

Machine/Deep Learning-Based Position Prediction of Pulmonary Nodules in Free- Breathing CT-Guided Lung Puncture: A Single-Center Prospective Cohort Study

Yaqi Zeng

Peking University People's Hospital

Tao Liu

Peking University People's Hospital

Wen Tang

Infervision Medical Technology Co., Ltd

Dawei Wang

Infervision Medical Technology Co., Ltd

Xizhao Sui

Peking University People's Hospital

Nan Hong

Peking University People's Hospital

Libao Hu

hulibao@bjmu.edu.cn

Peking University People's Hospital

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Abstract

Background

Cranio-caudal respiratory drift of pulmonary nodules severely compromises accuracy of free-breathing CT-guided thoracic interventions, contributing to repeated CT acquisitions, prolonged procedure time, elevated patient radiation burden, and higher complication risks of pneumothorax and pulmonary hemorrhage. Conventional motion mitigation approaches such as breath-holding and respiratory gating require high-level patient compliance and constrain needle insertion to narrow predefined respiratory phases, which limits real-world clinical utility. This work addresses this unmet clinical need by developing and validating novel real-time artificial-intelligence prediction models. Leveraging only one baseline planning CT together with low-cost, portable nasal airflow and respiratory inductive plethysmography (RIP) signals, our framework achieves sub-millimeter prediction of nodule cranio-caudal position without additional dynamic imaging.

Methods

This single-center prospective cohort enrolled 139 patients with 143 nodules undergoing pre-VATS CT microcoil localization. Synchronized respiratory waveforms, paired CT scans, clinical, lesion and procedural metadata were collected. Nodule vertical displacement was quantified via Z-axis coordinate shifts of each nodule's maximum cross-section geometric center. In total, 2275 paired CT datasets were split 4:1:1 for model training, validation and independent testing. Prediction performance was quantified using mean squared error (MSE).

Results

The nasal-airflow-driven SVM yielded validation/test MSE values of 0.099/0.166 mm², versus 0.120/0.186 mm² for ResNet-18. RIP-based SVM achieved validation/test MSE of 0.100/0.168 mm² compared with 0.122/0.198 mm² for ResNet-18. Across heterogeneous breathing patterns and lesion locations, absolute prediction errors of central Z-coordinates remained below 0.5 mm for all constructed models.

Conclusions

Portable respiratory monitoring coupled with machine-learning enables sub-millimeter nodule Z-position prediction without mandatory breath-hold or phase-locked gating. This solution can be directly integrated into existing manual CT-guided puncture workflows to improve procedural safety and efficiency with minimal additional hardware; it also provides an essential technical building block for next-generation robotic thoracic interventional platforms.

Trial registration:

ChiCTR2300068696 (2023-02-27)

Introduction

Percutaneous CT-guided procedures—including preoperative microcoil/wire localization, transthoracic needle biopsy, and thermal ablation—are cornerstone minimally invasive techniques for diagnosing and treating small, subsolid, or deep pulmonary nodules. However, respiratory motion—particularly pronounced cranial-caudal excursions in lower lobe lesions driven by diaphragmatic movement—remains the dominant obstacle to precision[1–3]. This motion induces target drift, necessitating frequent needle redirections and additional CT acquisitions. These factors directly contribute to prolonged procedure duration (often > 20 minutes), markedly elevated radiation exposure, and increased complication rates, such as pneumothorax, pulmonary hemorrhage, and hemoptysis[4–7].

To mitigate the effects of respiratory motion and enhance puncture precision, various strategies have been explored, including 4D-CT (for ablation), breath-holding, respiratory targeting (under free-breathing conditions), and robotic systems with gated respiratory compensation[3, 8–13]. However, these methods have inherent limitations: 4D CT entails higher costs and increased radiation exposure[11, 14, 15]; robot-assisted navigation for CT-guided puncture restricts needle insertion to deep inspiration phases, requiring patients to perform multiple brief breath-holding periods to improve accuracy[10, 16]. Breath-holding and respiratory targeting are also commonly used in CT-guided localization/biopsy procedures without robotic assistance. While breath-holding demands patient cooperation—potentially reducing comfort and compliance, especially in elderly patients or those with underlying diseases—studies suggest that puncture during the expiratory phase may reduce the risk of pneumothorax[17]. Another study suggests that interactive breath-hold control also carries an increased risk of pneumothorax[18], raising concerns about higher complication rates.

