

neural network” [Title/Abstract] OR “CNN”[Title/Abstract] OR “Artificial neuronal network” [Title/Abstract] OR “AI” [Title/Abstract]

#8 “Tomography, X-Ray Computed”[MeSH Terms] OR “tomography scanners, x-ray computed”[Title/Abstract] OR “computed tomography”[Title/Abstract] OR “computer assisted tomography”[Title/Abstract] OR “CT”[Title/Abstract]

#9 “Invasive”[Title/Abstract] OR “invasiveness”[Title/Abstract] OR “risk”[Title/Abstract] OR “Risk Stratification”[Title/Abstract] OR “Risk assessment”[Title/Abstract] OR “risk management”[Title/Abstract] OR “subtype classification”[Title/Abstract] OR “histological assessment”[Title/Abstract]

#10 #6AND#7AND#8AND#9

2. Strategy for Embase (n=1,327):

#1 ('lung cancer'/exp 'lung tumor'/exp 'lung nodule'/exp OR 'Multiple Pulmonary Nodules'/exp OR 'Adenocarcinoma of Lung'/exp OR 'Adenocarcinoma, Bronchiolo-Alveolar'/exp OR 'Carcinoma, Non-Small-Cell Lung'/exp OR 'Carcinoma, Bronchogenic'/exp OR 'Bronchial Neoplasms'/exp OR 'Lung Neoplasms'/exp OR 'Bronchiolo-Alveolar Carcinomas':ti,ab,kw OR 'Adenocarcinomas, Lung':ti,ab,kw OR 'Carcinoma, Alveolar':ti,ab,kw OR 'Bronchiolo-Alveolar Carcinoma':ti,ab,kw OR 'Carcinomas, Bronchial':ti,ab,kw OR 'Carcinomas, Alveolar':ti,ab,kw OR 'Pulmonary Nodules, Multiple':ti,ab,kw OR 'Non-Small-Cell Lung Carcinoma':ti,ab,kw OR 'Cancer, Pulmonary':ti,ab,kw OR 'Bronchiolar Carcinomas':ti,ab,kw OR 'Carcinomas, Bronchiolar':ti,ab,kw OR 'Lung Carcinomas, Non-Small-Cell':ti,ab,kw OR 'Nonsmall Cell Lung Cancer':ti,ab,kw OR 'Alveolar Carcinomas':ti,ab,kw OR 'Neoplasm, Bronchial':ti,ab,kw OR 'Adenocarcinomas, Alveolar':ti,ab,kw OR 'Carcinoma, Bronchiolo-Alveolar':ti,ab,kw OR 'Carcinoma, Bronchiolar':ti,ab,kw OR 'Lung Cancers':ti,ab,kw OR 'Alveolar Adenocarcinomas':ti,ab,kw OR 'Alveolar Cell Carcinoma':ti,ab,kw OR 'Bronchiolo-Alveolar Adenocarcinoma':ti,ab,kw OR 'Cancer, Lung':ti,ab,kw OR 'Carcinomas, Bronchogenic':ti,ab,kw OR 'Bronchiolar Carcinoma':ti,ab,kw OR 'Neoplasms, Pulmonary':ti,ab,kw OR 'Non-Small Cell Lung Cancer':ti,ab,kw OR 'Carcinoma, Bronchioloalveolar':ti,ab,kw OR 'Carcinoma, Non-Small Cell Lung':ti,ab,kw OR 'Alveolar Adenocarcinoma':ti,ab,kw OR 'Adenocarcinoma, Alveolar':ti,ab,kw OR 'Bronchial Carcinoma':ti,ab,kw OR 'Pulmonary Nodule, Multiple':ti,ab,kw OR 'Carcinoma, Bronchial':ti,ab,kw OR 'Carcinomas, Non-Small-Cell Lung':ti,ab,kw OR 'Carcinomas, Bronchiolo-Alveolar':ti,ab,kw OR 'Neoplasm, Pulmonary':ti,ab,kw OR 'Non-Small-Cell Lung Carcinomas':ti,ab,kw OR 'Neoplasms, Bronchial':ti,ab,kw OR 'Bronchioloalveolar Carcinoma':ti,ab,kw OR 'Bronchogenic Carcinomas':ti,ab,kw OR 'Carcinoma, Non Small Cell Lung':ti,ab,kw OR 'Alveolar Cell Carcinomas':ti,ab,kw OR 'Lung Neoplasm':ti,ab,kw OR 'Cancers, Pulmonary':ti,ab,kw OR 'Bronchogenic Carcinoma':ti,ab,kw OR 'Pulmonary Cancers':ti,ab,kw OR 'Adenocarcinoma, Bronchiolo Alveolar':ti,ab,kw OR 'Lung Adenocarcinoma':ti,ab,kw OR 'Non Small Cell Lung Carcinoma':ti,ab,kw OR 'Multiple Pulmonary Nodule':ti,ab,kw OR 'Lung Cancer':ti,ab,kw OR 'Cancer of Lung':ti,ab,kw OR 'Lung Adenocarcinomas':ti,ab,kw OR 'Neoplasm, Lung':ti,ab,kw OR 'Adenocarcinomas, Bronchiolo-Alveolar':ti,ab,kw OR 'Bronchial Neoplasm':ti,ab,kw OR 'Adenocarcinoma, Lung':ti,ab,kw OR 'Pulmonary Neoplasms':ti,ab,kw OR 'Carcinomas, Bronchioloalveolar':ti,ab,kw OR 'Bronchiolo-Alveolar Adenocarcinomas':ti,ab,kw OR 'Lung Carcinoma, Non-Small-Cell':ti,ab,kw OR 'Carcinoma, Bronchiolo Alveolar':ti,ab,kw OR 'Cancer of the Lung':ti,ab,kw OR 'Pulmonary Cancer':ti,ab,kw OR 'Neoplasms, Lung':ti,ab,kw OR 'Pulmonary Neoplasm':ti,ab,kw OR 'Alveolar Carcinoma':ti,ab,kw OR 'Carcinomas, Alveolar Cell':ti,ab,kw OR 'Cancers, Lung':ti,ab,kw OR 'Bronchial Carcinomas':ti,ab,kw OR 'Bronchioloalveolar Carcinomas':ti,ab,kw OR 'Carcinoma, Alveolar Cell':ti,ab,kw OR 'GGO':ti,ab,kw OR 'pGGN':ti,ab,kw OR 'PSN':ti,ab,kw OR 'GGN':ti,ab,kw OR 'mGGN':ti,ab,kw OR 'SSN':ti,ab,kw OR 'SPN':ti,ab,kw OR 'NSN':ti,ab,kw OR 'LUAD':ti,ab,kw)

