Proceedings of ICMMGH 2026 Symposium: Cell and Molecular Biology: Understanding Immune Cell Functions
DOI: 10.54254/2753-8818/2026.PJ30834

# *Artificial Intelligence for Prediction and Diagnosis of Pulmonary Nodules on CT*

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***Abstract.*** Pulmonary disease remains common worldwide, and lung cancer continues to account for a large proportion of cancer-related deaths. With the widespread use of low-dose CT (LDCT), many small and often asymptomatic pulmonary nodules are now detected at an early stage. This has improved opportunities for early lung cancer diagnosis, but it has also increased the reading workload for radiologists. In most centres, assessment of nodules still relies mainly on the visual judgement of experienced readers, which introduces subjectivity, limits reproducibility and makes the evaluation of very small nodules particularly difficult. In parallel, artificial intelligence (AI), especially deep learning and radiomics, has progressed rapidly and is now being applied to CT-based analysis of pulmonary nodules. These techniques can perform automatic detection and segmentation with high accuracy and provide quantitative descriptors for downstream analysis. Multi-parameter AI models have been shown to enhance benign–malignant classification, especially for small lesions, although issues such as control of false positives and limited generalisability across scanners and populations remain. Future work is likely to focus on multimodal data integration and automated feature learning. This review summarises current applications of AI to CT imaging of pulmonary nodules in three key areas including detection and segmentation, benign–malignant prediction and invasiveness assessment, and discusses directions for further clinical translation.

***Keywords:*** artificial intelligence, pulmonary nodules, segmentation, invasiveness, LDCT.

## 1. Introduction

In the years following the COVID-19 pandemic, respiratory diseases have continued to rank among the most frequent conditions encountered in clinical practice. Pulmonary nodules are an increasingly common finding, and lung cancer remains a leading cause of cancer mortality. The introduction and gradual roll-out of LDCT in tertiary hospitals as well as community screening programes have led to the detection of large numbers of small nodules, many of which are incidentally found in individuals with few or no symptoms. This shift facilitates earlier recognition of potentially malignant lesions but also places a heavy and sustained burden on imaging services. Importantly, approximately 95% of pulmonary nodules are ultimately benign [1]. The central question is therefore how to identify a relatively small number of malignant or high-risk nodules among a large pool of benign findings,

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while at the same time avoiding missed cancers and unnecessary repeat imaging. Chest CT is the main imaging basis on which these decisions are made.

At present, radiologists usually estimate the risk of malignancy using CT appearances such as size, attenuation pattern and morphology, and then apply guideline-based risk categories that inform follow-up intervals or the need for invasive procedures [2,3]. This approach, although widely used, has several well-recognised limitations. It depends heavily on reader experience and local equipment, and differences between scanners, reconstruction algorithms and individual observers can lead to inconsistent results. Visual assessment focuses on a small number of readily appreciable features, while much of the quantitative information in the CT data is not routinely used. Risk categories are often broad, typically divided into low, intermediate and high risk. As LDCT screening increases, each radiologist must review more studies per day, which inevitably raises the risk of oversight. Against this background, AI methods have been introduced to support nodule evaluation. Early studies suggest that AI can improve the consistency and efficiency of interpretation and assist in tailoring management strategies and prognostic estimates. The aim of this review is to summarise how different AI algorithms have been applied to CT-based automatic detection and segmentation of pulmonary nodules, benign–malignant stratification and prediction of invasiveness.

## 2. Detection and segmentation of pulmonary nodules

Reliable detection and accurate segmentation are the starting point for almost all AI-based pipelines in nodule analysis. They are also essential for subsequent tasks such as volumetry, growth assessment and risk prediction. In practice, these steps are challenging. Nodules are often small and of relatively low contrast compared with the surrounding lung parenchyma. Their shape and internal structure vary widely, and they may be attached to vessels, pleurae or mediastinal structures. Earlier rule-based computer-aided detection systems often suffered from high false-positive rates and inconsistent boundary delineation, and their performance was especially poor for very small or juxta-vascular nodules. As a result, they were difficult to integrate into high-volume LDCT screening workflows.