Emerging AI-driven approaches, such as the Population-Characteristic Weighted Sparse (PCWS) model (achieving ~ 0.20 mm error with only two standard CT scans) and deep learning frameworks for 3D motion estimation, demonstrate the feasibility of accurate prediction without full-cycle imaging[19]. Building on this momentum, we propose a clinically deployable, real-time prediction system that fuses continuous external respiratory signals (nasal airflow/RIP) with machine/deep learning to forecast nodule position at arbitrary breathing phases after initial planning CT. This method seeks to overcome current limitations, deliver superior targeting accuracy across localization/biopsy/ablation, and pave the way for intelligent, adaptive robotic platforms capable of radiation-sparing, dynamic compensation.

Materials and Methods

This prospective study has been approved by the Institutional Review Board and has obtained written informed consent from all participating patients.

Study population

From March 2023 to May 2024, this study recruited 153 participants who underwent preoperative CT-guided lung nodule localization before video-assisted thoracoscopic surgery (VATS) at our academic hospital. Figure 1 provides a summary of the participant enrollment and exclusion process. During the localization procedure, nasal airflow and respiratory inductive plethysmography (RIP) signals were simultaneously collected using the portable sleep monitor (PSM). A total of 5 participants discontinued intraoperative monitoring due to intolerance of nasal cannulas or thoracoabdominal belts; 3 were excluded for excessive body movement during the procedure; and 6 had invalid nasal airflow signals from cannula detachment (identified via postoperative data verification). Ultimately, 139 participants (143 lesions, with 4 patients undergoing concurrent localization for 2 nodules each) were enrolled in the final analysis.

Interventional Procedure

All percutaneous CT-guided localizations of lung nodules were carried out by two interventional radiologists, each with over five years of experience. The procedures were conducted using a 96-detector CT scanner (Force, Siemens Healthineers), with the following parameter settings: tube voltage of 90 kV; automatic tube current modulation tailored to body type (ranging from 100 to 500 mA); helical acquisition mode; slice thickness and increment of 1 mm; rotation time of 0.5 seconds; and a pitch of 1.2. A 21G Chiba needle (Skater; Argon Medical Devices) and a platinum microcoil with cilia (6/2-Tornado; Cook Incorporated) were utilized for the localization process.

Initially, the patient's position (supine, prone, or lateral) was determined based on the nodule's location using the first CT scan images to minimize puncture depth (Fig. 2a). A suitable puncture path was then carefully selected under real-time intraoperative CT guidance, avoiding critical structures such as ribs, the scapula, major blood vessels, lung fissures, and the liver.

Local anesthesia was administered using lidocaine. The Chiba needle was advanced into the lung tissue within a 10 mm distance from the target lesion under several CT scans guidance (Fig. 2b). During the procedure, a minimum of 5–6 CT scans would be performed at each step, including the initial planning, grid attachment, needle insertion into the chest wall, puncture over the pleura, and needle placement around the target lesion. Following this, the core of the Chiba needle was removed, and the microcoil was inserted through the needle. Once the needle and guidewire were withdrawn, the distal end of the microcoil was coiled within the lung tissue, extending approximately 10 mm beyond the visceral pleura (Fig. 2c). Throughout the procedure, patients were instructed to breathe quietly.

A post-procedural CT scan was performed to verify the precise location of the microcoil around the nodule and the visceral pleura, as well as to detect any complications. Routine thoracoscopic surgery was carried out within 24 hours following the localization procedure (Fig. 2d).

Respiratory Monitoring

Before the localization, the CT scanner and laptop were previously adjusted according to the institution's timestamp server. Participants were then fitted with a nasal cannula and a thoracic and abdominal belt. A PSM (T3; Nox Medical, Reykjavik, Iceland) was connected to simultaneously monitor nasal airflow and RIP signals.

Upon completion of the puncture localization procedure, the monitor was connected to the laptop. Subsequently, the Noxturnal software (version 5.1.0; Nox Medical) was employed to collect the data of nasal airflow and RIP.

Data Collection and Statistical Analysis

Patient Clinical Information

Characteristics of participants (age, sex, height, and weight), lesions (length, width, location, and density), and procedural information (position, times of CT scan, and procedure duration) were obtained from the electronic medical records and the picture archiving and communication system. The CT scan times referred to the number of all intra- and post-procedural CT scans.

Data were presented as “mean $\pm$ standard deviation” if normally distributed, or “median [interquartile range]” if non-normally distributed, or n (%) if categorical.

Nodule Position Information and Respiratory Monitoring Signals

For all participants, the InferScholar (InferVision) platform was used to annotate the nodule positions which defined as the Z-axis coordinates of the nodule's maximum cross-sectional geometric center across distinct respiratory phases. This process enabled the acquisition of information regarding the positions where the nodules were located and the specific time points of each CT scan (Fig. 3a). The Z-score normalization method was applied to the nodule position information, resulting in specific values representing the relative positions of the nodules during each scan. Regarding the respiratory data in the EDF format obtained from the Noxturnal software, data export and signal normalization processing were carried out. This led to the acquisition of specific signal values (equivalent to respiratory amplitude values) at the time points corresponding to each CT scan (Fig. 3b, c).

