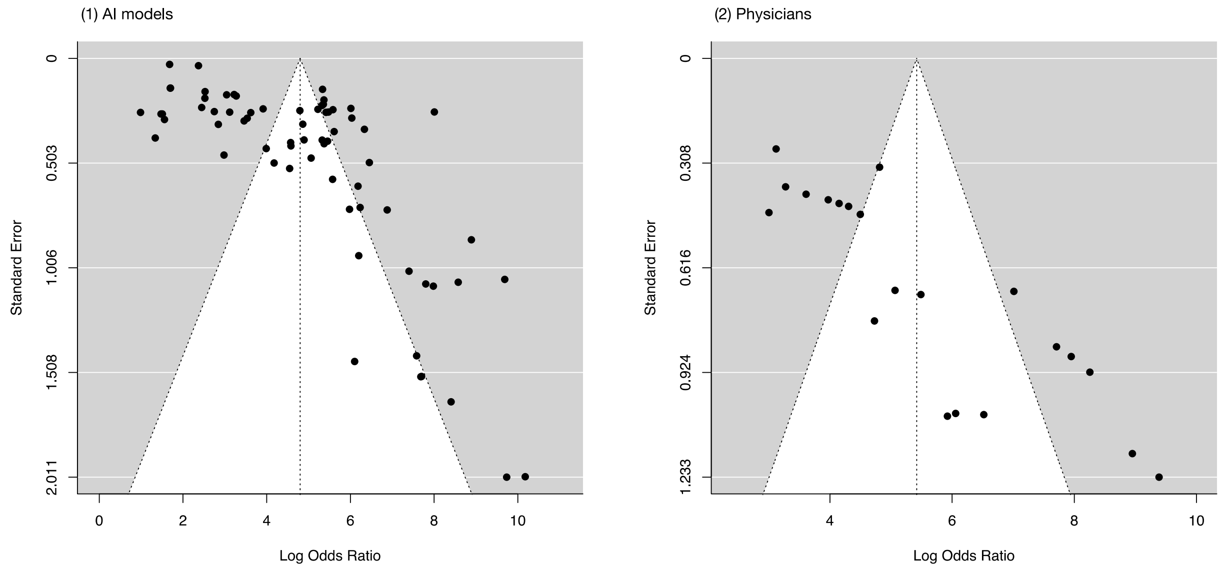
Deep learning for Pneumothorax Diagnosis: A Systematic Review and Meta-Analysis.

Running title: Review of AI for pneumothorax diagnosis

Table of Contents:

Section S1: Supplementary Figures



Appendix Figure S1: Funnel plots

These are funnel plots for deep learning models and physicians of odds ratio. Each dot represents a study; the y-axis represents study precision (standard error of effect size) and the x-axis shows the effect size. The outer dashed lines indicate the triangular region within which 95% of studies are expected to lie in the absence of both biases and heterogeneity. The lower left area shows almost no plots for both deep learning models and physicians. These asymmetric distributions indicate that there is a publication bias.

Section S2: Supplementary Table

Appendix Table S1: PROBAST modification

PROBAST Items	Modifications
Domain 1: Participants	Refer to participant data for image selection when scoring
Domain 2: Predictors	N/A–removed from scoring
Domain 3: Outcome	Items 3.3, 3.5 and 3.6 N/A
Domain 4: Analysis Items	Items 4.5, 4.6, and 4.9 N/A
Domain 5: Overall	No changes

Appendix Table S2: Database characteristics

	First Author	Year	Inclusion criteria	Exclusion criteria	Number of participants	Number of participants with pneumothorax	Percentage of female participants	Mean age (SD) years	Open source
[1]	Lee	2022	One radiologist reviewed the hospital database to extract patients who were aged between 18 and 74, underwent posteroanterior chest radiography between January 1st, 2017 and April 30th, 2021, and were tagged with normal, pneumothorax, or consolidation-related abnormalities. Second, radiographs were sampled in a computer-generated random order.	Radiographs were examined to exclude 1) radiographs with artifacts (e.g., central venous catheter, wires from sternotomy or thoracotomy), 2) duplicate radiographs, and 3) radiographs with incorrect patient information in the DICOM files. Third, when the predefined sample size was reached, remaining samples were excluded to prevent unnecessary use of patient data and ensure manageable workloads for participating clinicians.	Development set:1050 External test set:500 External test set:550	Development set:NR External test set:100 External test set:150	Development set:33.1 External test set:36.4 External test set:30.2	Development set:48.4(15.4) External test set:48(14) External test set:47(SD16)	No
[2]	Rudolph	2022	Radiology reports from 2010–2018	Inconclusive cases, for example, due to projected skin folds that mimic pleural dehiscence, were rejected. Inconclusive cases with a questionable very small trace PTX were included or rejected based on the plausibility by comparing with the medical history and previous CXRs.	Development set:NR External set(CXR EU):563 External set(SCXR PTX):468	Development set:NR External set(CXR EU):55 External set(SCXR PTX):117	Development set:NR External set(CXR EU):43.3 External set(SCXR PTX):NR	Development set:NR External set(CXR EU):49(19) External set(SCXR PTX):NR	No
[3]	Park	2022	ChestX-ray14	Expert consensus	Development set:NR External set:NR	Development set:NR(2379images) External set:NR(120images)	Development set:NR External set:NR	Development set:NR External set:NR	Yes
[4]	Shin	2022	Pediatric patients (≤ 18 years old) who underwent chest radiographs from March to May 2021	lateral and decubitus chest radiographs were excluded	Development set:NR External set:2273	Development set:NR External set:NR(67images)	Development set:NR External set:43.6	Development set:NR External set:7(5.8)	No
[5]	Hallinan	2022	Keyword matching from PACS	Expert opinion	Development A:30752 Development B:30805 External set:493	Development A:NR(2226images) Development B:NR(2637images) External set:NR(125images)	Development A:45.9 Development B:46.0 External set:44.0	Development A:46(16) Development B:46(16) External set:53(24)	Yes