CNN-based models allow detection and segmentation to be learned directly from annotated CT data. End-to-end architectures using 2D or 3D convolutions can exploit local and contextual information simultaneously and have been shown to improve sensitivity and reduce false positives compared with classical approaches [4]. In addition, classification or risk prediction tasks built on top of the segmentation benefit when the segmentation itself is accurate: volumes, diameter measurements and texture descriptors are then more reliable, which in turn supports more robust downstream models [5]. On the basis of U-Net and related encoder–decoder structures, many research groups have explored modifications to better handle small nodules and complex backgrounds. One such model, LST-ARBunet, combines multi-scale feature fusion, Swin-Transformer blocks and attention mechanisms to enhance both global context modelling and local detail preservation in lung CT images [6].

On the LIDC-IDRI public dataset, improved U-Net-based networks that incorporate multi-scale feature re-weighting and explicit edge-awareness modules have achieved higher Dice and intersection-over-union scores for both central and peripheral nodules, while maintaining processing times on the order of one to two seconds per scan [6]. These results suggest that high-quality segmentation is technically feasible at speeds compatible with clinical use. From a practical perspective, well-performed segmentation reduces the need for manual contouring, allows more accurate measurement of nodule size and density, and produces more stable inputs for later radiomics or deep-learning models.

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In recent years, several groups have gone beyond retrospective algorithm development and tested AI-based detection and segmentation systems in real screening or clinical cohorts [4–6]. In one study of thousands of adults undergoing LDCT screening, an AI system was used to detect pulmonary nodules and at the same time quantify coronary artery calcium from the same scans [7]. The system showed detection performance that matched or exceeded routine radiologist reading, while automated calcium scoring correlated with future cardiovascular events and mortality [7]. This type of work illustrates how a single CT examination can be used to assess multiple disease risks. At the same time, challenges remain. False positives, particularly near vessels and the pleura, are still a concern, and performance can be sensitive to differences in acquisition parameters between centres. Nonetheless, once detection and segmentation are sufficiently reliable, they provide a solid platform on which benign–malignant classification and invasiveness prediction can be built.

## 3. Prediction of benign versus malignant nodules

Once a nodule has been identified and segmented, the next central task is to determine the likelihood of malignancy. In day-to-day practice this is still largely done by integrating visual impressions of size, growth, morphology and ancillary signs with patient factors such as age and smoking history. This process is inherently subjective, and small or atypical nodules pose particular difficulties. AI-based models attempt to turn this judgement into a quantitative prediction problem by extracting and combining a wide range of image-derived features.

In a retrospective series of 500 nodules confirmed by pathology, with roughly twice as many malignant as benign lesions, investigators extracted morphological, attenuation and texture features and built an AI-based multi-parameter model for benign–malignant classification [8]. Compared with more traditional criteria, this model achieved higher AUC and sensitivity, suggesting that combining multiple quantitative descriptors yields more informative risk estimates than relying on a single measurement or qualitative impression [8]. Other work has concentrated on nodules ≤2 cm, a group that is clinically important but often difficult to classify confidently based on appearance alone. In such studies, AI-derived quantitative parameters have been used both to differentiate benign from malignant nodules and to estimate the risk of postoperative recurrence [9].

One study involving 594 patients with resected pulmonary nodules used an AI-assisted system to extract volumetric and attenuation-based parameters, among others, and then employed multivariable modelling to identify independent predictors of malignancy [9]. For non-solid nodules, features such as volume, mean CT value and three-dimensional long-axis diameter entered the model, and threshold values were derived for each. A combined model achieved an AUC of 0.957, outperforming individual parameters and traditional scoring schemes [9]. For solid nodules, analogous features also showed strong predictive value, and the integrated model again yielded the best performance. In this setting, quantitative descriptors provided information beyond that available from simple diameter measurements and supported more nuanced pre-operative risk stratification.