Considering the phase differences between the airflow and RIP monitoring curves (with the peak-to-valley corresponding to the maximum RIP pressure at the end of inhalation, and the corresponding pulmonary nodule being closer to the diaphragm), the airflow signal was first corrected by performing a 0-axis flip. Due to baseline drift in the RIP monitoring curve, which did not remain consistently centered around the 0-axis as observed in nasal airflow curves, we first applied a sliding window algorithm (with a window width of 6 seconds, corresponding to approximately two respiratory cycles) to perform baseline

correction in RIP signals. Subsequently, Z-score normalization was applied both for the nasal airflow and RIP curves.

Prediction Model for the Motion Trajectory of Pulmonary Nodules

All participants were divided into training, validation, and independent test sets in a 4:1:1 ratio, with two lesions from the same patient only assigned to the same group. For the same nodule, 2 of the different CT scan images were paired up. The spatial position at one CT scan was used as the initial input information, while the other position of the paired images served as the object for model prediction (Fig. 3f, g).

The model's input information encompassed patient clinical characteristics, the initial nodule position, the imaging features of the nodules, and the respiratory amplitude values at the time points corresponding to the initial and paired CT scans. The output information was the position of the nodule in the second scan.

The support vector machines (SVM) and Deep learning algorithms were used to build prediction models. The SVM model is configured with parameters set as SVR (kernel='linear', C = 0.0001, gamma='auto'). The hyper-parameters for the deep learning algorithm were set as follows: learning rate = 0.0001, batch size = 9, GPU: 3 GTX1080, max epoch = 200. For the deep learning model, feature extraction is divided into two parts. First, digital imaging and communications in medicine (DICOM) images corresponding to known lesions are input into ResNet-18 to extract image features. Second, non-image clinical features are processed through a ResNet-based clinical feature extractor to obtain clinical characteristics. The image and clinical features are then concatenated and input into the final predictor for prediction.

The Mean Squared Error (MSE), defined as $MSE = \frac{1}{n} \sum_{i=1}^n (y_{\text{true}} - y_{\text{pred}})^2$, was employed to quantify the model's accuracy in predicting the vertical motion amplitude of pulmonary nodules.

Results

Characteristics of participants and lesions

A total of 139 participants with 143 lung nodules (4 participants with 2 lesions) were enrolled in the study, The characteristics of the participants and lesions are shown in Table 1.

Table 1
Characteristics of Patients and Lesions

Sex	Value
Female	91 (65.5%)
Male	48 (34.5%)
Age	54.1 ± 12.0
Height(mm)	165.0 ± 7.0
Weight(kg)	65.2 ± 11.0
Location	
Lower	42 (29.4%)
Middle	20 (14.0%)
Upper	81 (56.6%)
Length(mm)	9.00 [5.00]
Width(mm)	7.00 [4.00]
Density	
Ground-glass	65 (45.5%)
Solid	6 (4.2%)
Sub-solid	72 (50.3%)
Data are presented as “mean ± standard deviation” if normally distributed, or “median, IQR [interquartile range]” if non-normally distributed, or n (%) if categorical. Upper lobes exclude the left upper lobe lingular segments. Middle lobes include the left upper lobe lingular segments.	

The study population predominantly consisted of female participants (91/139), with an average age of 54.1 years (standard deviation: 12.0 years). In terms of physical characteristics, the average height was 165.0 cm (standard deviation: 7.0 cm), and the average weight was 65.2 kg (standard deviation: 11.0 kg).

Concerning the location, size, and density of the lesions, 42 lesions (29.4%) were located in the lower lobes, 20 lesions (14.0%) were in the middle lobes (including the left upper lobe lingular segments), and 81 lesions (56.6%) were in the upper lobes, which excluded the left upper lobe lingular segments. The median length of the lesions was 9 mm (IQR, 5 mm), and the median width was 7 mm (IQR, 4 mm). As for lesion density, there were 65 (45.5%) ground-glass opacity lesions, 6 (4.2%) solid lesions, and 72 (50.3%) sub-solid lesions.

Characteristics of procedures

Table 2 illustrates the characteristics of the procedures.

Table 2
Characteristics of Nodule Localization

Characteristics	Values
Position	
Lateral	18(12.6%)
Prone	57 (39.9%)
Supine	68 (47.6%)
CT scan times	6.00 [2.00]
Procedure Duration(mins)	18.0 [5.00]
Motion amplitude(mm)	5[5.00]
Data are presented as “mean ± standard deviation” if normally distributed, or “median, IQR [interquartile range]” if non-normally distributed, or n (%) if categorical.	