[6]	Gipson	2022	All cases from January 2009 to June 2019 where patients who presented after blunt trauma underwent both chest radiograph and CT within 24h of arrival to hospital, where the imaging report for the radiograph was provided before the CT was performed.	Patients with prior imaging at the time of reporting of the chest radiograph were excluded	Development set:NR External set:1404	Development set:NR External set:NR(171images)	Development set:NR External set:32.0	Development set:NR External set:Median *52*	No
[7]	Shamrat	2022	There is a lot of variation from database to database, and no details on sampling are written.	NR	Development set:NR Internal set:NR	Development set:NR Internal set:NR(1600images)	Development set:NR Internal set:NR	Development set:NR Internal set:NR	Yes
[8]	Hong	2022	Consecutive cone-beam CT-guided PTNB procedures for lung lesions at Seoul National University Hospital from January 2018 to November 2020.	(a) patients whose initial follow-up chest radiographs were not obtained within 4 hours, (b) patients in whom PTNB failed, (c) patients who underwent repeat biopsies of a lesion in the same lung within a month, (d) patients with immediate drainage catheter insertion before follow-up chest radiography, (e) patients with pneumothorax on chest radiographs obtained before PTNB, and (f) patients with follow-up chest radiographs without CAD results between February 2020 and November 2020	Development set:3096 External set:665	Development set:NR External set:NR(123images)	Development set:42.1 External set:41.3	Development set:66(12) External set:67(11)	No
[9]	Jin	2022	Patients who visited respiratory outpatient clinics at three participating institutions in 2018	The patients who did not undergo chest CT or the procedure ≥ 1 month before chest radiography were excluded.	Development set:6006 External set (Institution B):2536 External set (Institution G):1470 External set (Institution K):2000	Development set:NR External set (Institution B):NR(5images) External set (Institution G):NR(2images) External set (Institution K):NR(8images)	Development set:43.0 External set (Institution B):46.0 External set (Institution G):44.0 External set (Institution K):40.0	Development set:61(16) External set (Institution B):61(16) External set (Institution G):61(14) External set (Institution K):61(16)	No
[10]	Kim	2022	Keyword matching from PACS	NR	Development set:30805 Internal set:NR	Development set:NR(5263images) Internal set:NR(1000images)	Development set:46 Internal set:NR	Development set:46(16) Internal set:NR	No
[11]	Wang	2022	ChestX-ray14	Expert consensus	Development set:NR Internal set:NR	Development set:NR(2381images)	Development set:NR Internal set:NR	Development set:NR Internal set:NR	Yes

						Internal set:NR(290images)			
[12]	Rudolph	2022	Patient presentation at one of the EUs affiliated to our university hospital from 2000 to 2018.	Patient's age older than 21, absence of intrathoracic foreign material that might imply the main pathology (eg, the presence of a port catheter might correlate to the presence of suspicious pulmonary nodules or thoracic tubes might correlate to the presence of a PTX), and posterior-anterior (PA) projection in patient's upright positioning.	Development set:NR External set:563	Development set:NR(11578 images) External set:NR(55images)	Development set:NR External set:43.3	Development set:NR External set:49.9(19)	No
[13]	Mangalmurti	2022	Keyword matching from PACS	NR	Development set:30805 Internal set:NR	Development set:NR(1200images) Internal set:NR(300images)	Development set:46 Internal set:NR	Development set:46(16) Internal set:NR	Yes
[14]	Kakkar	2022	Keyword matching from PACS	NR	Development set:30805	Development set:NR	Development set:46	Development set:46(16)	Yes
[15]	Iqbal	2022	The dataset chosen for our research purpose is a smaller version of the NIH-CXR dataset and contains 5% of the total number of samples, and each pathology is present in the same ratio as is present in the full dataset.	NR	Development set:NR	Development set:NR	Development set:NR	Development set:NR	Yes
[16]	Feng	2022	Retrospectively acquired between January 2010 and April 2020 in Dunedin Hospital.	Frontal chest radiographs (including bedside images) from patients over 16 years of age. Embedded annotations are excluded.	Development set:13745 Internal test set:NR External test set:9273	Development set:NR(2876images) Internal test set:NR(326imagws) External test set:NR	Development set:46.8 Internal test set:NR External test set:44.9	Development set:60(20) Internal test set:NR External test set:47(16.7)	Yes
[17]	Thian	2022	Keyword matching from PACS	Radiologist uncertain cases	Development set(ChestX-ray14):30805 Development set(CheXpert):65240 External set:493	Development set:NR(14010 images) External set:NR(125images)	Development set(ChestX-ray14):46 Development set(CheXpert):40.6 External set:46	Development set(ChestX-ray14):46(16) Development set(CheXpert):60(17) External set:54(24)	No

[18]	Lee	2022	The pneumothorax cases were collected from January 2016 to May 2019 in our ED with the following inclusion criteria: (1) at least one chest plain film to confirm pneumothorax, (2) needle decompression (clinically suspicious tension pneumothorax), tube thoracostomy, or catheter thoracostomy due to instability (respiratory rate ≥ 24 breaths/min; heart rate, < 60 beats/min or > 120 beats/min; hypotension; room air O2 saturation, < 90%; and patient couldn't speak in whole sentences between breaths), and 3) at least one ECG before intervention.	Minimal pneumothorax (< 20%), bilateral pneumothorax, traumatic pneumo- thorax, combined hemothorax and pneumothorax, or other indications of tube or catheter thoracostomy were excluded.	Development set:NR Internal set:NR	Development set:NR(88images) Internal set:NR(19images)	Development set:NR Internal set:NR	Development set:NR Internal set:NR	No
[19]	Tian	2022	Montgomery County's Tuberculosis screening program/The chest X-rays are from outpatient clinics and were captured as part of the daily hospital routine within a 1-month period, mostly in September 2012/Frontal-view chest X-ray images, which was obtained between January 1, 2009 to December 31, 2016 from the Second Affiliated Hospital, Zhejiang University School of Medicine /Keyword matching from PACS	(1) radiographs that were off center or angle; (2) lateral view chest X-ray images; (3) blurred images; and (4) images with more than five catheters.	Development set(Montgomery):138 Development set(Shenzhen):662 Development set(SAHZUSM):27955 Development set(ChestX-ray14):30805 Internal set:NR	Development set:NR(4396images) Internal set:NR(842images)	Development set(Montgomery):53.6 Development set(Shenzhen):31.7 Development set(SAHZUSM):NR Development set(ChestX-ray14):46 Internal set:NR	Development set(Montgomery):40(18) Development set(Shenzhen):35(14) Development set(SAHZUSM):NR Development set(ChestX-ray14):46(16) Internal set:NR	Yes
[20]	Seah	2021	Dataset from a large practice in Australia with hundreds of imaging clinics in a wide variety of inpatient, outpatient and critical care settings between 2016 and 2018. Collection timeline: 2004-2019.	NR	Development:2286 External set:NR	Development set:NR External set:NR(211images)	Development set:NR External set:NR	Development set:NR External set:NR	No,Yes
[21]	Kuo	2021	Keyword matching from PACS	NR	Development set:NR Internal set:NR External set:NR	Development set:NR Internal set:NR External set:NR	Development set:NR Internal set:NR External set:NR	Development set:NR Internal set:NR External set:NR	Yes
[22]	Hong	2021	Files provided after de-identification by Soonchunhyang University Hospital.	NR	Development set:NR Internal set:NR	Development set:NR(12493 images)	Development set:NR Internal set:NR	Development set:NR Internal set:NR	No

