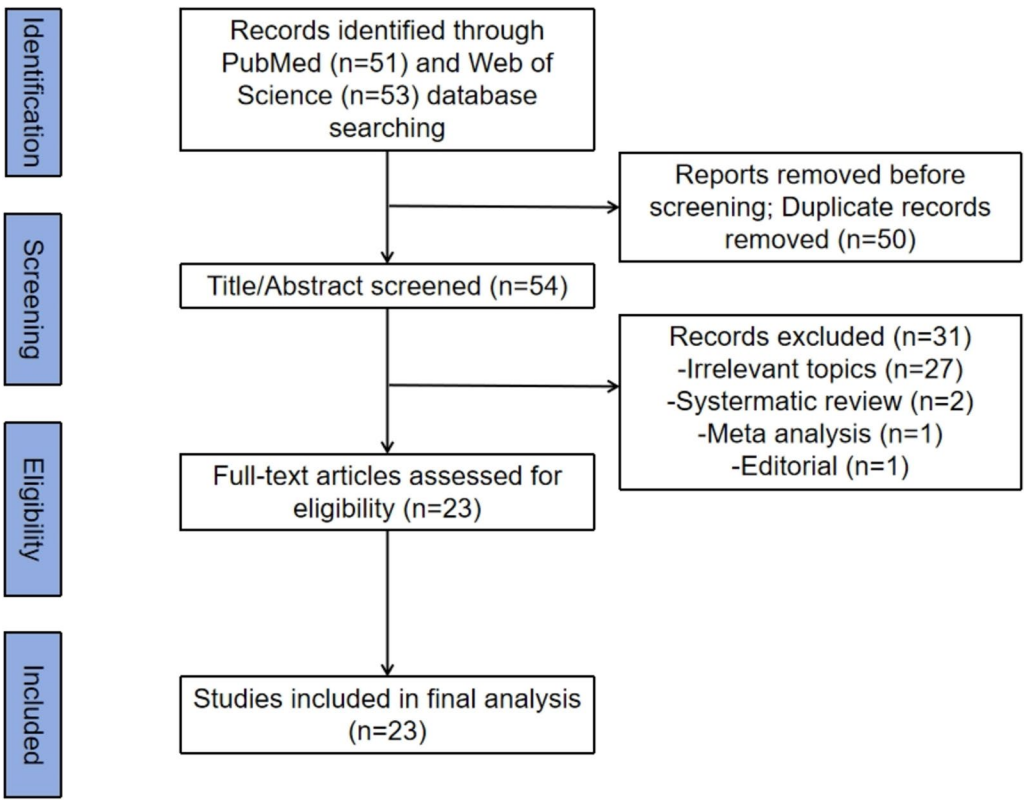

Fig. 1 Flowchart of the literature screening and selection process

In Supplementary Table S2, we present the radiomics workflow and model details for each study, including the imaging modalities used, segmentation methods, feature selection techniques, modeling methods, and validation approaches. The performance of optimal models is also summarized in Table S2, providing insights into the AUC values, sensitivity, specificity, and validation methods applied in the studies.

Diagnosis of TETs

Radiomics demonstrated significant improvements in the diagnostic accuracy of TETs compared to traditional imaging methods. Several studies focused on distinguishing TETs from specific types of mediastinal lesions.

For differentiating thymic cysts from TETs, Zhang C et al. [24] developed a CT-based radiomics nomogram, achieving an AUC of 0.992 in the validation cohort by integrating Rad-score with conventional imaging features. Yang Y et al. [30] also addressed this differentiation using a deep transfer learning model combined with radiomics, reporting AUCs of 0.965 in internal and 0.959 in external validation, thus showcasing the potential of advanced techniques to enhance diagnostic accuracy. Additionally, Shang L et al. [32] employed machine learning classifiers based on non-enhanced CT radiomics, achieving an AUC of 0.922 in the testing group for distinguishing thymomas from cysts, further highlighting the utility of radiomics in this setting.

Regarding the differentiation of thymic carcinoma from thymoma, Ohira R et al. [25] utilized two radiomics features—GLCM-energy and solidity—in a LR model, resulting in an AUC of 0.921. Similarly, Mayoral M et al. [26] combined conventional imaging and radiomics features, achieving AUCs of 0.941 and 0.810 in internal and external validation, respectively.