The mean procedure duration was 18.9 mins with a median of 18 mins. The mean number of CT scan times was 6.13 and the median was 6. A total of 57 lesions (39.9%) underwent prone position, 68 (47.6%) underwent supine position, and 18 (12.6%) underwent lateral position, one participant with 2 lesions might experience two positions during the whole localization procedure.

The nodule motion amplitude in the cranial-caudal direction ranged from 1 to 18 mm with a mean amplitude of 5.8 mm and a median amplitude of 4 mm.

Prediction model with data of nasal airflow and RIP

The workflow for constructing the predictive model is illustrated in Fig. 3. A total of 139 participants (143 lesions) and 2275 paired CT scans were included in the study for model training, validation, and testing. The training set included 83 participants with 1473 paired CT images, the validation set consisted of 28 participants with 361 paired CT images, and the test set included 28 participants with 441 paired CT images.

The grouped data and prediction results of machine learning / deep learning models are presented in Table 3. In the nasal airflow group, the SVM-based predictive model demonstrated prediction MSE values of 0.112, 0.099 (95% CI, 0.084, 0.113) and 0.166 (95% CI, 0.144, 0.187) mm² for the training, validation and test sets, respectively. The Deep Learning-based model demonstrated prediction MSE values of 0.097, 0.120 (95% CI, 0.104, 0.137) and 0.186 (95% CI, 0.162, 0.210) mm² for the training, validation and test sets, respectively.

Table 3
Predictive Metrics of the Model in the Training, Validation and Test Sets

Model with nasal airflow	Participants	Paired CT Images	Prediction MSE for SVM (mm²) (95% CI)	Prediction MSE for Deep learning (mm²) (95% CI)
	139	2275		
Training Set	83	1473	0.112	0.097
Validation Set	28	361	0.099(0.084, 0.113)	0.120(0.104, 0.137)
Test Set	28	441	0.166(0.144, 0.187)	0.186(0.162, 0.210)
Model with RIP	139	2275		
Training Set	83	1473	0.113	0.155
Validation Set	28	361	0.100(0.085, 0.114)	0.122(0.104, 0.140)
Test Set	28	441	0.168(0.146, 0.190)	0.198(0.171, 0.225)
MSE, Mean Squared Error; SVM, Support Vector Machine; RIP, respiratory inductive plethysmography; CI, confidence interval.				

As for the RIP group, the SVM-based predictive model demonstrated prediction MSE values of 0.113, 0.100 (95% CI, 0.085, 0.114) and 0.168 (95% CI, 0.146, 0.190) mm² for the training, validation and test sets, respectively. The Deep Learning-based model demonstrated prediction MSE values of 0.155, 0.122 (95% CI, 0.104, 0.140) and 0.198 (95% CI, 0.171, 0.225) mm² for the training, validation and test sets, respectively.

Discussion

The present study demonstrates that real-time respiratory signals (nasal airflow or RIP) combined with SVM or ResNet-18-based deep learning can predict pulmonary nodule cranial-caudal displacement with sub-millimeter accuracy (test MSE ~ 0.166–0.198 mm², errors consistently < 0.5 mm). This level of spatial precision directly addresses the core clinical bottleneck of free-breathing CT-guided lung interventions: unpredictable respiratory target drift that impairs needle targeting accuracy, necessitates frequent repeat CT acquisitions, extends procedure time, and increases the incidence of pneumothorax and pulmonary hemorrhage.

Current standard-of-care intraoperative respiratory motion mitigation strategies carry well-documented clinical limitations specific to percutaneous thoracic intervention. Coached breath-holding and fixed-phase respiratory gating demand sustained patient cooperation and strictly limit needle insertion to narrow predefined respiratory windows; repeated forced breath holds also correlate with elevated pneumothorax risk per prior interventional radiology cohorts. 4D-CT, frequently cited in motion management literature, is primarily optimized and clinically utilized for thoracic radiation therapy rather

than routine CT-guided lung puncture, as its extended scan time and substantially elevated cumulative radiation dose render it impractical for bedside interventional workflows[16, 19]. Early robotic puncture systems with respiratory gating show promise but still confine needle advancement to deep inspiration phases and require repeated patient breath-holds, introducing operational constraints absent from our predictive framework[9, 10].