						Internal set:NR(1000images)			
[23]	Rueckel	2021	Patients were retrospectively identified by data research on radiology reports from 2010 to 2018 to separately identify PTX-positive/negative images, consequently clinically non-consecutive cohort with a targeted PTX overall prevalence of approx. 25%) in our institutional Picture Archiving and Communication System (PACS). Data was directly extracted from clinical routine without applying any quality-related exclusion criteria; therefore, data also includes examinations of limited quality	without applying any quality-related exclusion criteria;	Development set:NR Internal set:4360	Development set:NR(3993images) Internal set:NR(760images)	Development set:NR Internal set:NR	Development set:NR Internal set:NR	No
[24]	Cho	2021	NR	NR	Development set:NR Internal set:NR External set:NR	Development set:NR(266images) Internal set:NR(65images) External set:NR(188images)	Development set:NR Internal set:NR External set:NR	Development set:NR Internal set:NR External set:NR	No
[25]	Niehues	2021	NLP (cardiac congestion, pleural effusion, air-space opacification, pneumothorax, central venous catheter, thoracic drain, gastric tube, and tracheal tube/cannula) extraction from patients examined between January 1, 2009, and March 31, 2019.	NR	Development set:18361 External set:65240	Development set:NR(1342images) Internal set:NR(62images) External set:NR	Development set:38.4 External set:40.6	Development set:62.6(16) External set:60(17)	No,Yes
[26]	Kao	2021	A retrospective search of the Picture Archiving and Communication System (PACS) and the MRAS for chest radiographs with pneumothorax alerts from 1 January 2015 to 31 December 2019, and another retrospective search of the PACS and the Radiology Information System (RIS) for chest radiographs with "pneumothorax" in the reports from 1 January 2013	Negative pneumothorax, age less than or equal to 6 years, poor positioning, poor image quality, metallic implants masking lung fields, and chest wall deformity.	Development set:NR External set:NR	Development set:NR(1235images) External set:NR(86images)	Development set:NR External set:NR	Development set:NR External set:NR	No

			to 31 December 2014 (before the MRAS went online) were performed /A retrospective search of the PACS and RIS for chest radio- graphs for health examination with negative findings in 2019 was performed and 337 chest radiographs were identified.						
[27]	Mos quer a	20 21	Radiological reports records of CXRs performed between 2008 and 2019 at a 650-bed university hospital. Inclusion criteria for CXR images were having a concluding report and belonging to a patient whose images were not used in any training dataset.	We excluded images with a confirmed "Support Devices" label,	Development set:NR IExternal set:30805 External set:NR	Development set:NR(2379images) External set:NR(238images) External set:NR(119images)	Development set:NR External set:46 External set:NR	Development set:NR External set:46(16) External set:NR	Yes,No
[28]	Wan g	20 21	The dataset was exported from the hospital through a keyword search in the data format of DICOM.	Independent and multi-blind screening mechanism by multiple physicians to guarantee that a certain image can only be enrolled as a pneumothorax sample if it was annotated by multiple physicians to be pneumothorax.	Development set:NR External set:NR	Development set:NR(7105images) External set:NR(108images)	Development set:NR External set:NR	Development set:NR External set:NR	Yes
[29]	Nam	20 21	Chest radiographs taken between March 2004 and December 2017 were retrospectively collected from Seoul National University Hospital	NR	Development set:108053 Internal set:190 External set(ER in SNUH):202 External set(PadChest):67000	Development set:NR(7638images) Internal set:NR(23images) External set(ER in SNUH):NR(2images) External set(PadChest):NR(11images)	Development set:48.7 Internal set:46.8 External set(ER in SNUH):53 External set(PadChest):49.7	Development set:56(14) Internal set:59(14) External set(ER in SNUH):57(17) External set(PadChest):58(20)	Yes,No

[30]	Choi	2021	Normal: Patients who visited a health screening center or oncology outpatient clinic and underwent both chest radiograph and chest CT within one month between May 2017 and July 2017 or between January 2019 and March 2019. Nodule: Patients who underwent both chest radiograph and chest CT within one month and underwent CT guided biopsy for lung nodules between January 2015 and March 2015 or between January 2019 and March 2019. Consolidation: Patients who visited an emergency department or respiratory medicine and underwent both chest radiograph and chest CT within one month between December 2014 and June 2015 or between October 2018 and March 2019. Pneumothorax: Patients who visited a thoracic surgery and underwent both chest radiograph and chest CT within one month between December 2015 and September 2017. All CRs were collected from patients over 19 years old.	Normal: Abnormal findings Nodule: Concurrent other abnormal findings, Not visible on CR, Multiple lesions Consolidation: Concurrent other abnormal findings Pneumothorax: Concurrent other abnormal findings, Chest draining catheter	Development set:NR External set:244	Development set:NR External set:NR(35images)	Development set:NR External set:61	Development set:NR External set:52(18)	No
[31]	Lyu	2021	Patients who visited the emergency department at Jinling Hospital with trauma and underwent chest CT from September 2019 and November 2019	Poor image quality	Development set:NR External set:403	Development set:NR External set:NR(29images)	Development set:NR External set:37	Development set:NR External set:50(19)	No
[32]	Kim	2021	Consecutive subjects who visited the health screening center underwent CXR and chest CT in 2018 were retrospectively investigated from the radiology database and medical records system.	Subjects who underwent chest CT from CXR with intervals of 1 month or more were excluded.	Development set:5887 External set(Institution B):1694 External set(Institution G):1858 External set(Institution K):2335	Development set:NR External set(Institution B):0 External set(Institution G):0 External set(Institution K):1	Development set:26.5 External set(Institution B)41.2: External set(Institution G):21.5 External set(Institution K):19.7	Development set:54(11) External set(Institution B):56(11) External set(Institution G):53(11) External set(Institution K):54(13)	No
[33]	Li	2021	CXRs were collected retrospectively from adult patients between June 2013 and July 2019.	NR	Development set:3526 External set:562	Development set:NR Internal set:NR	Development set:NR Internal set:NR External set:NR	Development set:NR Internal set:NR External set:NR	No,Yes