He W et al. [28] developed a model that integrated clinical and radiomics features from contrast-enhanced CT to differentiate TETs from lymphomas, achieving impressive AUCs of 0.955 in validation set. Similarly, Li J et al. [29] employed PET/CT-based radiomics for the same purpose, demonstrating a high diagnostic accuracy with an AUC of 0.907 in the testing phase.

Chang CC et al. [27] further demonstrated diagnostic efficacy by using a LightGBM model with Extra Trees, achieving AUCs of 0.9117 and 0.9464 in the external validation cohort for non-enhanced and contrast-enhanced CT, respectively, in distinguishing TETs from other prevascular mediastinal tumors.

Prediction of risk subtypes

Radiomics-based models showed strong performance in predicting TETs risk subtypes, offering valuable insights into tumor aggressiveness. Nakajo M et al. [31] used PET-based radiomics and machine learning to accurately predict high-risk thymomas and thymic carcinomas. Hu J et al. [33] applied a RF model with CT radiomics, achieving an AUC of 0.87 in the validation cohort for differentiating high-risk from low-risk TETs. Xiao G et al. [34] incorporated MRI-derived features into a nomogram, reaching an AUC of 0.878 in the test cohort for predicting thymoma subtypes. Feng XL et al. [35] used an SVM model with AUC of 0.844 in testing set, for thymoma risk classification. Liu W et al. [37] achieved superior results by combining clinical, radiomics, and deep learning features, with an AUC of 0.95 in testing set. Shang L et al. [32] utilized non-enhanced CT radiomics to classify thymoma risk subtypes, with an AUC of 0.783 in the testing group. Wang X et al. [19] demonstrated the use of texture features from both non-enhanced and contrast-enhanced CT, achieving AUCs of 0.801 and 0.827 for risk stratification. Chen X et al. [38] employed a deep learning radiomics nomogram, achieving AUCs of 0.868 (internal) and 0.846 (external) across cohorts. Gao C et al. [39] reported an AUC of 0.960 in the validation cohort using a combined radiomics nomogram. Dong W et al. [36] and Liang Z et al. [40] integrated clinical and radiomics features for an AUC of 0.870 and 0.967 in validation, while Shen Q et al. [41] demonstrated good results using a radiomics-TNM nomogram, achieving an AUC of 0.79 in external validation.

TNM and MK staging systems

Radiomics demonstrated effectiveness in predicting TNM and MK stages. Araujo-Filho JAB et al. [16] showed that a CT-based radiomics model could predict TNM staging with an AUC of 0.708 in the testing set. Xiao G et al. [42] achieved high accuracy for TNM staging using MRI-based radiomics nomogram, with an AUC of 0.957 in the test cohort. Blüthgen C et al. [43] reached an AUC of 0.838 for TNM staging with CT radiomics. Wang X et al. [19] applied texture features from non-enhanced and contrast-enhanced CT to differentiate advanced from early-stage thymomas under the MK system, reporting AUCs of 0.829 and 0.860, respectively.

Assessment of MG risk

Radiomics models showed promise in assessing MG risk in thymoma patients. Liu Z et al. [44] developed a deep learning-based 3D DenseNet model to detect MG, with AUCs of 0.766 and 0.730 for internal and external validation, respectively. Blüthgen C et al. [43] also explored radiomics for MG risk prediction but reported moderate

accuracy with an AUC of 0.639, suggesting room for improvement.

RQS study quality analysis and methodological limitations

The RQS analysis revealed variability in the methodological quality across the 23 included studies. The highest scores (20) were achieved by studies such as those by Yang Y et al. [30], Chen X et al. [38] and Shen Q et al. [41], which demonstrated strengths in calibration statistics, external validation, and clinical applicability. However, none of the studies incorporated phantom studies. Additionally, all studies lacked biological correlates, such as molecular or histopathological markers. Furthermore, all studies were retrospective, with no inclusion of prospective design elements. None of the studies conducted cost-effectiveness analysis, and all showed limited adherence to open science principles. Supplementary Table S3 provides the specific RQS scores and overall RQS scores for each included study.

Discussion

This review synthesizes the current status and advancements in the application of radiomics for managing TETs, drawing from a comprehensive analysis of 23 studies involving 4701 patients. The findings indicate that radiomics significantly enhances the accuracy of diagnosing, staging, and predicting risk subtypes for TETs compared to traditional imaging approaches. However, the retrospective nature and methodological variability across studies highlight several areas that require further standardization and validation to facilitate clinical translation.