Our machine learning pipeline delivers unique operational advantages over conventional respiratory control tools by integrating directly into unmodified standard CT-guided needle insertion workflows for manual interventional practice. The full clinical implementation sequence proceeds as follows: (1) a single baseline planning CT is acquired to segment the nodule and record its central Z coordinate reference; (2) lightweight, portable nasal cannula and thoracic-abdominal RIP belts are applied to the patient for continuous, noninvasive real-time respiratory waveform capture throughout the case; (3) the model ingests static baseline imaging features, patient clinical covariates, and live respiratory amplitude signals to output continuous, time-resolved predictions of the nodule's cranio-caudal central Z position at any arbitrary respiratory phase. Unlike phase-locked gating, which restricts safe needle advancement to only inspiratory or expiratory peaks, our predictive system provides uninterrupted positional forecasts across the full respiratory cycle. Interventional radiologists retain full flexibility to select optimal needle insertion timing and trajectories without mandatory breath-hold coordination, drastically reducing the number of confirmatory CT scans required to verify needle-tumor alignment. This workflow advantage directly reduces cumulative patient radiation exposure and cuts total procedural runtime, two high-priority quality metrics for contemporary interventional radiology practice reported across large CT lung biopsy and localization cohorts.

Notably, this predictive framework is designed first and foremost for immediate deployment in standard manual CT interventional suites, requiring only commercially available portable sleep monitoring hardware with no costly robotic navigation equipment or suite infrastructure renovations. The model's continuous real-time motion forecasts can be repurposed as a respiratory compensation add-on module for robotic thoracic puncture platforms to enable dynamic, autonomous needle path correction; however, its core clinical value lies in improving safety and efficiency for the vast majority of thoracic interventional procedures performed manually without robotic assistance. The model maintains robust predictive performance across heterogeneous nodule anatomies (56.6% upper lobe, 29.4% lower lobe lesions), variable nodule sizes, densities, and patient breathing patterns, supporting broad applicability to preoperative microcoil localization, diagnostic transthoracic needle biopsy, and thermal ablation. By minimizing needle redirections and repeat CT acquisitions, this tool mitigates two key drivers of procedural complications while expanding feasible treatment windows for high-risk patient subgroups (elderly patients, those with impaired pulmonary function unable to sustain prolonged breath-holds).

Beyond CT imaging and real-time respiratory monitoring data, we incorporated additional clinical variables into the model, including patient gender, age, height, weight, and scanning position (prone, supine, or lateral). These factors are known to influence nodule motion amplitude: for instance, taller individuals or male patients may exhibit larger breathing amplitudes, while variations in weight and body

position can alter nodule movement relative to diaphragmatic motion. Specifically, the prone position restricts chest and rib cage mobility, potentially resulting in smaller breathing amplitudes. Additionally, nodules located in the upper lobes generally exhibit less motion compared to those in the lower lobes[2] – a factor explicitly integrated into our model. To account for potential confounding, we also included nodule size, density, and other imaging characteristics as input features.

This real-time motion prediction pipeline carries meaningful forward-looking implications for the evolution of minimally invasive thoracic interventional radiology. Beyond immediate manual procedural optimization, continuous submillimeter nodule positional forecasting can be fused with electromagnetic tracking or low-dose fluoroscopy to develop radiation-sparing navigation workflows that reduce or eliminate intraprocedural CT confirmation scans entirely.

This study has several acknowledged limitations that warrant contextualization. First, its single-center design and moderate sample size may introduce institutional selection bias; multicenter prospective validation across diverse patient populations and CT scanner platforms is required to confirm generalizability. Second, we exclusively quantified and predicted cranio-caudal Z-axis nodule displacement via central cross-sectional coordinates, without modeling anterior-posterior and left-right translational motion, which may impact targeting accuracy for complex ablation protocols requiring full 3D positional awareness. Finally, all predictive performance data were derived from preoperative VATS microcoil localization cases; dedicated prospective validation within standalone CT-guided lung biopsy and thermal ablation cohorts will strengthen evidence supporting widespread clinical adoption across all percutaneous thoracic interventional indications.

In conclusion, this work presents a low-cost, readily translatable solution to overcome free-breathing respiratory motion artifacts during standard CT-guided thoracic needle interventions, with measurable benefits for procedural speed, radiation reduction, and complication mitigation for manual interventional practice. The platform additionally delivers a robust technical foundation for future respiratory-adaptive robotic puncture systems, bridging near-term routine clinical utility and long-term technical innovation within interventional radiology.

Abbreviations

4DCT

four-dimensional computed tomography

LDCT

low-dose CT

PSM

portable sleep monitor

RIP

respiratory inductive plethysmography

SPNs

small pulmonary nodules
SVM
support vector machines
VATS
video-assisted thoracoscopic surgery

Declarations

Ethics approval and consent to participate

This study was performed in accordance with the Declaration of Helsinki. The Institutional Review Board approval was obtained from the Ethics Review Committee of Peking University People's Hospital (2022PHB276-001). Written informed consent was obtained from all participating patients.

Consent for publication

Not applicable. No individual patient-level identifiable images or personal participant data are presented within this manuscript.