The comparison between AI models and human readers is crucial for understanding how these tools might be used in practice. In studies where AI systems and radiologists independently classified nodules with known outcomes, AI generally performed better than less experienced readers and was comparable to experts [10]. AI also tended to produce more consistent results when the same cases were evaluated repeatedly. Nonetheless, human input remains essential, particularly when imaging findings must be interpreted in the light of clinical history, comorbidities and patient preferences. A realistic view is that AI will function as a decision-support system—highlighting concerning nodules, providing calibrated risk estimates and improving consistency—rather than entirely replacing radiologists in benign–malignant assessment.

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## 4. Prediction of lung nodule invasiveness

For pulmonary adenocarcinomas that appear as subsolid nodules, the degree of invasiveness has a direct impact on the choice of surgical procedure, the required resection margin and long-term outcomes. On CT, these lesions frequently manifest as pure or part-solid ground-glass nodules, and the visual differences between atypical adenomatous hyperplasia, adenocarcinoma in situ, minimally invasive adenocarcinoma and frankly invasive adenocarcinoma can be subtle. As a result, assessments based solely on visual inspection are often uncertain and show limited reproducibility.

Radiomics provides a way to quantitatively describe nodule heterogeneity using a large number of intensity- and texture-based features, while machine-learning methods can be used to construct prediction models from these features [11]. In a study of 215 patients with resected subsolid nodules covering the full histological spectrum from pre-invasive to invasive disease, nodules were divided into non-invasive and invasive groups. After segmentation and standardised pre-processing, high-dimensional radiomics features were extracted, and multiple machine-learning classifiers were trained and evaluated. The resulting models achieved high AUCs, with good sensitivity and specificity, and performed consistently across internal and external validation sets, indicating that radiomics-based signatures can capture relevant aspects of tumour biology and assist in grading invasiveness [12].

Other investigators have directly compared CT semantic features—such as lesion size, attenuation pattern, margin character, presence of pleural retraction and other visually scored findings—with radiomics features for the same task. Separate models were built using only semantic features, only radiomics features and a combination of both. In these analyses, radiomics-based models performed at least as well as semantic models, and the combined models showed the best overall discrimination between invasive adenocarcinoma and less invasive entities. These observations suggest that semantic and radiomics features carry partly complementary information, and that integrating them yields a more complete characterisation of subsolid nodules. Looking further ahead, it is likely that radiomics and deep-learning features will be combined with clinical variables, blood biomarkers and genomic data to build richer prediction models, and that representation learning will increasingly replace hand-crafted feature extraction.

## 5. Conclusion

AI has already changed the way CT images of pulmonary nodules can be analysed and interpreted. In the area of detection and segmentation, deep-learning models make it possible to identify and delineate nodules automatically with a level of accuracy and consistency that is difficult to achieve manually, while keeping processing times short enough for clinical use. This in turn provides high-quality inputs for volumetric assessment, growth analysis and downstream predictive modelling. For benign–malignant classification, multi-parameter AI models that incorporate morphological, attenuation and texture information generally perform better than traditional qualitative approaches and, in some settings, approach the performance of expert radiologists, particularly for small and subsolid nodules. In the assessment of invasiveness, radiomics- and machine-learning-based approaches, frequently combined with conventional semantic features, show encouraging ability to distinguish invasive from non-invasive disease and to support decisions regarding surgical management.

Despite these advances, several practical issues must be addressed before AI systems can be widely adopted. Models need to be robust to differences in scanners, protocols and patient populations; their outputs must be interpretable enough for clinicians to understand and trust; and their impact on patient outcomes should be demonstrated in prospective, real-world studies rather than only in retrospective datasets. Integration into clinical workflows also requires careful design to avoid increasing complexity or workload. As these challenges are progressively resolved, AI-driven tools have the potential to standardise nodule assessment, reduce unwanted variability, and make high-quality interpretation more widely accessible. Ultimately, such developments may contribute to more precise risk stratification, more tailored treatment decisions and improved control of early-stage lung cancer at the population level.

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