Radiomics has consistently demonstrated superior diagnostic performance compared to conventional imaging techniques in distinguishing thymomas from other mediastinal masses, such as thymic cysts and lymphomas. Many studies [24, 25, 28, 29] achieved high AUC values (>0.9) using radiomics-based models, including LR, RF, and deep learning approaches. While these results suggest that radiomics offers a non-invasive and precise alternative to traditional imaging methods, the high AUC values raise concerns about potential overfitting. Given the relatively small sample sizes and high-dimensional feature space in radiomics, there is a risk that some models may not generalize well to independent datasets. Another key limitation is the variability in segmentation techniques; some studies rely on manual delineation, while others use semi-automated approaches [25, 28, 29]. Manual segmentation introduces observer variability, which can affect the reproducibility of radiomics features. Standardizing segmentation protocols and incorporating AI-driven automated segmentation tools could reduce variability and enhance feature consistency across studies.

Radiomics-based models have also demonstrated strong potential in stratifying TETs risk subtypes and refining TNM and MK staging, offering valuable insights into tumor aggressiveness and supporting personalized treatment planning. Several studies demonstrated high predictive accuracy in differentiating high-risk thymomas and thymic carcinomas from low-risk subtypes, with AUCs frequently exceeding 0.85 in the validation cohort. Other studies providing quantitative assessments of tumor invasion and surrounding tissue involvement. However, most studies were also conducted in single-institution settings with small sample sizes, limiting their reproducibility.

The role of radiomics in predicting the risk of MG in thymoma patients remains an emerging area, with studies reporting moderate predictive success. While these results indicate that radiomics may assist in perioperative risk assessment, predictive performance remains lower than in diagnostic and staging applications. This may be attributed to the complex interaction between imaging features and the autoimmune mechanisms underlying MG.

Several imaging modalities are utilized in radiomics for TETs, including CT, MRI, and PET/CT, each offering distinct advantages. CT offers high spatial resolution and accessibility but has limited soft tissue contrast. MRI provides superior soft tissue contrast, making it valuable for distinguishing thymomas from other tumors, though it is less accessible and more time-consuming. PET/CT combines metabolic and anatomical information, aiding in the identification of aggressive TETs, but has lower spatial resolution. Given these strengths and limitations, multi-modal radiomics, integrating CT, MRI, and PET/CT data, has the potential to improve diagnostic accuracy, staging, and risk stratification by capturing both structural and functional tumor characteristics. This approach could enhance predictive accuracy and overcome individual modality limitations. Future research should explore multi-modal radiomics to develop more robust and clinically applicable models for TETs management.

Despite the promising findings, several methodological challenges hinder the clinical translation of radiomics in TETs. The RQS analysis revealed that most studies scored below 50% of the maximum possible score, highlighting key deficiencies such as the absence of phantom studies, limited external validation, and reliance on retrospective designs. Phantom studies, which are crucial for ensuring feature reproducibility across different scanners, were not included in any study, likely due to the lack of standardized imaging phantoms and logistical challenges. Similarly, external validation was performed in only 6 studies, limiting model generalizability. Barriers

to external validation include data-sharing restrictions, variability in imaging protocols, and the scarcity of multi-center datasets for rare tumors like TETs. Furthermore, all studies were retrospective, with no inclusion of prospective design elements. Retrospective studies are prone to biases such as selection and recall bias, which can affect the validity and generalizability of the findings. The absence of prospective elements limits the ability to assess the real-world applicability of radiomics models and hinders their integration into clinical practice. None of the studies conducted cost-effectiveness analyses, which are necessary to evaluate the practical and economic feasibility of implementing radiomics in clinical settings. Additionally, all studies showed limited adherence to open science principles, including insufficient data sharing and transparency, which are essential for reproducibility and independent verification.

To address these challenges, federated learning approaches can facilitate multi-center validation while ensuring patient privacy, thus enabling more robust and generalizable model testing. It is crucial to adopt more rigorous validation strategies, such as nested cross-validation and the use of external test sets, to more accurately assess model generalizability and reduce the risk of overfitting. The adoption of standardized imaging protocols, such as the IBSI (Image Biomarker Standardization Initiative) guidelines [45], should be prioritized to ensure consistency in feature extraction across different institutions, further enhancing the reliability of radiomics models. Prospective clinical trials should be prioritized to improve the reliability and generalizability of the findings, reducing biases inherent in retrospective designs. Additionally, cost-effectiveness analyses should be incorporated into future studies to assess the value of radiomics in real-world clinical settings. Finally, adherence to open science principles should be enhanced by encouraging data sharing and transparency, which would facilitate reproducibility, increase collaboration, and accelerate the clinical adoption of radiomics models in TETs.