Competing interests

The authors of this manuscript declare no relationships with any companies, whose products or services may be related to the subject matter of the article.

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Author Contribution

Authors' contributions
Conceptualization: Yaqi Zeng, Xizhao Sui, Nan Hong, Libao Hu
Data curation: Yaqi Zeng, Tao Liu
Formal analysis: Yaqi Zeng, Tao Liu, Wen Tang, Dawei Wang
Funding acquisition: Libao Hu
Investigation: Yaqi Zeng, Wen Tang, Dawei Wang
Methodology: Xizhao Sui, Nan Hong, Libao Hu
Project administration: Nan Hong, Libao Hu
Resources: Xizhao Sui, Nan Hong, Libao Hu
Software: Yaqi Zeng, Tao Liu
Supervision: Libao Hu
Validation: Yaqi Zeng, Wen Tang, Dawei Wang
Visualization: Yaqi Zeng, Wen Tang, Dawei Wang
Writing – original draft: Yaqi Zeng
Writing – review & editing: Nan Hong, Libao Hu

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Not applicable.

Data Availability

The datasets generated and/or analysed during the current study are not publicly available due to restrictions related to patient privacy under local institutional requirements, but are available from the corresponding author on reasonable request.

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Figures

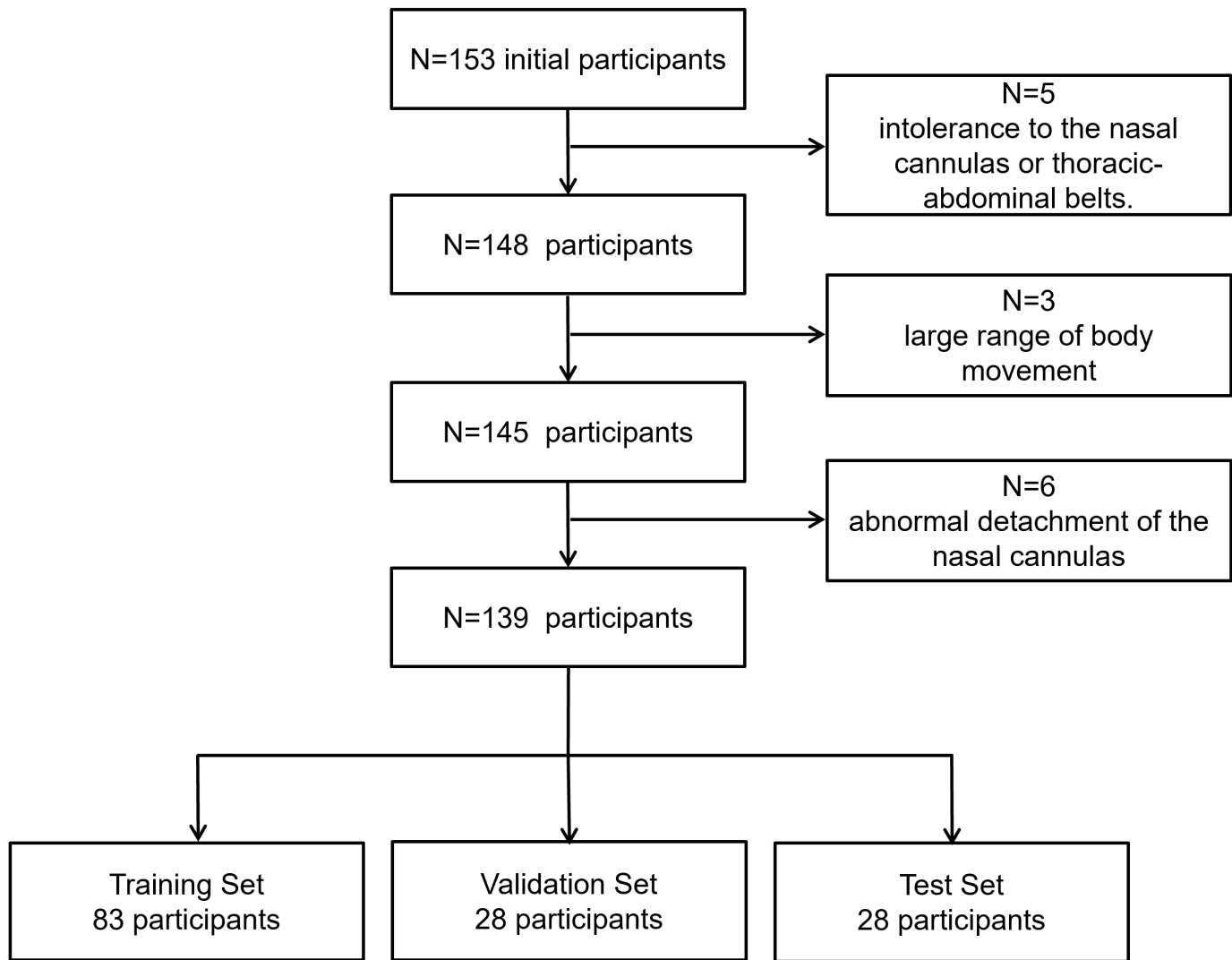


Figure 1

Overview of the participant enrollment and exclusion process.