#2 ('Artificial Intelligence'/exp OR 'Neural Networks, Computer'/exp OR 'Knowledge Bases'/exp OR 'Robotics'/exp OR 'Unsupervised Machine Learning'/exp OR 'Fuzzy Logic'/exp OR 'Natural Language Processing'/exp OR 'Deep Learning'/exp OR 'Expert Systems'/exp OR 'Supervised Machine Learning'/exp OR 'Computer Heuristics'/exp OR 'Machine Learning'/exp OR 'Vision System, Computer':ti,ab,kw OR 'Machine Learning, Unsupervised':ti,ab,kw OR 'Semi supervised Learning':ti,ab,kw OR 'Computer Vision Systems':ti,ab,kw OR 'Knowledge Representations':ti,ab,kw OR 'Machine Learning, Supervised':ti,ab,kw OR 'Remote Operation':ti,ab,kw OR 'Systems, Computer Vision':ti,ab,kw OR 'Network Models, Neural':ti,ab,kw OR 'Intelligence, Artificial':ti,ab,kw OR 'Computational Neural Network':ti,ab,kw OR 'Network, Computer Neural':ti,ab,kw OR 'Networks, Computational Neural':ti,ab,kw OR 'Soft Robotics':ti,ab,kw)

OR 'Neural Network Models':ti,ab,kw OR 'Computer Vision System':ti,ab,kw OR 'Perceptrons':ti,ab,kw OR 'Soft Robotic':ti,ab,kw OR 'System, Computer Vision':ti,ab,kw OR 'Models, Neural Network':ti,ab,kw OR 'Neural Network Model':ti,ab,kw OR 'Networks, Computer Neural':ti,ab,kw OR 'Learning, Unsupervised Machine':ti,ab,kw OR 'Connectionist Model':ti,ab,kw OR 'Intelligence, Computational':ti,ab,kw OR 'Expert System':ti,ab,kw OR 'Intelligence, Machine':ti,ab,kw OR 'Learning, Hierarchical':ti,ab,kw OR 'Neural Networks, Computational':ti,ab,kw OR 'Operation, Remote':ti,ab,kw OR 'Learning, Transfer':ti,ab,kw OR 'Robotic, Soft':ti,ab,kw OR 'Transfer Learning':ti,ab,kw OR 'Learning, Active Machine':ti,ab,kw OR 'Telerobotics':ti,ab,kw OR 'Network, Neural':ti,ab,kw OR 'Systems, Expert':ti,ab,kw OR 'Model, Neural Network':ti,ab,kw OR 'Models, Connectionist':ti,ab,kw OR 'Perceptron':ti,ab,kw OR 'Knowledge Bases':ti,ab,kw OR 'Computational Intelligence':ti,ab,kw OR 'Network, Computational Neural':ti,ab,kw OR 'Learning from Labeled Data':ti,ab,kw OR 'Reasoning, Computer':ti,ab,kw OR 'Knowledge Representation':ti,ab,kw OR 'Logic, Fuzzy':ti,ab,kw OR 'Heuristics, Computer':ti,ab,kw OR 'Neural Network, Computer':ti,ab,kw OR 'Neural Network':ti,ab,kw OR 'Bases, Knowledge':ti,ab,kw OR 'Learning, Inductive Machine':ti,ab,kw OR 'Operations, Remote':ti,ab,kw OR 'Learning, Deep':ti,ab,kw OR 'Learning, Supervised Machine':ti,ab,kw OR 'Machine Learning, Inductive':ti,ab,kw OR 'Model, Connectionist':ti,ab,kw OR 'Hierarchical Learning':ti,ab,kw OR 'Learning, Machine':ti,ab,kw OR 'Networks, Neural':ti,ab,kw OR 'Connectionist Models':ti,ab,kw OR 'Semi-supervised Learning':ti,ab,kw OR 'System, Expert':ti,ab,kw OR 'Natural Language Processings':ti,ab,kw OR 'Computer Reasoning':ti,ab,kw OR 'Computer Neural Network':ti,ab,kw OR 'Neural Network, Computational':ti,ab,kw OR 'Heuristic, Computer':ti,ab,kw OR 'Machine Learning with a Teacher':ti,ab,kw OR 'Knowledgebase':ti,ab,kw OR 'Language Processing, Natural':ti,ab,kw OR 'Knowledge Base':ti,ab,kw OR 'Knowledge Acquisition':ti,ab,kw OR 'Base, Knowledge':ti,ab,kw OR 'Computational Neural Networks':ti,ab,kw OR 'Representation, Knowledge':ti,ab,kw OR 'Vision Systems, Computer':ti,ab,kw OR 'Learning, Semi-supervised':ti,ab,kw OR 'Processings, Natural Language':ti,ab,kw OR 'Acquisition, Knowledge':ti,ab,kw OR 'Neural Networks':ti,ab,kw OR 'Machine Intelligence':ti,ab,kw OR 'Machine Learning, Active':ti,ab,kw OR 'Active Machine Learning':ti,ab,kw OR 'Knowledgebases':ti,ab,kw OR 'Robotics, Soft':ti,ab,kw OR 'Network Model, Neural':ti,ab,kw OR 'Inductive Machine Learning':ti,ab,kw OR 'Computer Heuristic':ti,ab,kw OR 'Remote Operations':ti,ab,kw OR 'Computer Neural Networks':ti,ab,kw OR 'Language Processings, Natural':ti,ab,kw OR 'Processing, Natural Language':ti,ab,kw OR 'AI':ti,ab,kw OR 'CNN':ti,ab,kw)