						External set:NR			
[34]	Thian	2021	Retrospectively collected a random selection of pneumothorax-positive cases and pneumothorax-negative controls obtained in their respective emergency departments over a 4-year time period from 2016 to 2019, with a ratio of between one to four controls to each case of pneumothorax being used	NR	Development set(ChestX-ray14):27967 Development set(CheXpert):45766 External set(Hospital A):511 External set(Hospital B):519 External set(Hospital C):321 External set(Hospital D):525 External set(Hospital E):517 External set(Hospital F):538	Development set:NR(10928 images) External set(Hospital A):200 External set(Hospital B):136 External set(Hospital C):41 External set(Hospital D):125 External set(Hospital E):117 External set(Hospital F):138	Development set(ChestX-ray14):NR Development set(CheXpert):NR External set(Hospital A):25 External set(Hospital B):37 External set(Hospital C):46 External set(Hospital D):46 External set(Hospital E):27 External set(Hospital F):NR	Development set(ChestX-ray14):NR Development set(CheXpert):NR External set(Hospital A):57(23) External set(Hospital B):52(22) External set(Hospital C):70(20) External set(Hospital D):53(24) External set(Hospital E):52(21) External set(Hospital F):NR	Yes,No
[35]	Abedalla	2021	ChestX-ray14	Expert consensus	Development set:NR	Development set:NR(2669images)	Development set:NR	Development set:NR	Yes
[36]	Sung	2021	Posteroanterior chest radiographs obtained in adult patients (both inpatients and outpatients) between January 2016 and December 2017 at Asan Medical Center were retrieved. Examinations including the various types of findings (normal, abnormal [five types of abnormal findings]) were consecutively collected until the numbers defined earlier were achieved.	NR	228	Development set:NR External set:NR(11images)	GroupA:37,GroupB:47	GroupA:54(14),GroupB:57(14)	No
[37]	Draelos	2021	Chest CT volumes obtained without intravenous contrast material and their associated reports from Duke University Health System spans January 2012 – April 2017		Development set:NR Internal set:NR	Development set:NR Internal set:NR	Development set:NR Internal set:NR	Development set:NR Internal set:NR	No
[38]	Wang	2021	Keyword matching from PACS	NR	Development set:30805 Internal set:30805	Development set:NR(2637images) Internal set:NR(2661images)	Development set:NR Internal set:NR	Development set:NR Internal set:NR	Yes

[39]	Rueckel	2020	Chest radiographs were retrospectively identified by data research (search criteria based on radiology reports from 2010–2018) in our institutional Picture Archiving and Communication System (PACS).	Inconclusive cases, for example, due to projected skin folds that mimic pleural dehiscence, were rejected. Inconclusive cases with a questionable very small trace PTX were included or rejected based on the plausibility by comparing with the medical history and previous CXRs.	Development set:NR External set:4688	Development set:NR External set:1173	Development set:NR External set(Positive):44.7 External set(Negative):40.3	Development set:NR External set(Positive):56(21) External set(Negative):64(19)	Yes,No
[40]	Chen	2020	Radiographs in children and adolescents 1–17 years in age that admitted the Department of Pediatrics, Kaohsiung Chang Gung Memorial Hospital from January 1, 2018 to December 31, 2019 for acute lower airway infections, pneumothorax, or other non-respiratory disease with a normal chest X-ray were recruited.	NR	Development set:NR Internal set:NR	Development set:NR(172images) Internal set:NR(42images)	Development set:NR Internal set:NR	Development set:NR Internal set:NR	No
[41]	Röhrich	2020	We collected all chest CT scans from the clinical routine over a timeframe of 2.5 years from 2013 to 2015 and generated labels for ‘pneumothorax’ and ‘no pneumothorax’ based on the radiological reports and visual verification by a radiologist with three years of subspecialty training in thoracic radiology	NR	610	Development set:NR(34images) Internal set:NR(167images)	37	54(19)	No
[42]	Wang	2020	ChestX-ray14	Expert consensus	Development set:NR	Development set:NR(2379images)	Development set:NR	Development set:NR	Yes
[43]	Yi	2020	Keyword matching from PACS	NR	Development set:30805 External set:NR	Development set:NR External set:NR(176images)	Development set:46 External set:NR	Development set:46(16) External set:NR	Yes
[44]	Hwang	2020	Patients underwent PTNB between Jan 2017 and Dec 2017/Patients underwent PTNB between Jan 2013 and Dec 2014/Patients underwent PTNB between Mar 2013 and Dec 2016/January and February 2017 from Institution A	No available post-PTNB CR, Immediate drainage catheter insertion before CR/	Development set:1757 External set(Institution A):1055 External set(Institution B):388 External set(Institution C):314 External set(Reader Test):170	Development set:NR External set(Institution A):208 External set(Institution B):67 External set(Institution C):33 External set(Reader Test):44	Development set:40 External set(Institution A):40.3 External set(Institution B):43.3 External set(Institution C):34.7 External set(Reader Test):38	Development set:65(12) External set(Institution A):65(11) External set(Institution B):65(12) External set(Institution C):65(13) External set(Reader Test):63(12)	No

[45]	Kitamura	2020	Our data for this study was collected from the Vendor Neutral Archive across the years 2013 to 2017. Positive and negative cases were collected concurrently with the same sex and age distribution by searching radiology reports for the term "pneumothorax." There was no patient overlap between the two datasets, and only 1 chest X-ray study was obtained from each unique patient.	NR	Development set:NR	Development set:NR(207images)	Development set:NR	Development set:NR	No
[46]	Park	2020	We retrospectively collected and anonymized 15,809 chest radiographs from two institutions (Asan Medical Center (institution A) and Seoul National University Bundang Hospital (institution B)).	NR	Institution A:100 Institution B:100	Institution A:NR Institution B:NR	Institution A:37 Institution B:35	Institution A(Positive):56(18) Institution A(Negative):48(8) Institution B(Positive):62(15) Institution B(Negative):49(7)	No
[47]	Wang	2020	Keyword matching from PACS	NR	30805	Development set:NR Internal set:NR(2661images)	46	46(16)	Yes
[48]	Elkins	2020	Keyword matching from PACS	NR	30805	NR	46	46(16)	Yes
[49]	Lai	2020	Keyword matching from PACS	NR	Development set:NR External set:NR	Development set:NR(1028images) External set:NR(115images)	Development set:NR External set:NR	Development set:NR External set:NR	Yes,No
[50]	Majkowska	2020	This data set consists of all consecutive inpatient and outpatient images in DICOM format obtained from five regional centers across a large hospital group in India (Ban- galore, Bhubaneswar, Chennai, Hyderabad, and New Delhi) between November 2010 and January 2018. /Keyword matching from PACS	NR	DS1:538390 ChestX-ray14:30805	Development set:NR(2609images) Internal set(DS1):NR(88images) Internal set(Chest X-Ray14):NR(195images)	DS1:38.2 ChestX-ray14:46	DS1:Median 50 ChestX-ray14:46(16)	No,Yes
[51]	Li	2019	We identified chest CT cases of patients, using a free text search in a radiology report repository with keywords ("pneumothorax" and "chest CT") and subsequent consensus of two expert thoracic radiologists.	NR	280	Development set:NR(50images) Internal set:NR(160images)	30.7	56(22)	No