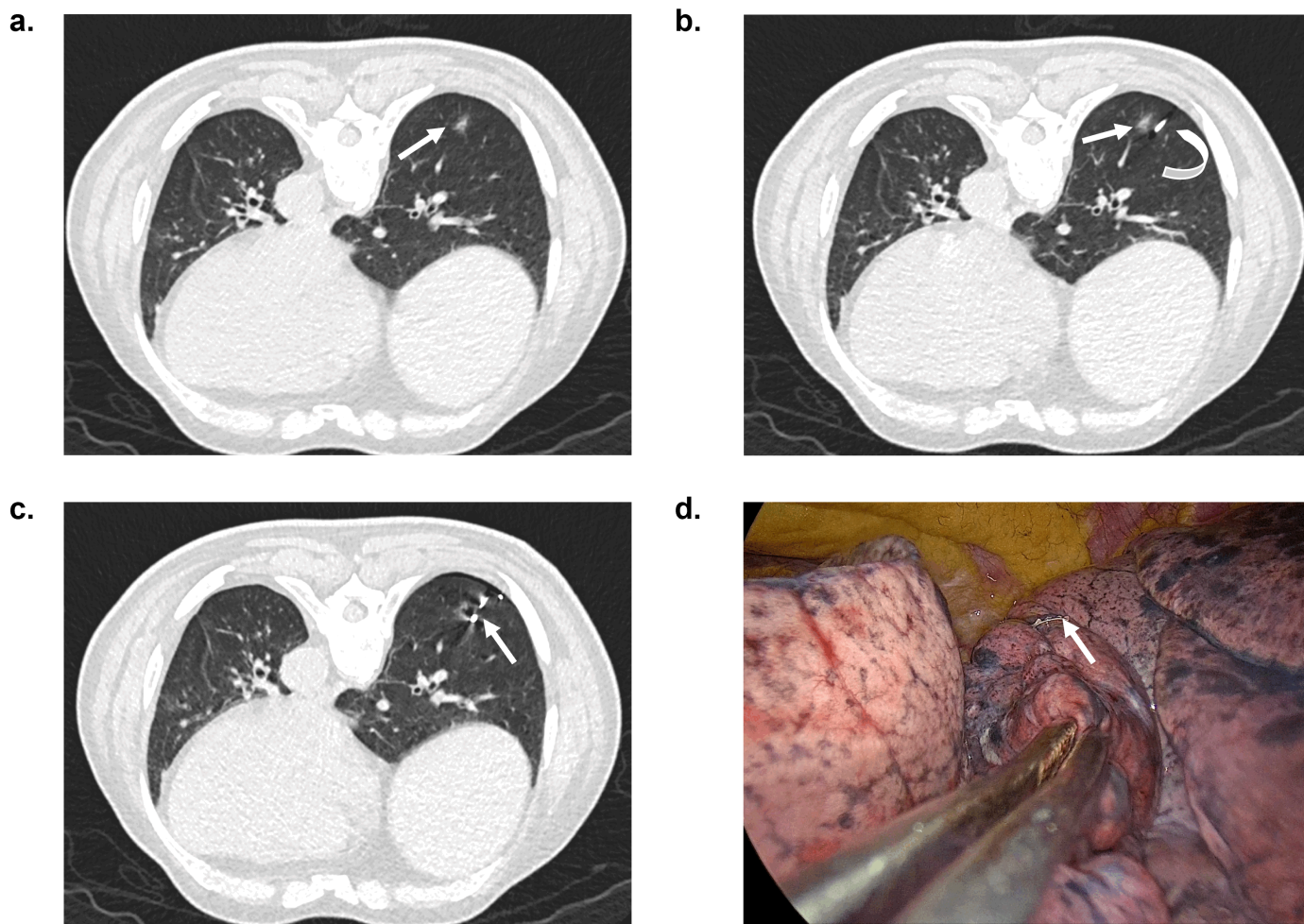


Figure 2

CT-guided microcoil localization of a mixed ground-glass nodule (14 × 12-mm) in the right lower lobe in a patient who underwent subsequent video-assisted thoracoscopic wedge resection. a. The axial CT image shows the nodule (straight arrow) in the right lower lobe. b. The needle tip (curved arrow) is positioned adjacent to the nodule (straight arrow). c. The entire microcoil (straight arrow) is visible close to the nodule, with the distal end extending beyond the visceral pleura. d. The tail of the microcoil (straight arrow) is seen on the visceral pleural surface during the VATS.