Interpretability remains a significant challenge in the clinical adoption of radiomics. Many machine learning-based models function as "black-box" systems, making it difficult for clinicians to understand how specific features contribute to predictions. To improve clinical acceptance, efforts should focus on developing explainable AI models with intuitive visualizations and feature importance rankings. Key radiomics features, such as GLCM-energy and solidity [25], have biological relevance. GLCM-energy, which measures texture uniformity, reflects tumor heterogeneity, a hallmark of aggressive phenotypes, with lower energy values linked to more heterogeneous, invasive tumors [46]. Solidity, a shape-based feature, indicates tumor invasiveness, as lower values suggest irregular, more invasive shapes [47]. Integrating radiomics with histopathological data and molecular biomarkers (such as genetic mutations or immune markers) could enhance feature interpretability, providing more precise and individualized predictions and improving diagnosis, staging, and prognosis for TETs.

Conclusion

While radiomics holds substantial potential in advancing the diagnosis, risk stratification, and staging of TETs, achieving clinical implementation requires addressing standardization, validation, and interpretability challenges. Future research should prioritize multi-center prospective studies with well-defined imaging protocols, independent external validation, and the integration of multi-modal imaging data. The combination of radiomics with artificial intelligence and molecular biomarkers may further refine risk assessment and improve personalized treatment strategies. By overcoming these barriers, radiomics could transition from an experimental tool to a clinically actionable imaging biomarker, ultimately improving patient outcomes in TETs management.

Abbreviations

TETs	Thymic epithelial tumors
MG	Myasthenia gravis
RQS	Radiomics quality score
MK	Masaoka-Koga
CT	Computed tomography
MRI	Magnetic resonance imaging
LR	Logistic regression
SVM	Support Vector Machine
RF	Random forest
AUC	Area under the curve
LightGBM	Light gradient boosting machine

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s12885-025-13909-3.

Supplementary Material 1.

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Authors' contributions

XW and PH wrote the manuscript and created the figures. XW, ZW and YL participated in literature screening and data extraction. WD and BF wrote the manuscript and conceived the final approval of the version to be submitted. All authors read and approved the final manuscript.

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Data availability

No datasets were generated or analysed during the current study.

Declarations

Ethics approval and consent to participate
Not applicable.

Consent for publication
Not applicable.

Competing interests
The authors declare no competing interests.

