

Appendix 1 Questionnaire items

No.	Items
Respondents' characteristics	
1	The hospital that you work for: _____
2	Your working department: _____
3	Sex: <input type="checkbox"/> Male <input type="checkbox"/> Female
4	Age: _____ (years)
5	Educational level: <input type="checkbox"/> PhD <input type="checkbox"/> Master's degree <input type="checkbox"/> Bachelor's degree <input type="checkbox"/> College diploma <input type="checkbox"/> Others
6	Type of employees: <input type="checkbox"/> Physician <input type="checkbox"/> Manager <input type="checkbox"/> Others
7	Working years: <input type="checkbox"/> <5 <input type="checkbox"/> 5- <input type="checkbox"/> 10- <input type="checkbox"/> 15- <input type="checkbox"/> 20-
Perceptions of AI-assisted CT diagnostic technology for classification of pulmonary nodules as benign or malignant	
8	Do you know about AI-assisted CT diagnostic technology for pulmonary nodules? <input type="checkbox"/> No <input type="checkbox"/> Yes, but without practical experience <input type="checkbox"/> Yes, with experience in clinical research <input type="checkbox"/> Yes, with experience in clinical practice
9	What do you think the main benefits of AI-assisted CT diagnostic technology for pulmonary nodules (Check the top three)? <input type="checkbox"/> High diagnostic accuracy <input type="checkbox"/> Improved diagnostic efficiency <input type="checkbox"/> Reduced diagnostic expense <input type="checkbox"/> Improved patient satisfaction <input type="checkbox"/> Reduced workload of radiologists <input type="checkbox"/> Reduced number of radiologists <input type="checkbox"/> Others
10	What do you think the main risks of AI-assisted CT diagnostic technology for pulmonary nodules (Check the top three)? <input type="checkbox"/> Leakage of patient privacy <input type="checkbox"/> Increased risk of misdiagnosis <input type="checkbox"/> Increased risk of missed diagnosis <input type="checkbox"/> Increased diagnostic expense <input type="checkbox"/> Reduced diagnostic competence of radiologists <input type="checkbox"/> Lack of unified diagnostic standard <input type="checkbox"/> Increased workload of radiologists <input type="checkbox"/> Others
11	Do you support the clinical application of AI-assisted CT diagnostic technology for pulmonary nodules? <input type="checkbox"/> Strongly supported <input type="checkbox"/> Somewhat supported <input type="checkbox"/> Neutral <input type="checkbox"/> Somewhat unsupported <input type="checkbox"/> Strongly unsupported

Appendix 2 Study Characteristics

Characteristics	No.	Percent (%)	Characteristic	No.	Percent (%)
Year of publication			Data source		
2010	3	10.71	Hospital	9	32.14
2011	1	3.57	LIDC-IDRI dataset [†]	7	25.00
2012	4	14.29	Hospital and LIDC-IDRI	3	10.71
2013	3	10.71	Others	9	32.14
2014	2	7.14	Total	28	100.00
2015	2	7.14	Algorithms		
2016	2	7.14	Support vector machine	15	29.41
2017	3	10.71	Deep belief network	8	15.69
2018	7	25.00	Decision tree	7	13.73
2019	1	3.57	Convolutional neural network	5	9.80
Total	28	100.00	Artificial neural network	3	5.88
Countries where the first author was from			Bayesian network	2	3.92
China	20	71.43	Fuzzy C-means	2	3.92
USA	4	14.29	Others	9	17.65
Turkey	2	7.14	Total	51	100.00
Others	2	7.14			
Total	28	100.00			
Golden criterion					
Diagnosis according to the LIDC-IDRI dataset	7	25.00			
Pathologic diagnosis	6	21.43			
Pathologic diagnosis or follow-up	6	21.43			
Radiologist' diagnosis	6	21.43			
Others	3	10.71			
Total	28	100.00			

[†]LIDC-IDRI dataset: the dataset of the Lung Image Database Consortium (LIDC) of the Image Database Resource Initiative (IDRI).