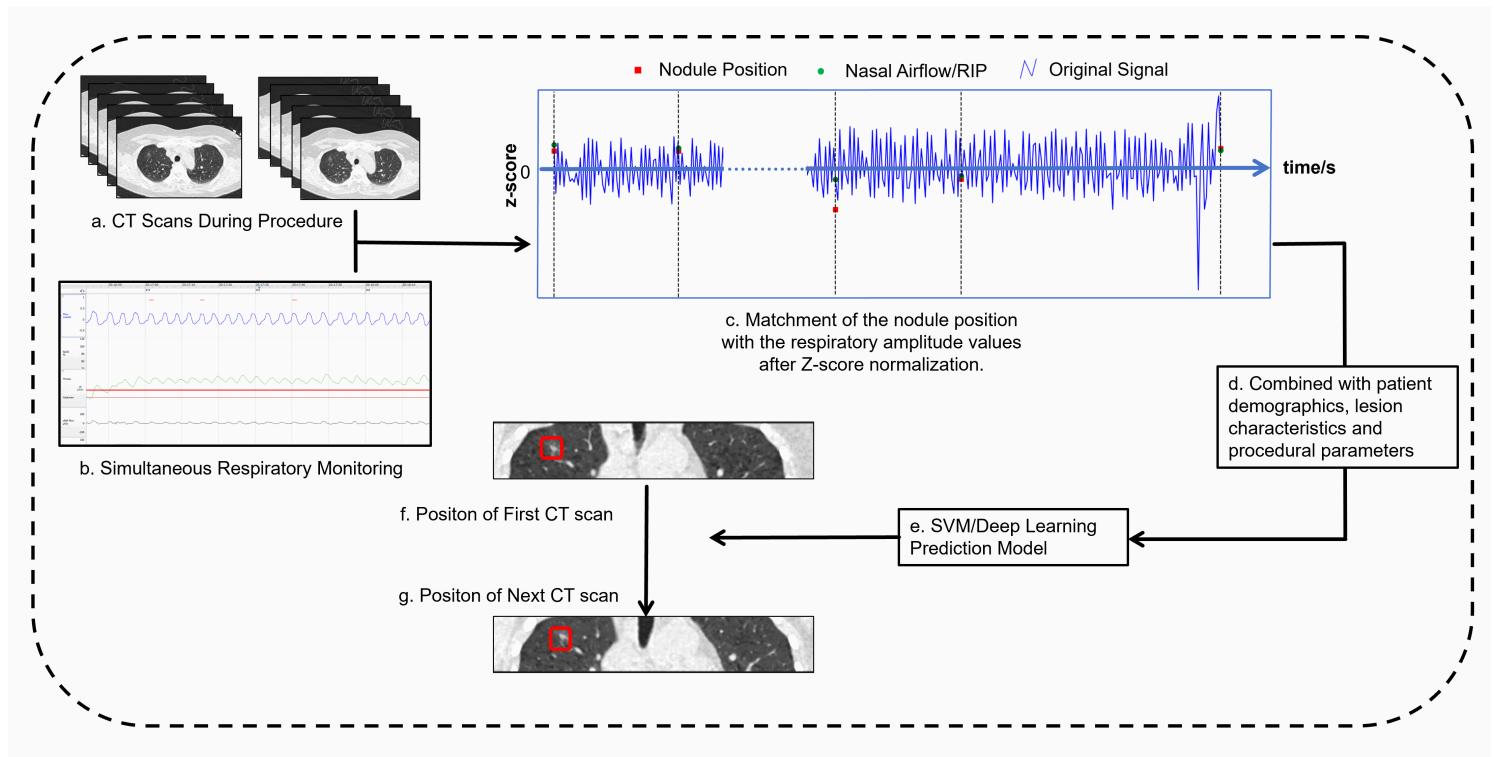


Figure 3

Predictive model development workflow. a. Nodule position data and CT scan time points were acquired during localization. b. Nasal airflow and RIP signals were simultaneously collected for real-time respiratory monitoring. c. Z-score normalization was performed on nodule positions and respiratory amplitude (nasal airflow/RIP), followed by time-point matching. d. Two CT scan images of the same nodule were paired with patient demographics, lesion/procedural parameters, and paired CT respiratory amplitudes were applied for model training. e-g. SVM and deep learning algorithms were used to predict pulmonary nodule positions in follow-up CT scans from initial CT data. SVM=Support Vector Machine; RIP=respiratory inductive plethysmography.