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References

1. Marx A, Chan JKC, Chalabreysse L, Dacic S, Detterbeck F, French CA, et al. The 2021 WHO classification of tumors of the thymus and mediastinum: what is new in thymic epithelial, germ cell, and mesenchymal tumors? J Thorac Oncol. 2022;17(2):200–13. https://doi.org/10.1016/j.jtho.2021.10.010.
2. Conforti F, Pala L, Giaccone G, De Pas T. Thymic epithelial tumors: From biology to treatment. Cancer Treat Rev. 2020;86: 102014. https://doi.org/10.1016/j.ctrv.2020.102014.
3. Gentili F, Monteleone I, Mazzei FG, Luzzi L, Del Roscio D, Guerrini S, et al. Advancement in diagnostic imaging of thymic tumors. Cancers (Basel). 2021;13(14):3599. https://doi.org/10.3390/cancers13143599.
4. Koyasu S. Imaging of thymic epithelial tumors-a clinical practice review. Mediastinum. 2024;7(8):41. https://doi.org/10.21037/med-23-66.
5. Xu C, Zhang Y, Wang W, Wang Q, Li Z, Song Z, et al. Chinese expert consensus on the diagnosis and treatment of thymic epithelial tumors. Thorac Cancer. 2023;14(12):1102–17. https://doi.org/10.1111/1759-7714.14847.
6. Hu YC, Yan WQ, Yan LF, Xiao G, Han Y, Liu CX, et al. Differentiating thymoma, thymic carcinoma and lymphoma based on collagen fibre patterns with T2- and diffusion-weighted magnetic resonance imaging. Eur Radiol. 2022;32(1):194–204. https://doi.org/10.1007/s00330-021-08143-x.
7. Jung W, Cho S, Yum S, Lee YK, Kim K, Jheon S. Differentiating thymoma from thymic cyst in anterior mediastinal abnormalities smaller than 3 cm. J Thorac Dis. 2020;12(4):1357–65. https://doi.org/10.21037/jtd.2020.02.14.
8. Yamada D, Matsusako M, Kurihara Y. Review of clinical and diagnostic imaging of the thymus: from age-related changes to thymic tumors and everything in between. Jpn J Radiol. 2024;42(3):217–34. https://doi.org/10.1007/s11604-023-01497-w.
9. Girard N, Ruffini E, Marx A, Faivre-Finn C, Peters S; ESMO Guidelines Committee. Thymic epithelial tumours: ESMO Clinical Practice Guidelines for diagnosis, treatment and follow-up. Ann Oncol. 2015;26 Suppl 5:v40–55. https://doi.org/10.1093/annonc/mdv277.
10. Huang Q, Zhu L, Liu Y, Zhang Y. Thymic epithelial tumor medical treatment: A narrative review. Biochim Biophys Acta Rev Cancer. 2024;1879(5):189167. https://doi.org/10.1016/j.bbcan.2024.189167.
11. den Bakker MA, Roden AC, Marx A, Marino M. Histologic classification of thymoma: a practical guide for routine cases. J Thorac Oncol. 2014;9(9 Suppl 2):S125–30. https://doi.org/10.1097/JTO.0000000000000297.
12. Venuta F, Rendina EA, Anile M, de Giacomo T, Vitolo D, Coloni GF. Thymoma and thymic carcinoma. Gen Thorac Cardiovasc Surg. 2012;60(1):1–12. https://doi.org/10.1007/s11748-011-0814-0.
13. Molina TJ. Update on the TNM 8th Edition-staging of thymic epithelial tumors, a pathologist's perspective. Mediastinum. 2022;25(6):28. https://doi.org/10.21037/med-21-63.
14. Detterbeck FC, Stratton K, Giroux D, Asamura H, Crowley J, Falkson C, et al. The IASLC/ITMIG Thymic Epithelial Tumors Staging Project: proposal for an evidence-based stage classification system for the forthcoming (8th) edition of the TNM classification of malignant tumors. J Thorac Oncol. 2014;9(9 Suppl 2):S65-72. https://doi.org/10.1097/JTO.0000000000000290.
15. Ruffini E, Huang J, Cilento V, Goren E, Detterbeck F, Ahmad U, et al. The international association for the study of lung cancer thymic epithelial tumors staging project: proposal for a stage classification for the forthcoming (Ninth) Edition of the TNM Classification of Malignant Tumors. J Thorac Oncol. 2023;18(12):1655–71. https://doi.org/10.1016/j.jtho.2023.09.002.
16. Araujo-Filho JAB, Mayoral M, Zheng J, Tan KS, Gibbs P, Shepherd AF, et al. CT radiomic features for predicting resectability and tnm staging in thymic epithelial tumors. Ann Thorac Surg. 2022;113(3):957–65. https://doi.org/10.1016/j.athoracsur.2021.03.084.