[52]	Park	2019	Cases from two tertiary referral hospitals were collected from a picture archiving and communication system. Diagnoses were searched using the radiologic reports and diagnosis codes in the electronic medical records. /1d follow-up cases with chest radiographs after PTNB in our hospital between January 2016 and December 2016./3h follow-up cases with chest radiographs after PTNB in our hospital between January 2016 and December 2016.	NR	Development set:NR Internal set:NR	Development set:NR(1343images) Internal set:NR(253images) Internal set(Temporal 3-h):NR(247images) Internal set(Temporal 1-d):NR(309images)	Development set:NR Internal set:NR	Development set:NR Internal set:NR	No
[53]	Liang	2019	This database were collected from 13 medical centers in Japan and one institution in the United States under the following conditions: only one nodule on an image for nodule cases; confirmation of presence or absence of a lung nodule by CT examination; and nodule classification as malignant based on histologic and cytologic examination or as benign based on histology, definitive isolation of a pathogenic organism, shrinkage and disappearance with the use of antibiotics, or no change observed during a follow-up period of 2 years./Keyword matching from PACS	NR	Development set(JSRT):248 Development set(ChestX-ray14):30805 Internal set:30805	Development set:NR(2637images) Internal set:NR(2661images)	Development set(JSRT):51.6 Development set(ChestX-ray14):46 Internal set:46	Development set(JSRT):58(13) Development set(ChestX-ray14):46(16) Internal set:46(16)	Yes
[54]	Hwang	2019	Normal CRs: CRs from patients with no referable abnormality on chest CT. CRs taken within 2 weeks from the chest CT. CRs taken between September and October 2017. Pulmonary malignancies: CRs from patients with pathologically or clinically diagnosed pulmonary malignancies. CRs with corresponding chest CT taken within 1 month. CRs taken between December 2016 and October 2017. Active pulmonary tuberculosis: CRs from	Pulmonary malignancies: CRs without visible lesions. CRs with >3 lesions. CRs with other clinically relevant abnormalities. Active pulmonary tuberculosis: CRs without visible abnormality. CRs with other clinically relevant abnormalities Pneumonia: CRs without visible abnormality. CRs with other clinically relevant abnormalities Pneumothorax: CRs with drainage catheter or subcutaneous emphysema. CRs with other clinically	Development set:62019 Internal set:200 External set(Institution B):245 External set(Institution C):190 External set(Institution D):184 External set(Institution E):196	Development set:2670 Internal set:24 External set(Institution B):30 External set(Institution C):25 External set(Institution D):20 External set(Institution E):20	Development set:67 Internal set:43.5 External set(Institution B):35.5 External set(Institution C):42.1 External set(Institution D):47.3 External set(Institution E):23.5	Development set:Normal:51(16),Abnormal:62(15) Internal set:54(15) External set(Institution B):55(17) External set(Institution C):51(19) External set(Institution D):49(18) External set(Institution E):56(16)	No

			patients with active pulmonary tuberculosis diagnosed via culture or PCR. CRs taken within 2 weeks from the date of initial treatment. CRs with corresponding chest CT taken within 1 month. CRs taken between March 2017 and September 2017 Pneumonia: CRs from patients with microbiologically or clinically diagnosed pneumonia. CRs taken within 1 week from the date of diagnosis. CRs with corresponding chest CT taken within 1 week. CRs taken between March 2016 and September 2017 Pneumothorax: CRs with an unequivocal finding of pneumothorax. CRs taken between April 2016 and August 2017	relevant abnormalities. CRs taken immediately after thoracic surgery					
[55]	Taylor	2018	Candidate chest X-rays of adult patients were obtained from 1 January 2006 to 31 December 2016. Candidate images for inclusion in the positive group were identified by using the search terms "small pneumothorax," "trace pneumothorax," "moderate pneumothorax," and "large pneumothorax" with mPower's standard filters in place to minimize negative occurrences. Candidate images for inclusion in the negative group were identified both by searching for negative phrases such as "no pneumothorax" and by including X-rays from the same time period that did not meet the criteria for inclusion in the positive group.	NR	Development set:NR External set:30805	Development set:NR(2670images) Internal set:NR(148images) External set:NR(5302images)	Development set:NR External set:46	Development set:NR External set:46(16)	No, Yes
[56]	Rajpurkar	2018	Keyword matching from PACS	NR	30805	Development set:NR(4597images) Internal set:NR(45images)	46	46 (16)	Yes

[57]	Cicero	2017	Two-view chest radiographic examinations performed between January 1, 2005, and December 31, 2015, on patients at least 18 years of age.	The AP and lateral projections	NR	Development set:NR(1132images) Internal set:NR(167images)	44	56(NR)	No
[58]	Chen	2019	Keyword matching from PACS	NR	30805	Development set:NR Internal set:NR	46	46 (16)	Yes
[59]	Zhou	2021	This database were collected from 13 medical centers in Japan and one institution in the United States under the following conditions: only one nodule on an image for nodule cases; confirmation of presence or absence of a lung nodule by CT examination; and nodule classification as malignant based on histologic and cytologic examination or as benign based on histology, definitive isolation of a pathogenic organism, shrinkage and disappearance with the use of antibiotics, or no change observed during a follow-up period of 2 years./Montgomery County's Tuberculosis screening program/Keyword matching from PACS	NR	Development set(JSRT):248 Development set(Montgomery):138 Development set(MIMIC):63478 Development set(ChestX-ray14):30805 Development set(CheXpert):65240 Internal set:30805	Development set(JSRT):NR Development set(Montgomery):NR Development set(MIMIC):NR Development set(ChestX-ray14):NR Development set(CheXpert):NR Internal set:NR	Development set(JSRT):51.6 Development set(Montgomery):53.6 Development set(MIMIC):NR Development set(ChestX-ray14):46 Development set(CheXpert):40.6 Internal set:46	Development set(JSRT):58(13) Development set(Montgomery):40(18) Development set(MIMIC):NR Development set(ChestX-ray14):46(16) Development set(CheXpert):60(17) Internal set:46(16)	Yes
[60]	Luo	2022	NR	NR	NR	NR(1720images)	45	NR	No
[61]	Lin	2020	NR	NR	NR	NR	44	Male:48(17),Female:46(15)	Yes
[62]	Haq	2021	Keyword matching from PACS	NR	Development set(ChestX-ray14):30805 Development set(CheXpert)):65240 Internal set:30805	Development set(ChestX-ray14):NR Development set(CheXpert):NR Internal set:NR	Development set(ChestX-ray14):46 Development set(CheXpert):40.6 Internal set:46	Development set(ChestX-ray14):46(16) Development set(CheXpert):60(17) Internal set:46(16)	Yes
[63]	Wang	2020	NR	NR	NR	Development set:NR(4483images) Internal set:NR(1083images)	NR	NR	No