#3 ('x-ray computed tomography'/exp OR 'computed tomography scanner'/exp OR 'computed tomography':ti,ab,kw OR 'computer assisted tomography':ti,ab,kw OR 'ct':ti,ab,kw)

#4 ('invasiveness analysis':ti,ab,kw OR 'Invasive':ti,ab,kw OR 'invasiveness':ti,ab,kw OR 'risk':ti,ab,kw OR 'Risk Stratification':ti,ab,kw OR 'Risk assessment':ti,ab,kw OR 'risk management':ti,ab,kw OR 'subtype classification':ti,ab,kw OR 'histological assessment':ti,ab,kw)

#5 #1AND#2AND#3AND#4

3. Strategy for Cochrane Library (n=76):

#1 MeSH descriptor: [Lung Neoplasms] explode all trees

#2 MeSH descriptor: [Adenocarcinoma of Lung] explode all trees

#3 MeSH descriptor: [Solitary Pulmonary Nodule] explode all trees

#4 MeSH descriptor: [Adenocarcinoma, Bronchiolo-Alveolar] explode all trees

#5 MeSH descriptor: [Carcinoma, Non-Small-Cell Lung] explode all trees

#6 MeSH descriptor: [Carcinoma, Bronchogenic] explode all trees

#7 MeSH descriptor: [Bronchial Neoplasms] explode all trees

#8 MeSH descriptor: [Multiple Pulmonary Nodules] explode all trees

#9 (Bronchiolo-Alveolar Carcinomas):ti,ab,kw OR (Adenocarcinomas, Lung):ti,ab,kw OR (Carcinoma, Alveolar):ti,ab,kw OR (Bronchiolo-Alveolar Carcinoma):ti,ab,kw OR (Carcinomas, Bronchial):ti,ab,kw OR (Carcinomas, Alveolar):ti,ab,kw OR (Pulmonary Nodules, Multiple):ti,ab,kw OR (Non-Small-Cell Lung Carcinoma):ti,ab,kw OR (Cancer, Pulmonary):ti,ab,kw OR (Bronchiolar Carcinomas):ti,ab,kw OR (Carcinomas, Bronchiolar):ti,ab,kw OR (Lung Carcinomas, Non-Small-Cell):ti,ab,kw OR (Nonsmall Cell Lung Cancer):ti,ab,kw OR (Alveolar Carcinomas):ti,ab,kw OR (Neoplasm, Bronchial):ti,ab,kw OR (Adenocarcinomas, Alveolar):ti,ab,kw OR (Carcinoma, Bronchiolo-Alveolar):ti,ab,kw OR