17. Lee GD, Kim HR, Choi SH, Kim YH, Kim DK, Park SI. Prognostic stratification of thymic epithelial tumors based on both Masaoka-Koga stage and WHO classification systems. J Thorac Dis. 2016;8(5):901–10. https://doi.org/10.21037/jtd.2016.03.53.
18. Chiappetta M, Lococo F, Pogliani L, Sperduti I, Tabacco D, Bria E, et al. Masaoka-Koga and TNM staging system in thymic epithelial tumors: prognostic comparison and the role of the number of involved structures. Cancers (Basel). 2021;13(21):5254. https://doi.org/10.3390/cancers13215254.
19. Wang X, Sun W, Liang H, Mao X, Lu Z. Radiomics signatures of computed tomography imaging for predicting risk categorization and clinical stage of thymomas. Biomed Res Int. 2019;28(2019):3616852. https://doi.org/10.1155/2019/3616852.
20. Dresser L, Wlodarski R, Rezania K, Soliven B. Myasthenia gravis: epidemiology, pathophysiology and clinical manifestations. J Clin Med. 2021;10(11):2235. https://doi.org/10.3390/jcm10112235.
21. Claytor B, Cho SM, Li Y. Myasthenic crisis. Muscle Nerve. 2023;68(1):8–19. https://doi.org/10.1002/mus.27832.
22. Chen M, Copley SJ, Viola P, Lu H, Aboagye EO. Radiomics and artificial intelligence for precision medicine in lung cancer treatment. Semin Cancer Biol. 2023;93:97–113. https://doi.org/10.1016/j.semcancer.2023.05.004.
23. Lambin P, Leijenaar RTH, Deist TM, Peerlings J, de Jong EEC, van Timmeren J, et al. Radiomics: the bridge between medical imaging and personalized medicine. Nat Rev Clin Oncol. 2017;14(12):749–62. https://doi.org/10.1038/nrclinonc.2017.141.
24. Zhang C, Yang Q, Lin F, Ma H, Zhang H, Zhang R, et al. CT-based radiomics nomogram for differentiation of anterior mediastinal thymic cyst from thymic epithelial tumor. Front Oncol. 2021;10(11):744021. https://doi.org/10.3389/fonc.2021.744021.
25. Ohira R, Yanagawa M, Suzuki Y, Hata A, Miyata T, Kikuchi N, et al. CT-based radiomics analysis for differentiation between thymoma and thymic carcinoma. J Thorac Dis. 2022;14(5):1342–52. https://doi.org/10.21037/jtd-21-1948.
26. Mayoral M, Pagano AM, Araujo-Filho JAB, Zheng J, Perez-Johnston R, Tan KS, et al. Conventional and radiomic features to predict pathology in the preoperative assessment of anterior mediastinal masses. Lung Cancer. 2023;178:206–12. https://doi.org/10.1016/j.lungcan.2023.02.014.
27. Chang CC, Tang EK, Wei YF, Lin CY, Wu FZ, Wu MT, et al. Clinical radiomics-based machine learning versus three-dimension convolutional neural network analysis for differentiation of thymic epithelial tumors from other prevascular mediastinal tumors on chest computed tomography scan. Front Oncol. 2023;13:1105100. https://doi.org/10.3389/fonc.2023.1105100. Erratum in: Front Oncol. 2023 May 31;13:1220962. https://doi.org/10.3389/fonc.2023.1220962.
28. He W, Xia C, Chen X, Yu J, Liu J, Pu H, et al. Computed tomography-based radiomics for differentiation of thymic epithelial tumors and lymphomas in anterior mediastinum. Front Oncol. 2022;13(12):869982. https://doi.org/10.3389/fonc.2022.869982.
29. Li J, Cui N, Jiang Z, Li W, Liu W, Wang S, et al. Differentiating thymic epithelial tumors from mediastinal lymphomas: preoperative nomograms based on PET/CT radiomic features to minimize unnecessary anterior mediastinal surgery. J Cancer Res Clin Oncol. 2023;149(15):14101–12. https://doi.org/10.1007/s00432-023-05054-w.
30. Yang Y, Cheng J, Peng Z, Yi L, Lin Z, He A, et al. Development and validation of contrast-enhanced CT-based deep transfer learning and combined clinical-radiomics model to discriminate thymomas and thymic cysts: a multicenter study. Acad Radiol. 2024;31(4):1615–28. https://doi.org/10.1016/j.acra.2023.10.018.
31. Nakajo M, Takeda A, Katsuki A, Jinguji M, Ohmura K, Tani A, et al. The efficacy of 18F-FDG-PET-based radiomic and deep-learning features using a machine-learning approach to predict the pathological risk subtypes of