Appendix Table S3: Deep learning characteristics

	First Author	Year	AI model	AI results: sensitivity, specificity (%, 95% CI)	AI results: other metrics
[1]	Lee	2022	DEEP:CHEST-XR-03	95.6(92.3-97.8),99.6(98.9-99.9)	AUROC:0.978(0.965-0.991)
[2]	Rudolph	2022	CheXNet (DenseNet)	51,82	AUC:0.723 Accuracy:79% Positive predictive value:0.24 Negative predictive value:0.94
[3]	Park	2022	ViT (supervised) ViT (self-training)	NR	AUC: Supervised:0.909 Proposed:0.913
[4]	Shin	2022	Lunit INSIGHT for Chest Radiography, version 3 (ResNet34)	98.5(92.0-99.9),99.6(99.3-99.8)	PPV:89.2%(80.5-94.3) NPV:99.9%(99.7-99.9) Accuracy:99.6(99.3-99.8)
[5]	Hallinan	2022	DenseNet121 ResNet50 EfficientNetB3	NR	AUC(NLP): DenseNet121:0.839(0.831-0.847) ResNet50: 0.838(0.830-0.846) EfficientNetB3:0.869(0.863-0.876) AUC(RD): DenseNet121:0.880(0.873-0.887) ResNet50: 0.881(0.873-0.887) EfficientNetB3:(0.943(0.939-0.946)
[6]	Gipson	2022	Annalise CXR software, version 1.2	39.2(31.8-46.9),99.8(99.4-100)	Cohen's κ:0.53(0.45-0.60)
[7]	Shamrat	2022	LungNet22 (VGG-based)		
[8]	Hong	2022	Lunit INSIGHT for Chest Radiography, version 2.0	74.8(66.2-82.2),99.8(99-100)	Accuracy:95.3%(93.4-96.7) Positive predictive value.:98.9(94.2-100) Negative predictive value:94.7(92.5-96.4)
[9]	Jin	2022	Lunit INSIGHT for Chest Radiography	NR	NR
[10]	Kim	2022	EfficientNetv2-M		
[11]	Wang	2022	SE-ResNext50 EfficientNet-B3	98.02,99.60	Accuracy:99.25% Dice:98.27%

[12]	Rudolph	2022	FCOS (RetinaNet-based)	89,95	AUC:0.957 Accuracy:94% Positive predictive value:0.64 Negative predictive value:0.99
[13]	Mangalmurti	2022	VGG16 VGG19	VGG16:47,NR VGG19:46.6,NR	Accuracy: VGG16:78.2% VGG19:78.2% Precision: VGG16:45.7% VGG19:45.7% F1-score: VGG16:46.3% VGG19:46.2%
[14]	Kakkar	2022	NR	NR	NR
[15]	Iqbal	2022	VDV	SIIM:85.17,NR RS-NIH(Randam):90.9,NR RS-NIH(Patient wise):85.45,NR	AUC: SIIM:0.86 RS-NIH(Randam):0.95 RS-NIH(Patient wise):0.77 Accuracy: SIIM:78.27% RS-NIH(Randam):82.68% RS-NIH(Patient wise):69.12%
[16]	Feng	2022	DeepLabV3 EfficientNetB3	DeepLabV3+ with Efficientnet-B3 :93,95 SIIM-ACR:81,86	AUC: DeepLabV3+ with Efficientnet-B3 :0.94 SIIM-ACR:0.83 Mean Dice: DeepLabV3+ with Efficientnet-B30.91: SIIM-ACR:0.69 TP-Dice: DeepLabV3+ with Efficientnet-B3:0.69: SIIM-ACR:0.50
[17]	Thian	2022	ResNet50 DenseNet121 EfficientNetB2	ResNet50:71(67-76),100(99-100) DenseNet121:66(61-70),93(91-96) EfficientNetB2:86(82-89)	AUC: ResNet50:0.95(0.93-0.97) DenseNet1210.93(0.91-0.96) EfficientNetB2:0.98(0.96-0.99)
[18]	Lee	2022	ECG12Net	NR	Kappa:0.806
[19]	Tian	2022	ResNet InceptionV3 DenseNet VGG NASNet InceptionResNetV2	SAHZUSM(Private):94.4,93.2 NIH(Public):38.4,86.2	Accuracy: SAHZUSM(Private):93.8% NIH(Public):62.3% AUC: SAHZUSM(Private):0.982 NIH(Public):0.641 Precision: SAHZUSM(Private):93.3% NIH(Public):73.9% F1-score: SAHZUSM(Private):93.9 NIH(Public):45.0

[20]	Seah	2021	Annalise CXR V.1.2	NR	AUC: Simple:0.981(0.976-0.986) Tension:0.997(0.995-0.999)
[21]	Kuo	2021	Model-ORIG Model-RECA	NR	AUC: Model-ORIG:0.78 Model-RECA:0.84
[22]	Hong	2021	EfficientNet B7-based	96.70,99.03	Accuracy:98.45%
[23]	Rueckel	2021	Algorithm 2 (DenseNet-based)	NR	AUC: Unilateral:0.877(0.861-0.893) Bilateral:0.923(0.889-0.957)
[24]	Cho	2021	ResNet50	AMC:90.50,84.62 SNUBH:98.89,84.57	AUC: AMC:0.8756 SNUBH:0.9173 Accuracy: AMC:90.30% SNUBH:96.41% PPV: AMC:99.40% SNUBH:96.83% NPV: AMC:24.12% SNUBH:94.08%
[25]	Niehues	2021	ResNet51	NR	AUC:0.776
[26]	Kao	2021	Unet (ResNet34)	83.7(74.2-90.8),99.1(98.7-99.4)	PPV (Precision):68.6%(60.5-75.6) NPV:99.6%(99.4-99.8) Accuracy:98.7%(98.3-99.1) AUC:0.914(0.905-0.923) F1 score:0.754(0.740-0.768)
[27]	Mosquera	2021	Albunet	81.71(75.22-87.39),98.4(97.66-99.05)	PPV:86.51%(80.80-91.80) NPV:97.72%(96.84-98.52)
[28]	Wang	2021	ChestNet	NR	Accuracy:94.51% AUC:0.9906
[29]	Nam	2021	DLAD-10 (ResNet34)	100,98.2	NR
[30]	Choi	2021	Lunit INSIGHT for Chest Radiography	97.26(95.21-99.31),92.86(89.63-96.09)	AUC:0.9935(0.9868-1.0000) Positive rate:95.3%(92.65-97.96) Negative rate:92.86%(89.63-96.09) Accuracy:95.49%(92.89-98.10)
[31]	Lyu	2021	Dr. Wise Lung Analyzer (Faster RCNN)	93.1(78.0-98.1),99.7(98.4-99.9)	Accuracy:99.3%(97.9-99.8)
[32]	Kim	2021	Lunit INSIGHT for Chest Radiography, version 2.5.7.4 (ResNet34)	HospitalA:81(75-86),90(87-93) HospitalB:84(77-90),98(96-99) HospitakC:85(80-92),77(75-80) HospitalD:98(95-100),92(89-95) HospitalE:92(87-97),92(89-94) HospitalF:89(83-95),79(75-84)	PPV: HospitalA:84%(78-89) HospitalB:93%(88-97) HospitalC:35%(30-40) HospitalD:80%(73-86) HospitalE:77%(69-84) HospitalF:60%(53-67) NPV: HospitalA:88%(84-91) HospitalB:94%(92-97) HospitalC:97%(96-98) HospitalD:99%(98-100) HospitalE:98%(96-99)