Appendix 3 Basic information of the included studies

Study	Algorithms	N	TP	FP	FN	TN	Sensitivity (%)	Specificity (%)	Accuracy (%)
Di., 2010 (1)	a. BP neural network	193	121	32	23	17	a. 84.03	a. 34.69	a. 71.50
	b. Support vector machine	193	94	10	50	39	b. 65.28	b. 79.59	b. 68.91
El-Baz <i>et al.</i> , 2010 (2)	Bayes	55	24	0	2	29	92.31	100.00	96.36
Liu <i>et al.</i> , 2010 (3)	Not reported	48	23	3	1	21	95.83	87.50	91.67
El-Baz <i>et al.</i> , 2011 (4)	K-nearest	327	143	11	10	163	93.46	93.68	93.58
Chang., 2012 (5)	Support vector machine (testing dataset 1)	16	9	2	3	2	75.00	50.00	68.75
	Support vector machine (testing dataset 2)	15	10	1	1	3	90.91	75.00	86.67
	Support vector machine (testing dataset 3)	16	7	1	5	3	58.33	75.00	62.50
	Support vector machine (testing dataset 4)	15	8	2	3	2	72.73	50.00	66.67
	Support vector machine (testing dataset 5)	31	20	3	3	5	86.96	62.50	80.65
	Support vector machine (testing dataset 6)	31	19	3	4	5	82.61	62.50	77.42
He <i>et al.</i> , 2012 (6)	Support vector machine	500	250	4	8	238	96.90	98.35	97.60
Liu., 2012 (7)	Fuzzy pattern recognition	10	5	1	1	3	83.33	75.00	80.00
Luo., 2012 (8)	Least squares support vector machine	20	7	1	3	9	70.00	90.00	80.00
Dilger., 2013 (9)	Artificial neural network	27	10	2	0	15	100.00	88.24	92.59
Gu., 2013 (10)	Discrimination method of large log-likelihood	100	40	10	10	40	80.00	80.00	80.00
Zhang <i>et al.</i> , 2013 (11)	a. Decision tree (C4.5)	40	15	5	6	14	a.71.43	a. 73.68	a. 72.50
	b. Bayesian network	40	16	4	5	15	b.76.19	b. 78.95	b. 77.50
	c. Support vector machine	40	17	3	4	16	c.80.95	c. 84.21	c. 82.50
Dandil <i>et al.</i> , 2014 (12)	Artificial neural network	64	24	4	2	34	92.31	89.47	90.63
Li., 2014 (13)	a. Fuzzy C-Means	132	60	21	12	39	a.83.33	a. 65.00	a. 75.00
	b. Automatically weighted fuzzy C mean clustering	132	63	9	9	51	b.87.50	b. 85.00	b. 86.36
Dilger., 2015 (14)	a. Artificial neural network	50	20	2	2	26	a.90.91	a. 92.86	a. 92.00
	b. Linear discriminant analysis	50	17	3	5	25	b.77.27	b. 89.29	b. 84.00
Zhang <i>et al.</i> , 2015 (15)	Not reported	60	25	4	5	26	83.33	86.67	85.00
Manikandan <i>et al.</i> , 2016 (16)	Support vector machine	257	22	16	0	219	100.00	93.19	93.77
Wang <i>et al.</i> , 2016 (17)	Support vector machine	193	91	15	31	56	74.59	78.87	76.17
da Silva <i>et al.</i> , 2017 (18)	Convolutional neural network	200	98	9	2	91	98.00	91.00	94.50
Wei., 2017 (19)	Deep belief network	210	85	8	5	112	94.44	93.33	93.81
Yang., 2017 (20)	Deep belief network (testing dataset 1)	200	98	2	3	97	97.03	97.98	97.50
	Deep belief network (testing dataset 2)	200	99	1	2	98	98.02	98.99	98.50
	Deep belief network (testing dataset 3)	200	96	4	4	96	96.00	96.00	96.00
	Deep belief network (testing dataset 4)	200	97	3	2	98	97.98	97.03	97.50
	Deep belief network (testing dataset 5)	200	98	2	3	97	97.03	97.98	97.50
	Deep belief network (testing dataset 6)	200	98	2	3	97	97.03	97.98	97.50
Dong., 2018 (21)	Support vector machine	1500	765	36	50	649	93.87	94.74	94.27
Dandil <i>et al.</i> , 2018 (22)	Probabilistic neural network	220	113	6	3	98	97.41	94.23	95.91
Guan., 2018 (23)	Convolutional neural network	200	94	9	6	91	94.00	91.00	92.50
Li <i>et al.</i> , 2018 (24)	Random forest (testing dataset 1)	100	17	13	3	67	85.00	83.75	84.00
	Random forest (testing dataset 2)	200	62	22	8	108	88.57	83.08	85.00
	Random forest (testing dataset 3)	300	52	22	6	220	89.66	90.91	90.67
	Random forest (testing dataset 4)	400	120	16	16	248	88.24	93.94	92.00
	Random forest (testing dataset 5)	500	147	31	13	309	91.88	90.88	91.20
	Random forest (testing dataset 6)	600	184	40	16	360	92.00	90.00	90.67
Liu <i>et al.</i> , 2018 (25)	a. Support vector machine based on texture features	150	39	30	36	45	a. 52.00	a. 60.00	a. 56.00
	b. Support vector machine based on multi-resolution histogram features	150	69	21	6	54	b. 92.00	b. 72.00	b. 82.00
	c. Deep belief network	150	72	18	3	57	c. 96.00	c. 76.00	c. 86.00
Yang, K.Q., 2018 (26)	Convolutional neural network and residual neural network	220	130	24	10	56	92.86	70.00	84.55
Yang, F., 2018 (27)	Convolutional neural network	91	40	6	4	41	90.91	87.23	89.01
Ren <i>et al.</i> , 2019 (28)	a. Manifold regularized classification deep neural network	245	70	8	16	151	a. 81.40	a. 94.97	a. 90.20
	b. Classification deep neural network	245	54	10	32	149	b. 62.79	b. 93.71	b. 82.86
All		9646	4009	515	460	4662	89.71	90.05	89.89