(Carcinoma, Bronchiolar):ti,ab,kw OR (Lung Cancers):ti,ab,kw OR (Alveolar Adenocarcinomas):ti,ab,kw OR (Alveolar Cell Carcinoma):ti,ab,kw OR (Bronchiolo-Alveolar Adenocarcinoma):ti,ab,kw OR (Cancer, Lung):ti,ab,kw OR (Carcinomas, Bronchogenic):ti,ab,kw OR (Bronchiolar Carcinoma):ti,ab,kw OR (Neoplasms, Pulmonary):ti,ab,kw OR (Non-Small Cell Lung Cancer):ti,ab,kw OR (Carcinoma, Bronchioloalveolar):ti,ab,kw OR (Carcinoma, Non-Small Cell Lung):ti,ab,kw OR (Alveolar Adenocarcinoma):ti,ab,kw OR (Adenocarcinoma, Alveolar):ti,ab,kw OR (Bronchial Carcinoma):ti,ab,kw OR (Pulmonary Nodule, Multiple):ti,ab,kw OR (Carcinoma, Bronchial):ti,ab,kw OR (Carcinomas, Non-Small-Cell Lung):ti,ab,kw OR (Carcinomas, Bronchiolo-Alveolar):ti,ab,kw OR (Neoplasm, Pulmonary):ti,ab,kw OR (Non-Small-Cell Lung Carcinomas):ti,ab,kw OR (Neoplasms, Bronchial):ti,ab,kw OR (Bronchioloalveolar Carcinoma):ti,ab,kw OR (Bronchogenic Carcinomas):ti,ab,kw OR (Carcinoma, Non Small Cell Lung):ti,ab,kw OR (Alveolar Cell Carcinomas):ti,ab,kw OR (Lung Neoplasm):ti,ab,kw OR (Cancers, Pulmonary):ti,ab,kw OR (Bronchogenic Carcinoma):ti,ab,kw OR (Pulmonary Cancers):ti,ab,kw OR (Adenocarcinoma, Bronchiolo Alveolar):ti,ab,kw OR (Lung Adenocarcinoma):ti,ab,kw OR (Non Small Cell Lung Carcinoma):ti,ab,kw OR (Multiple Pulmonary Nodule):ti,ab,kw OR (Lung Cancer):ti,ab,kw OR (Cancer of Lung):ti,ab,kw OR (Lung Adenocarcinomas):ti,ab,kw OR (Neoplasm, Lung):ti,ab,kw OR (Adenocarcinomas, Bronchiolo-Alveolar):ti,ab,kw OR (Bronchial Neoplasm):ti,ab,kw OR (Adenocarcinoma, Lung):ti,ab,kw OR (Pulmonary Neoplasms):ti,ab,kw OR (Carcinomas, Bronchioloalveolar):ti,ab,kw OR (Bronchiolo-Alveolar Adenocarcinomas):ti,ab,kw OR (Lung Carcinoma, Non-Small-Cell):ti,ab,kw OR (Carcinoma, Bronchiolo Alveolar):ti,ab,kw OR (Cancer of the Lung):ti,ab,kw OR (Pulmonary Cancer):ti,ab,kw OR (Neoplasms, Lung):ti,ab,kw OR (Pulmonary Neoplasm):ti,ab,kw OR (Alveolar Carcinoma):ti,ab,kw OR (Carcinomas, Alveolar Cell):ti,ab,kw OR (Cancers, Lung):ti,ab,kw OR (Bronchial Carcinomas):ti,ab,kw OR (Bronchioloalveolar Carcinomas):ti,ab,kw OR (Carcinoma, Alveolar Cell):ti,ab,kw OR (pulmonary nodule):ti,ab,kw OR (lung nodule):ti,ab,kw OR (ground-glass nodule):ti,ab,kw OR (solid nodule):ti,ab,kw OR (subsolid nodule):ti,ab,kw OR (GGO):ti,ab,kw OR (pGGN):ti,ab,kw OR (PSN):ti,ab,kw OR (GGN):ti,ab,kw OR (mGGN):ti,ab,kw OR (SSN):ti,ab,kw OR (SPN):ti,ab,kw OR (NSN):ti,ab,kw OR (LUAD):ti,ab,kw

#10 #1 OR #2 OR #3 OR #4 OR #5 OR #6 OR #7 OR #8 OR #9

#11 MeSH descriptor: [Artificial Intelligence] explode all trees

#12 MeSH descriptor: [Neural Networks, Computer] explode all trees

#13 MeSH descriptor: [Knowledge Bases] explode all trees

#14 MeSH descriptor: [Biological Ontologies] explode all trees

#15 MeSH descriptor: [Robotics] explode all trees

#16 MeSH descriptor: [Unsupervised Machine Learning] explode all trees

#17 MeSH descriptor: [Fuzzy Logic] explode all trees

#18 MeSH descriptor: [Natural Language Processing] explode all trees

#19 MeSH descriptor: [Machine Learning] explode all trees

#20 MeSH descriptor: [Deep Learning] explode all trees

#21 MeSH descriptor: [Expert Systems] explode all trees

#22 MeSH descriptor: [Supervised Machine Learning] explode all trees

#23 MeSH descriptor: [Computer Heuristics] explode all trees

#24 (Vision System, Computer):ti,ab,kw OR (Machine Learning, Unsupervised):ti,ab,kw OR (Semi supervised Learning):ti,ab,kw OR (Computer Vision Systems):ti,ab,kw OR (Knowledge Representations):ti,ab,kw OR (Machine Learning, Supervised):ti,ab,kw OR (Remote Operation):ti,ab,kw OR (Systems, Computer Vision):ti,ab,kw OR (Network Models, Neural):ti,ab,kw OR (Intelligence, Artificial):ti,ab,kw OR (Computational Neural Network):ti,ab,kw OR (Network, Computer Neural):ti,ab,kw OR (Networks, Computational Neural):ti,ab,kw OR (Soft Robotics):ti,ab,kw OR (Neural Network Models):ti,ab,kw OR (Computer Vision System):ti,ab,kw OR (Perceptrons):ti,ab,kw OR (Soft Robotic):ti,ab,kw OR (System, Computer Vision):ti,ab,kw OR (Models, Neural Network):ti,ab,kw OR (Neural Network Model):ti,ab,kw OR (Networks, Computer Neural):ti,ab,kw OR (Learning, Unsupervised Machine):ti,ab,kw OR (Connectionist Model):ti,ab,kw OR (Intelligence, Computational):ti,ab,kw OR (Expert System):ti,ab,kw OR (Intelligence, Machine):ti,ab,kw OR (Learning, Hierarchical):ti,ab,kw OR (Neural Networks, Computational):ti,ab,kw OR (Operation, Remote):ti,ab,kw OR (Learning, Transfer):ti,ab,kw OR (Robotic, Soft):ti,ab,kw OR (Transfer Learning):ti,ab,kw OR (Learning, Active Machine):ti,ab,kw OR (Telerobotics):ti,ab,kw OR (Network, Neural):ti,ab,kw OR (Systems, Expert):ti,ab,kw OR (Model,

