Supplementary Table 1

Table S1. Summary of articles in which AI was used to analyze LDCT images for lung cancer diagnosis.

Study	**Algorithm**				**Model Availability (Open-Access)**	**Analysis and Additional Features**
	Transfer Learning Applied	**Algorithm Name Architecture**	**Algorithm Structure**	**Model Task**		
Ciompi F. [1] 2017	No	ConvNets CNN “multi-stream multi-scale” architecture	Nine streams of ConvNets, grouped into three sets of three streams. Each set of streams is fed with a triplet of orthogonal patches extracted at the same scale. Optimal architecture for each stream defined using the VGG-net approach	Nodule segmentation, classification, and prediction of nodule type	Yes	SVM to assess intensity features from training set. Features automatically learned from raw data (unsupervised), using the K-means algorithm. Parameters of the network updated using the ADAM algorithm.
Petousi P [2]	No	DBN models: -Expert-driven DBNs two Forward-Arrow DBNs and one Reversed-Arrow DBN using a NoisyMax gate -Learned DBNs created through structure learning methods.	DBN models design process: 1-variable selection 2-defining the structure (network topology) 3-computing the probabilities 4-computing the probabilities of the transition model. 5-training and testing.	Positive case prediction Both DBN A and B tend to discriminate cancer and non-cancer cases better with increasing number of screenings. Comparison with expert radiologists	No	All DBN models were compared with a naïve Bayes model, in which each screening was modeled as independent. The model was trained using the EM algorithm, and tested in Genie. Decision tree model using Rapid Miner (modified C4.5 algorithm)

Zhang C [3]	No	CNN	CNN implemented on the Pytorch platform. A 3-steps model: Preprocessing module, Nodule Cancer Diagnosis Network, and Output Module	Segmentation A 3D pulmonary nodule detection network built to obtain 3D features from the lung images. Calculate image-level malignancy score.	No	PASS 11 software for sample evaluation. Used a two-stage training strategy to increase the stability of CNN learning. Batch normalization and dropout used in the network to improve the training effectiveness and avoid over-fitting
Petousi P [4].	No	ML and DBN	ML and sequential decision-making methods. A framework for learning using a POMDP with the QMDP approximation algorithm. .	Nodule detection and classification. Suggest optimal screening timeline and evaluation metrics.	No	Clinical variables selected in the Tammemägi model. Integrated a DBN into the MDP to predict the chance of developing lung cancer. Applied IRL to formulate a rewards model
Huang [5]	Yes	DL	Neural network built to develop the model using an MLP. Included two MLP structures with two hidden layers each. The first had sizes of five and two and the second had sizes of 51 and eight. Weights optimized using a quasi-Newton method and stochastic gradient-based method	Discriminate between benign and malign lesions. Lung cancer risk assessment and cancer incidence prediction at 1 year, 2 years, and 3 years with the Lung-RADS and volume doubling time, using time-dependent AUC analysis.	Yes	Primary analysis compared the lung cancer prediction accuracy among three predictors (DeepLR, Lung-RADS, and VDT). Secondary analysis compared cancer incidence among high-risk and low-risk subgroups. Exploratory survival analyses were done to study

						whether the model can detect more aggressive lung cancers.
Ardila, [6] 2019	Yes	Mask RCNN; RetinaNet; Inception V1	CNN; Inception. The system consists of four components, all trained using the Google Inc. TensorFlow platform: Lung segmentation. Cancer ROI detection model. Full-volume model. Cancer risk prediction model.	The model was trained to take the entire CT volume (the entire set of axial Images) and automatically generated a score predicting whether the patient will have a cancer diagnosis in the same study year	Code not publicly available but some components of this work are available in open source repositories such as Tensorflow, and others	Malignant prediction, nodule localization performed by selecting the ROI with the highest malignancy score
Cui [7] 2020	Yes	50-layer deep CNN	CNN architecture deep residual network using ResNet	Pulmonary nodule identification. Evaluated diagnostic metrics and agreement between human reviewers and the DL algorithm.	No	Python library and R. Radiologists and algorithm performance assessed using the FROC score, ROC-AUC, and average time consumption

DL: Deep learning; ML: Machine learning; CNN: convolutional neural network; NR: not reported; AUC: area under the curve; ROC: receiver operating characteristic; DBN: Dynamic Bayesian networks; AUROC: area under the receiver operator characteristic curve; MLP: multilayer perceptron; LUNG-RADS: Lung CT Screening Reporting and Data System; POMDP: Partially observable Markov decision process; IRL: inverse reinforcement learning; SVM: Support Vector Machine; VGG-net: Visual Geometry Group neural network; ADAM: Adam stochastic optimization algorithm; EM algorithm: expectation–maximization algorithm ; 3D: three-dimensions; CT: computer tomography; VDT: vulnerability detection tools; ROI: tumor region of interest; R: refers to a language and environment for statistical computing and graphics; FROC: Free-Response ROC Curve.

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