TP: true positive; FP: false positive; FN: false negative; TN: true negative.

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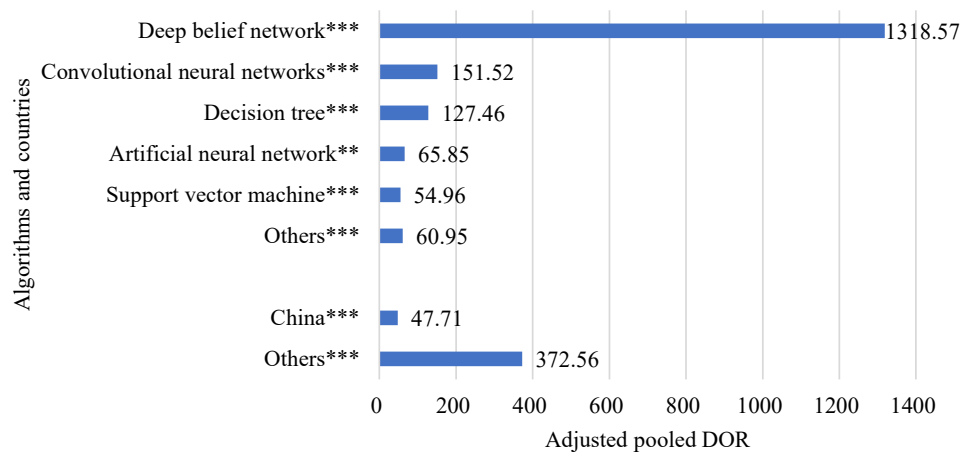


Figure S1 Adjusted pooled diagnostic odds ratio of AI-assisted CT diagnostic technology for pulmonary nodules†. †A multilevel linear regression model (method=REML, weight=1/variance of odds) was used to control for a study random effect and other fixed effects (number of nodules and algorithms or countries). “***” and “**” indicate that the adjusted pooled DOR for the group was significantly higher than 1, with $P < 0.01$ and with $P < 0.001$, respectively.

Appendix 4 Characteristics of the physicians who were surveyed

Characteristic	No.	Percent (%)	Characteristic	No.	Percent (%)
Region			Sex		
Shanghai	112	32.46	Male	170	49.28
Hubei province	134	38.84	Female	175	50.72
Gansu province	99	28.70	Total	345	100.00
Total	345	100.00	Educational level		
Hospital type			PhD	94	27.25
General hospitals	239	69.28	Master's degree	181	52.46
Specialty hospitals	106	30.72	Bachelor's degree or college diploma	70	20.29
Total	345	100.00	Total	345	100.00
Department			Type of employees		
Oncology department	174	50.43	Physicians	288	83.48
Imaging department	111	32.17	Managers	57	16.52
Others	60	17.39	Total	345	100.00
Total	345	100.00	Experiences with AI-assisted		
Age group (years)			CT diagnostic technology		
20-	72	20.87	for pulmonary nodules		
30-	162	46.96	Had experience	72	20.87
40-	67	19.42	Did not have experience	273	79.13
50-	44	12.75	Total	345	100.00
Total	345	100.00			