Neural Network):ti,ab,kw OR (Models, Connectionist):ti,ab,kw OR (Perceptron):ti,ab,kw OR (Knowledge Bases):ti,ab,kw OR (Computational Intelligence):ti,ab,kw OR (Network, Computational Neural):ti,ab,kw OR (Learning from Labeled Data):ti,ab,kw OR (Reasoning, Computer):ti,ab,kw OR (Knowledge Representation):ti,ab,kw OR (Logic, Fuzzy):ti,ab,kw OR (Heuristics, Computer):ti,ab,kw OR (Neural Network, Computer):ti,ab,kw OR (Neural Network):ti,ab,kw OR (Bases, Knowledge):ti,ab,kw OR (Learning, Inductive Machine):ti,ab,kw OR (Operations, Remote):ti,ab,kw OR (Learning, Deep):ti,ab,kw OR (Learning, Supervised Machine):ti,ab,kw OR (Machine Learning, Inductive):ti,ab,kw OR (Model, Connectionist):ti,ab,kw OR (Hierarchical Learning):ti,ab,kw OR (Learning, Machine):ti,ab,kw OR (Networks, Neural):ti,ab,kw OR (Connectionist Models):ti,ab,kw OR (Semi-supervised Learning):ti,ab,kw OR (System, Expert):ti,ab,kw OR (Natural Language Processings):ti,ab,kw OR (Computer Reasoning):ti,ab,kw OR (Computer Neural Network):ti,ab,kw OR (Neural Network, Computational):ti,ab,kw OR (Heuristic, Computer):ti,ab,kw OR (Machine Learning with a Teacher):ti,ab,kw OR (Knowledgebase):ti,ab,kw OR (Language Processing, Natural):ti,ab,kw OR (Knowledge Base):ti,ab,kw OR (Knowledge Acquisition):ti,ab,kw OR (Base, Knowledge):ti,ab,kw OR (Computational Neural Networks):ti,ab,kw OR (Representation, Knowledge):ti,ab,kw OR (Vision Systems, Computer):ti,ab,kw OR (Learning, Semi-supervised):ti,ab,kw OR (Processings, Natural Language):ti,ab,kw OR (Acquisition, Knowledge):ti,ab,kw OR (Neural Networks):ti,ab,kw OR (Machine Intelligence):ti,ab,kw OR (Machine Learning, Active):ti,ab,kw OR (Active Machine Learning):ti,ab,kw OR (Knowledgebases):ti,ab,kw OR (Robotics, Soft):ti,ab,kw OR (Network Model, Neural):ti,ab,kw OR (Inductive Machine Learning):ti,ab,kw OR (Computer Heuristic):ti,ab,kw OR (Remote Operations):ti,ab,kw OR (Computer Neural Networks):ti,ab,kw OR (Language Processings, Natural):ti,ab,kw OR (Processing, Natural Language):ti,ab,kw OR (AI):ti,ab,kw OR (CNN):ti,ab,kw

#25 #11 OR #12 OR #13 OR #14 OR #15 OR #16 OR #17 OR #18 OR #19 OR #20 OR #21 OR #22 OR #23 OR #24

#26 MeSH descriptor: [Tomography, X-Ray Computed] explode all trees

#27 (tomography scanners, x-ray computed):ti,ab,kw OR (computed tomography):ti,ab,kw OR (computer assisted tomography):ti,ab,kw OR (CT):ti,ab,kw OR (CAT):ti,ab,kw

#28 #26 OR #27

#29 (“invasiveness analysis”):ti,ab,kw OR (“Invasive”):ti,ab,kw OR (“invasiveness”):ti,ab,kw OR (“risk”):ti,ab,kw OR (“Risk Stratification”):ti,ab,kw OR (“Risk assessment”):ti,ab,kw OR (“risk management”):ti,ab,kw OR (“subtype classification”):ti,ab,kw OR (“histological assessment”):ti,ab,kw

#30 #10 AND #25 #28 AND #29

4. Strategy for Web of Science (n=1,066):

#1 TS=(“lung neoplasm”) OR TS=(“pulmonary neoplasm”) OR TS=(“lung cancer”) OR TS=(“lung tumor”) OR TS=(“lung carcinoma”) OR TS=(“pulmonary cancer”) OR TS=(“pulmonary tumor”) OR TS=(“pulmonary carcinoma”) OR TS=(“non-small-cell lung cancer”) OR TS=(“lung adenocarcinoma”) OR TS=(“pulmonary nodule”) OR TS=(“lung nodule”) OR TS=(“ground-glass nodule”) OR TS=(“solid nodule”) OR TS=(“subsolid nodule”) OR TS=(“part-solid nodule”) OR TS=(“non-solid nodule”) OR TS=(“GGO”) OR TS=(“pGGN”) OR TS=(“PSN”) OR TS=(“NSN”) OR TS=(“GGN”) OR TS=(“mGGN”) OR TS=(“SPN”) OR TS=(“SSN”) OR TS=(“LUAD”)