thymic epithelial tumors. Br J Radiol. 2022;95(1134):20211050. https://doi.org/10.1259/bjr.20211050.
32. Shang L, Wang F, Gao Y, Zhou C, Wang J, Chen X, et al. Machine-learning classifiers based on non-enhanced computed tomography radiomics to differentiate anterior mediastinal cysts from thymomas and low-risk from high-risk thymomas: A multi-center study. Front Oncol. 2022;24(12):1043163. https://doi.org/10.3389/fonc.2022.1043163.
33. Hu J, Zhao Y, Li M, Liu Y, Wang F, Weng Q, et al. Machine-learning-based computed tomography radiomic analysis for histologic subtype classification of thymic epithelial tumours. Eur J Radiol. 2020;126:108929. https://doi.org/10.1016/j.ejrad.2020.108929.
34. Xiao G, Hu YC, Ren JL, Qin P, Han JC, Qu XY, et al. MR imaging of thymomas: a combined radiomics nomogram to predict histologic subtypes. Eur Radiol. 2021;31(1):447–57. https://doi.org/10.1007/s00330-020-07074-3.
35. Feng XL, Wang SZ, Chen HH, Huang YX, Xin YK, Zhang T, et al. Optimizing the radiomics-machine-learning model based on non-contrast enhanced CT for the simplified risk categorization of thymic epithelial tumors: A large cohort retrospective study. Lung Cancer. 2022;166:150–60. https://doi.org/10.1016/j.lungcan.2022.03.007.
36. Dong W, Xiong S, Lei P, Wang X, Liu H, Liu Y, et al. Application of a combined radiomics nomogram based on CE-CT in the preoperative prediction of thymomas risk categorization. Front Oncol. 2022;23(12):944005. https://doi.org/10.3389/fonc.2022.944005.
37. Liu W, Wang W, Zhang H, Guo M, Xu Y, Liu X. Development and validation of multi-omics thymoma risk classification model based on transfer learning. J Digit Imaging. 2023;36(5):2015–24. https://doi.org/10.1007/s10278-023-00855-4.
38. Chen X, Feng B, Xu K, Chen Y, Duan X, Jin Z, et al. Development and validation of a deep learning radiomics nomogram for preoperatively differentiating thymic epithelial tumor histologic subtypes. Eur Radiol. 2023;33(10):6804–16. https://doi.org/10.1007/s00330-023-09690-1.
39. Gao C, Yang L, Xu Y, Wang T, Ding H, Gao X, et al. Differentiating low-risk thymomas from high-risk thymomas: preoperative radiomics nomogram based on contrast enhanced CT to minimize unnecessary invasive thoracotomy. BMC Med Imaging. 2024;24(1):197. https://doi.org/10.1186/s12880-024-01367-5.
40. Liang Z, Li J, Tang Y, Zhang Y, Chen C, Li S, et al. Predicting the risk category of thymoma with machine learning-based computed tomography radiomics signatures and their between-imaging phase differences. Sci Rep. 2024;14(1):19215. https://doi.org/10.1038/s41598-024-69735-3.
41. Shen Q, Shan Y, Xu W, Hu G, Chen W, Feng Z, et al. Risk stratification of thymic epithelial tumors by using a nomogram combined with radiomic features and TNM staging. Eur Radiol. 2021;31(1):423–35. https://doi.org/10.1007/s00330-020-07100-4.
42. Xiao G, Rong WC, Hu YC, Shi ZQ, Yang Y, Ren JL, et al. MRI Radiomics Analysis for Predicting the Pathologic Classification and TNM Staging of Thymic Epithelial Tumors: A Pilot Study. AJR Am J Roentgenol. 2020;214(2):328–40. https://doi.org/10.2214/AJR.19.21696.
43. Blüthgen C, Patella M, Euler A, Baessler B, Martini K, von Spiczak J, et al. Computed tomography radiomics for the prediction of thymic epithelial tumor histology, TNM stage and myasthenia gravis. PLoS ONE. 2021;16(12):e0261401. https://doi.org/10.1371/journal.pone.0261401.
44. Liu Z, Zhu Y, Yuan Y, Yang L, Wang K, Wang M, et al. 3D DenseNet deep learning based preoperative computed tomography for detecting myasthenia gravis in patients with thymoma. Front Oncol. 2021;5(11):631964. https://doi.org/10.3389/fonc.2021.631964.
45. Zwanenburg A, Vallières M, Abdalah MA, Aerts HJWL, Andrearczyk V, Apte A, et al. The image biomarker standardization initiative: standardized quantitative radiomics for high-throughput image-based phenotyping. Radiology. 2020;295(2):328–38. https://doi.org/10.1148/radiol.2020191145.
46. Kim HS, Kim JH, Yoon YC, Choe BK. Tumor spatial heterogeneity in myxoid-containing soft tissue using texture analysis of diffusion-weighted MRI. PLoS ONE. 2017;12(7):e0181339. https://doi.org/10.1371/journal.pone.0181339.
47. Limkin EJ, Reuzé S, Carré A, Sun R, Schernberg A, Alexis A, et al. The complexity of tumor shape, spiculatedness, correlates with tumor radiomic shape features. Sci Rep. 2019;9(1):4329. https://doi.org/10.1038/s41598-019-40437-5.

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