					HospitalF:95%(93-98) F1 score: HospitalA:82%(78-86) HospitalB:88%(83-92) HospitalC:50%(44-55) HospitalD:88%(83-92) HospitalE:84%(78-89) HospitalF:72%(66-77)
[33]	Li	2021	LACNN	80.4(78.3-82.5),93.2(90.7-95.7)	F1:0.807(0.764-0.850) AUC:0.914(0.886-0.942)
[34]	Thian	2021	EfficientNetB3		
[35]	Abedalla	2021	Ens4B-UNet	NR	Accuracy:99.81% Recall:56.94,Precision:71.19 F-measure:633.27
[36]	Sung	2021	Med-Chest X-Ray system (version 1.0.0, VUNO)	87.7(80-93),99.1(95-100)	JAFROC FOM:0.96(0.94-0.99) AUC:0.98(0.96-1.00)
[37]	Draelos	2021	CT-NET	NR	AUC:0.904 Average Precision:35.5%
[38]	Wang	2021	A3 Net	NR	AUC:0.878
[39]	Rueckel	2020	AI_CheXNet AI_1.5	NR	AUC: AI_CheXNet:0.765 AI_1.5:0.704
[40]	Chen	2020	YOLOv3 + DenseNet/ResNet	Original images: 80.95(66.00-91.11),97.26(92.12-100.00) Cropped images:,90.48(90.26-98.92),96.47(89.22-98.86)	Accuracy: Original images: 92.25(85.29-95.35), Cropped images: 94.49(88.18-96.85)
[41]	Röhrich	2020	Unet	91.6,99.9	AUC:0.976 Precision:0.886 Recall:0.880 DSC:0.883 Average precision::0.954
[42]	Wang	2020	CheXLocNet (Mask R-CNN base)	78(73-83),78(76-81)	AUC:0.87 F1:0.60 PPV:49%(45-54)
[43]	Yi	2020	ResNet152	85(79-90),67(62-71)	AUC:0.84(0.81-0.88)
[44]	Hwang	2020	Lunit INSIGHT for Chest Radiography, version 4.7.2	70.2(65.0-75.5),97.7(96.9-98.5)	Positive predictive value:87.2%(83.0-91.5) Negative predictive value:93.7%(92.5-95.0)
[45]	Kitamura	2020	The algorithm by Li	77,93	AUC:0.90
[46]	Park	2020	NR	NR	FOM:1.0
[47]	Wang	2020	Thorax-Net	NR	AUC: Patient wise:0.8254 Image wise:0.941

[48]	Elkins	2020	DenseNet121	NR	AUC:0.83 Precision:0.17
[49]	Lai	2020	AI-one AI-two	AI-one:33.04,61.74 AI-two:46.09,71.30	Precision: AI-one:80.3% AI-two:84.5% Positive prediction: AI-one:80.3% AI-two:84.5% AUC: AI-one:0.89 AI-two:0.91 AUC(prediction): AI-one:0.50(0.45-0.57) AI-two:0.62(0.56-0.69) Mean of the change in probability:19.7%(9.7-29.7)
[50]	Majkowska	2020	Xception	CXR14:72.8(64.1-81.0),90.8(88.9-93.1) DS1:64.8(47.7-78.4),99.7(99.3-100)	Positive predictive value: CXR14:48.7%(43.8-55.8) DS1:90.0%(78.9-100)
[51]	Li	2019	CNN (segmentation) + SVM (classidfication)	100,82.5	Accuracy:94%
[52]	Park	2019	YOLO9000 (Darknet19)	Model:89.7,96.4 3-h follow-up:61.1,93.0 1-day follow-up:63.4,93.5	PPV: 3-h follow-up:65.7% 1-day follow-up:74.8% NPV: 3-h follow-up:91.6% 1-day follow-up:89.4% AUC: Model:0.984 3-h follow-up:0.898 1-day follow-up:0.905 Accuracy: 3-h follow-up:87.3% 1-day follow-up:86.5%
[53]	Liang	2019	DenseNet121 (Unet-implemented)	NR	AUC:0.869
[54]	Hwang	2019	DenseNet	NR	AUC: InstitutionA:0.833(0.626-0.953) InstitutionB:1.000(0.884-1.000) InstitutionC:1.000(0.863-1.000) InstitutionD:1.000(0.832-1.000) InstitutionE:0.850(0.621-0.968)
[55]	Taylor	2018	VGG19 Inception	High sensitivity model(Internal):84(78-90),90(89-92) High specificity model(Internal):80(72-86),97(96-98)	AUC: High sensitivity model(Internal):0.94 High specificity model(Internal):0.96 PPV: High sensitivity model(Internal):0.45(0.39-0.51) High specificity model(Internal):0.71(0.63-0.77)
[56]	Rajpurkar	2018	CheXNeXt (DenseNet)	88.9(78.8-97.5),89.1(85.8-92.1)	AUC:0.944(0.915-0.969)
[57]	Cicero	2017	Inception	78,78	AUC:0.861 Accuracy:78 PPV:49

					NPV:95
[58]	Chen	2019	DenseNet169 DenseNet121 ResNet101 ResNet50	NR	AUN:0.893
[59]	Zhou	2021	NR	NR	AUC:0.8472
[60]	Luo	2022	Fusion model	NR	AUC: Private dataset:0.975 Image level annotation:0.977 Frontal image+Lateral image:0.979 Accuracy: Private dataset:0.943 Image level annotation:0.944 Frontal image+Lateral image:0.948 Presicion: Private dataset:0.951 Image level annotation:0.932 Frontal image+Lateral image:0.925 Recall: Private dataset:0.873 Image level annotation:0.897 Frontal image+Lateral image:0.908 F1-score Private dataset:0.910 Image level annotation:0.914 Frontal image+Lateral image:0.916
[61]	Lin	2020	NR	NR	Recall:99.66% Precision:87.78% Accuracy:88.88% F1 score:0.9334
[62]	Haq	2021	NR	NR	AUC: With the NIH dataset:LR0.76,HR0.83 With the Stanford dataset:LR0.80,HR0.90
[63]	Wang	2020	MS_ScSE_DenseNet	88.55,98.14	Accuracy:93.45% PPV:97.86% NPV:89.94% F1-score:92.97%