#2 TS= (“machine learning”) OR TS=(“Artificial Intelligence”) OR TS=(“Machine Intelligence”) OR TS=(“Computational Intelligence”) OR TS=(“computer-aided”) OR TS= (“deep learning”) OR TS= (“Computer Reasoning”) OR TS= (“Computer Vision System”) OR TS= (“Knowledge Representation”) OR TS= (“Knowledge Acquisition”) OR TS= (“Expert System”) OR TS= (“Computer Heuristic”) OR TS= (“Neural Network”) OR TS=(“AI”) OR TS=(“CNN”)

#3 TS= (“Tomography, X-Ray Computed”) OR TS= (“computed tomography”) OR TS=(“computer assisted tomography”) OR TS=(“CT”) OR TS=(“CAT”)

#4 TS=(“invasiveness analysis”) OR TS=(“Invasive”) OR TS= (“invasiveness”) OR TS=(“Risk Stratification”) OR TS=(“Risk assessment”) OR TS=(“risk management”) OR TS=(“risk”) OR TS=(“subtype classification”) OR TS= (“histological assessment”)

#5 #1 AND #2 AND #3 AND #4

Appendix 2

Risk of Bias Assessment:

The detailed evaluation criteria:

DOMAIN 1: PATIENT SELECTION

A. Risk of Bias

Were the data sources clear?

Was a consecutive or random sample of patients enrolled?

Were the inclusion/exclusion criteria specified?

Did the study avoid inappropriate exclusions?

B. Applicability

Are there concerns that the included patients and setting do not match the review question?

DOMAIN 2: INDEX TEST(S)

A. Risk of Bias

Were the imaging acquisition protocol and the segmentation annotation method detailed?

Were the datasets composed of several types of scanners?

Was there an independent set of external validations?

B. Applicability

Are there concerns that the index test, its conduct, or interpretation differ from the review question?

DOMAIN 3: REFERENCE STANDARD

A. Risk of Bias

Was the reference standard adequate?

Is the reference standard likely to correctly classify the target condition?

B. Applicability

Are there concerns that the target condition as defined by the reference standard does not match the question?

DOMAIN 4: FLOW AND TIMING

A. Risk of Bias

Was the database clear partition into training, and validation sets?

Was there an appropriate interval between index tests and reference standard?

Appendix 3

Studies that seemed promising for inclusion during the screening phase but were later excluded.

No.	Study	Reason for exclusion
1.	Chen X, Feng B, Chen Y, <i>et al.</i> A CT-based deep learning model for subsolid pulmonary nodules to distinguish minimally invasive adenocarcinoma and invasive adenocarcinoma. <i>Eur J Radiol.</i> 2021;145:110041. doi:10.1016/j.ejrad.2021.110041	No precise nodule segmentation
2.	Chen L, Qi H, Lu D, <i>et al.</i> A deep learning based CT image analytics protocol to identify lung adenocarcinoma category and high-risk tumor area. <i>STAR Protoc.</i> 2022;3(3):101485. doi:10.1016/j.xpro.2022.101485	No precise nodule segmentation
3.	K Gao R, Gao Y, Zhang J, Zhu C, Zhang Y, Yan C. A nomogram for predicting invasiveness of lung adenocarcinoma manifesting as pure ground-glass nodules: incorporating subjective CT signs and histogram parameters based on artificial intelligence. <i>J Cancer Res Clin Oncol.</i> 2023;149(17):15323-15333. doi:10.1007/s00432-023-05262-4	No precise nodule segmentation
4.	Le, V., Yang, D., Zhu, Y., Zheng, B., Bai, C., Nguyen, Q., & Shi, H. (2017). Automated Classification of Pulmonary Nodules for Lung Adenocarcinomas Risk Evaluation: An Effective CT Analysis by Clustering Density Distribution Algorithm. <i>Journal of Medical Imaging and Health Informatics</i> , 7, 1753-1758. for	No deep learning-based classification
5.	Gao C, Xiang P, Ye J, Pang P, Wang S, Xu M. Can texture features improve the differentiation of infiltrative lung adenocarcinoma appearing as ground glass nodules in contrast-enhanced CT?. <i>Eur J Radiol.</i> 2019;117:126-131. doi:10.1016/j.ejrad.2019.06.010e <i>Medicine</i> , 199(9). https://doi.org/10.1164/ajrcm-conference.2019.199.1_meetingabstracts.a2605	No deep learning-based classification
6.	Vaidya P, Bera K, Linden PA, <i>et al.</i> Combined Radiomic and Visual Assessment for Improved Detection of Lung Adenocarcinoma Invasiveness on Computed Tomography Scans: A Multi-Institutional Study. <i>Front Oncol.</i> 2022;12:902056. doi:10.3389/fonc.2022.902056, Lo, S.-C. B	No deep learning-based classification
7.	Zhang H, Wang S, Deng Z, Li Y, Yang Y, Huang H. Computed tomography-based radiomics machine learning models for prediction of histological invasiveness with sub-centimeter subsolid pulmonary nodules: a retrospective study. <i>PeerJ.</i> 2023;11:e14559. doi:10.7717/peerj.14559	No deep learning-based classification
8.	Chae HD, Park CM, Park SJ, Lee SM, Kim KG, Goo JM. Cd-glass nodules: differentiation of preinvasive lesions from invasive pulmonary adenocarcinomas. <i>Radiology.</i> 2014;273(1):285-293. doi:10.1148/radiol.14132187	No deep learning-based classification
9.	Sun J, Liu K, Tong H, <i>et al.</i> CT Texture Analysis for Differentiating Bronchiolar Adenoma, Adenocarcinoma In Situ, and Minimally Invasive Adenocarcinoma of the Lung. <i>Front Oncol.</i> 2021;11:634564. Published 2021 Apr 26. doi:10.3389/fonc.2021.634564 <i>etection.</i> <i>Journal of Global Oncology</i> , 5, 27–27. https://doi.org/10.1200/jgo.2019.5.suppl.27	No deep learning-based classification
10.	Sun J, Zhang L, Hu B, <i>et al.</i> Deep learning-based solid component measuring enabled interpretable prediction of tumor invasiveness for lung adenocarcinoma. <i>Lung Cancer.</i> 2023;186:107392. doi:10.1016/j.lungcan.2023.107392 18.08.020	No precise nodule segmentation
11.	Gong J, Liu J, Li H, <i>et al.</i> Deep Learning-Based Stage-Wise Risk Stratification for Early Lung Adenocarcinoma in CT Images: A Multi-Center Study. <i>Cancers (Basel).</i> 2021;13(13):3300. Published 2021 Jun 30. doi:10.3390/cancers13133300	No precise nodule segmentation
12.	Pei G, Wang D, Sun K, <i>et al.</i> Deep learning-enhanced radiomics for histologic classification and grade stratification of stage IA lung adenocarcinoma: a multicenter study. <i>Front Oncol.</i> 2023;13:1224455. doi:10.3389/fonc.2023.1224455	No precise nodule segmentation
13.	Li Q, Gu YF, Fan L, Li QC, Xiao Y, Liu SY. Effect of CT window settings on size measurements of the solid component in subsolid nodules: evaluation of prediction efficacy of the degree of pathological malignancy in lung adenocarcinoma. <i>Br J Radiol.</i> 2018;91(1088):20180251. doi:10.1259/bjr.20180251	No deep learning-based classification
14.	Lee J, Bartholmai B, Peikert T, <i>et al.</i> Evaluation of Computer-Aided Nodule Assessment and Risk Yield (CANARY) in Korean patients for prediction of invasiveness of ground-glass opacity nodule. <i>PLoS One.</i> 2021;16(6):e0253204. doi:10.1371/journal.pone.0253204	No deep learning-based classification

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Table S1 Clinical characteristics of the selected studies

Author (year)	Nodule type	No. of Patient	No. of nodules	Diameter (mm) ^a	Pathological pattern				Tumor Location					Patient Characteristics	
					AAH	AIS	MIA	IAC	LUL	LLL	RUL	RML	RLL	Age (years) ^a	Gender (M:F)
Chunlong Fu 2023 (37)	GGN	911	999	NR	0	0	529	470	263	124	36	98	152	58.1±18.4	304:695
Jun Wang 2021 (36)	GGN	1626	1640	NR	125 ^b	397 ^b	309 ^b	609 ^b						56±10.8 ^c	400:1026 ^c
Kang Qi 2024 (35)	pGGN	402	448	12.0±5.01	29	83	235	101	101	65	168	35	79	53.2±11.4	119:283
Sohee Park 2021 (32)	GGN	423	501	Three ^d	8	26	131	336	115 ^e	68 ^e	154 ^e	38 ^e	122 ^e	Three ^f	181:242
Tianle Shen 2021 (34)	GGN	368	368	1.0 (0.2-4.5)	AAH+AIS (298)		618	875	670	328	949	198	469	57 (15-84)	924:1690
Xiang Wang 2021 (40)	GGN	622	687	Four ^d	113	148	115	311						57 (27-87)	205:417
Yanqiu Wang 2021 (33)	GGN	156	470	NR	benign (143)		AIS+MIA (87)		240					NR	NR
Yao Xu 2021 (38)	GGN	168	168	Two ^h	13	35	107	13	48	22	43	19	36	Two ⁱ	53:115

^a, denotes as years mean ± standard deviation or mean (range); ^b, results of 1440 nodules in the internal set (external dataset: AAH+AIS+MIA =100, IACs =100); ^c, 1426 patients in the internal set; ^d, total: 13.6±5.9; development set: 13.9±6.2; validation set: 12.1±4.3; ^e, four other nodules at the junction of the two lobes: RUL/RLL (n=2); RUL/RML (n=1); LUL/LLL (n=1); ^f, total: 59.5±10.1; development set: 59.9±10.1; validation set: 58.0±10.0; ^g, AAH: 11 (9-13); AIS: 11 (10-13); MIA:13 (11-16); IAC:18 (15-22); ^h, noninvasive: 7.6±2.3; invasive: 9.1±3.9; ⁱ, noninvasive: 46.8±10.4; invasive:49.8±13.0. NR, not reported; GGN, ground-glass nodule; pGGN, pure GGN; AAH, atypical adenomatous hyperplasia; AIS, adenocarcinoma in situ; MIA, minimally invasive adenocarcinoma; IAC, invasive adenocarcinoma; LUL, left upper lobe; LLL, left lower lobe; RUL, right upper lobe; RML, right middle lobe; RLL, right lower lobe; M:F, male: female.

Table S2 Characteristics of image scans

Author (year)	Imaging modality	Scanners	kVp	Reconstruction slice thickness (mm)	Reconstruction modality
Chunlong Fu 2023 (37)	CT	5	120	0.67, 1.0	NR
Jun Wang 2021 (36)	CT	2	120	1.0, 0.75	Sharp kernel (B46/C Filter)
Kang Qi 2024 (35)	CT	8	100 to 120	0.625 to 1.25	NR
Sohee Park 2021 (32)	CT	8	120	1, 1.25, 1.5	B50f kernel
Tianle Shen 2021 (34)	CT	1	NR	1, 5	NR
Xiang Wang 2021 (40)	CT	5	120	0.625, 1.0	STR
Yanqiu Wang 2021 (33)	CT	NR	NR	NR	NR
Yao Xu 2021 (38)	CT	2	120	0.625	NR

NR, not reported; CT, computed tomography; STR, standard algorithm reconstruction.

Table S3 Segmentation results

Author (year)	Manual or automatic	Segmentation method	Compared with the unsegmented model	Segmentation Performance (Dice)
Chunlong Fu 2023 (37)	Manual	ITK-SNAP	No	-
Jun Wang 2021 (36)	Automatic	IMAL-Net	Yes	81.9±1.0
Kang Qi 2024 (35)	Automatic	R3D-18 model for feature extraction; 3D-optimized modified version of the 2D U-Net	No	IAC:0.860 (0.814–0.887); other lesions: 0.838 (0.825–0.876)*
Sohee Park 2021 (32)	Automatic	built-in segmentation engine	No	training set: 0.754; tuning set: 0.742
Tianle Shen 2021 (34)	Manual	MIM software	Yes	-
Xiang Wang 2021 (40)	Manual	MITK	No	-
Yanqiu Wang 2021 (33)	Automatic	region adaptive MRF segmentation model	Yes	0.9144 [#]
Yao Xu 2021 (38)	Manual	ITK-SNAP	Yes	-

*, results of the hold-out test set; [#], denotes as overlapping area ratio. NR, not reported; RRCNN, recurrent residual convolutional neural network; MRF, Markov random field; IAC, invasive adenocarcinoma; MITK, Medical Imaging Interaction Toolkit.

Table S4 Summary of bias risks and applicability concerns across included studies using the QUADAS-2 tool

Study	Risk of bias				Applicability concerns		
	Patient selection	Index test	Reference standard	Flow and timing	Patient selection	Index test	Reference standard
Chunlong Fu 2023 (37)	🟢	🟢	🟢	🟢	?	?	🟢
Jun Wang 2021 (36)	🔴	🔴	?	?	🟢	🟢	🟢
Kang Qi 2024 (35)	🟢	🟢	🟢	🟢	🔴	🟢	🟢
Sohee Park 2021 (32)	🟢	🟢	🟢	🟢	🟢	🟢	🟢
Tianle Shen 2021 (34)	🟢	🔴	🟢	?	🟢	🟢	🟢
Xiang Wang 2021 (40)	🔴	🔴	?	🟢	🟢	🟢	🟢
Yanqiu Wang 2021 (33)	🟢	🔴	🟢	?	🟢	🟢	🟢
Yao Xu 2021 (38)	🟢	🔴	🟢	?	🔴	🟢	🟢

🟢, low risk; 🔴, High risk; ?, unclear risk.

Table S5 Comparison of classification performance between the human observers and the deep-learning models

Author (year)	Method	AUC	ACC	Sensitivity (%)	Specificity (%)	F1 (%)
Kang Qi 2024 (35)	AI model	0.911 (0.776–0.978)	76.9 (30/39)	50.0 (7/14)	92.0 (23/25)	60.9 (7/11.5)
	reader 1	NR	51.3 (20/39)	64.3 (9/14)	44.0 (11/25)	51.3 (20/39)
	reader 2	NR	79.5 (31/39)	85.7 (12/14)	76.0 (19/25)	75.0 (12/16.0)
	reader 3	NR	66.7 (26/39)	100.0 (14/14)	48.0 (12/25)	68.3 (14/20.5)
	reader 4	NR	71.8 (28/39)	28.6 (4/14)	96.0 (24/25)	42.1 (4/9.5)
Sohee Park 2021 (32)	AI model	0.956	NR	68.0 (56–79)	90.0 (79–96)	NR
	7-mm threshold*	0.835 (0.766–0.904)	76.5 (68.5–82.9)	62.2 (50.1–73.0)	90.7 (82.6–95.3)	NR
	5-mm threshold*	0.835 (0.766–0.904)	75.9 (69.2–81.6)	75.2 (65.2–83.1)	75.2 (65.2–83.1)	NR

*, average performance of six observers to evaluate the predictive value of measurements of the solid portion size. NR, not reported.

Table S6 GRADE summary of evidence

Test result	Study design	Factors that may decrease quality of evidence					Test property (95% CI)	Test result	Certainty of evidence
		Risk of bias	Indirectness	Inconsistency	Imprecision	Publication bias			
Sensitivity (TP + FN)	8 Cross-sectional study	Serious ¹	Serious ²	Serious ³	Not serious	Undetected	0.81 (0.73, 0.87)	TPs	⊕○○○
								FNs	Very low
Specificity (FP + TN)	8 Cross-sectional study	Serious ¹	Serious ²	Serious ³	Not serious	Undetected	0.86 (0.80, 0.90)	FPs	⊕○○○
								TNs	Very low

¹, several studies with high risk of bias in the QUADAS-2 domains: patient selection and index test. ², two study with high concerns for applicability in the QUADAS-2 domains: patient selection. ³, large differences in sensitivity and specificity. CI, confidence interval.