Appendix Table S4: Physicians characteristics

	First Author	Year	Physician results: sensitivity, specificity (%, 95% CI)	Physician results: other metrics
[1]	Lee	2022	94.3(91.4-96.4),99.5(99.1-99.7)	Accuracy :98.8%(98.3-99.1)
[2]	Rudolph	2022	Radiology residents:96,99 Non-radiology residents:73,96	AUC: Radiology residents[RR]:0.981 Non-radiology residents[NRR]:0.856 Accuracy: RR99% NRR:94% Positive predictive value: RR:0.90 NRR:0.68 Negative predictive value: RR:1.00 NRR:0.97
[6]	Gipson	2022	33.1(26.2-40.7),99.4(98.7-99.7)	Cohen's κ:0.44(0.36-0.52)
[8]	Hong	2022	67.1(59.6-74.6),99.6(99.1-100)	Accuracy:92.3%(90.3-94.3) Positive predictive value.:98.1(95.4-100) Negative predictive value:91.3(88.9-93.6)
[9]	Jin	2022	NR	NR
[12]	Rudolph	2022	Radiology residents:86,99 Non-radiology residents:73,96	AUC: Radiology residents[RR]:0.981 Non-radiology residents[NRR]:0.856 Accuracy: RR:99% NRR94% Positive predictive value: RR:0.90 NRR:0.68 Negative predictive value: RR:1.00 NRR:0.97
[18]	Lee	2022	NR	CV-V8,ER-V15,ER-V6 Kappa:0.110,0.067,0.052
[26]	Kao	2021	25.6(16.8–36.1),100 (99.9-100)	PPV (Precision):1.000(1.000-1.000) NPV:0.983(0.981-0.985) Accuracy:0.983(0.978-0.987) AUC:0.628(0.612-0.643) F1 score:0.407(0.391-0.423)
[29]	Nam	2021	91.3,99.6	NR
[30]	Choi	2021	82.53(80.58-84.48),81.97(80.00-83.95)	AUC:0.8679(0.8507-0.8850) Positive rate:87.14(85.42-88.85) Negative rate:76.03(73.83-78.22) Accuracy:82.30(80.35-84.26)
[33]	Li	2021	61.9(56.2-67.6),96.1(93.3-98.9)	F1:0.681(0.518-0.844) AUC:0.912(0.885-0.939)
[36]	Sung	2021	88(57-99),NR	JAFROC FOM:0.92(0.83-1.01)
[43]	Yi	2020	Resident1:91(86-95),67(62-71) Resident2:89(84-93),73(69-78)	AUC: Resident1:0.94(0.92-0.96) Resident2:0.91(0.88-0.94)

[44]	Hwang	2020	55.5(49.8-61.2),99.8(99.6-100)	Positive predictive value:98.8%(97.1-100) Negative predictive value:91.1%(89.6-92.6)
[46]	Park	2020	NR	NR
[50]	Majkowska	2020	CXR14:79.2(75.5-83.0),92.8(92.0-93.7) DS1:51.7(43.2-60.2),99.5(99.3-99.7)	Positive predictive value: CXR14:54.8%(51.8-58.2) DS1:83.5%(77.5-89.4)
[51]	Li	2019	Three test radiologists sensitivity:91.3,95.6,86.3 Three test radiologists specificity:90.0,90.0,85.0	Accuracy: Three test radiologists:91.0%,94.5%,86.0%
[54]	Hwang	2019	NR	NR
[56]	Rajpurkar	2018	Resident radiologists:65.9(57.9-74.0),97.2(96.3-98.2) BC radiologists:61.5(55.9-67.3),97.1(96.4-97.8)	AUC:0.940(0.912-0.962)

References

1. Lee SY, Ha S, Jeon MG, et al. Localization-adjusted diagnostic performance and assistance effect of a computer-aided detection system for pneumothorax and consolidation. npj Digital Medicine, 2022; 5(1): 107.
2. Rudolph J, Schachtner B, Fink N, et al. Clinically focused multi-cohort benchmarking as a tool for external validation of artificial intelligence algorithm performance in basic chest radiography analysis. Sci Rep, 2022; 12(1): 12764.
3. Park S, Kim G, Oh Y, et al. Self-evolving vision transformer for chest X-ray diagnosis through knowledge distillation. Nat Commun, 2022; 13(1): 3848.
4. Shin HJ, Son NH, Kim MJ, et al. Diagnostic performance of artificial intelligence approved for adults for the interpretation of pediatric chest radiographs. Sci Rep, 2022; 12(1): 10215.
5. Hallinan J, Feng M, Ng D, et al. Detection of Pneumothorax with Deep Learning Models: Learning From Radiologist Labels vs Natural Language Processing Model Generated Labels. Acad Radiol, 2022; 29(9): 1350-1358.
6. Gipson J, Tang V, Seah J, et al. Diagnostic accuracy of a commercially available deep-learning algorithm in supine chest radiographs following trauma. Br J Radiol, 2022; 95(1134): 20210979.
7. Shamrat F, Azam S, Karim A, et al. LungNet22: A Fine-Tuned Model for Multiclass Classification and Prediction of Lung Disease Using X-ray Images. J Pers Med, 2022; 12(5).
8. Hong W, Hwang EJ, Lee JH, et al. Deep Learning for Detecting Pneumothorax on Chest Radiographs after Needle Biopsy: Clinical Implementation. Radiology, 2022; 303(2): 433-441.
9. Jin KN, Kim EY, Kim YJ, et al. Diagnostic effect of artificial intelligence solution for referable thoracic abnormalities on chest radiography: a multicenter respiratory outpatient diagnostic cohort study. Eur Radiol, 2022; 32(5): 3469-3479.
10. Kim S, Rim B, Choi S, et al. Deep Learning in Multi-Class Lung Diseases' Classification on Chest X-ray Images. Diagnostics (Basel), 2022; 12(4).
11. Wang X, Yang S, Lan J, et al. Automatic Segmentation of Pneumothorax in Chest Radiographs Based on a Two-Stage Deep Learning Method. IEEE Transactions on Cognitive and Developmental Systems, 2022; 14(1): 205-218.

12. Rudolph J, Huemmer C, Ghesu FC, et al. Artificial Intelligence in Chest Radiography Reporting Accuracy: Added Clinical Value in the Emergency Unit Setting Without 24/7 Radiology Coverage. Invest Radiol, 2022; 57(2): 90-98.

13. Mangalmurti Y, Wattanapongsakorn N. Practical Machine Learning Techniques for COVID-19 Detection Using Chest. Intelligent Automation and Soft Computing, 2022: 733-752.

14. Kakkar B, Johri P, Kumar Y, et al. An IoMT-Based Federated and Deep Transfer Learning Approach to the Detection of Diverse Chest Diseases Using Chest X-Rays. HUMAN-CENTRIC COMPUTING AND INFORMATION SCIENCES, 2022; 12.

15. Iqbal T, Shaukat A, Akram MU, et al. A Hybrid VDV Model for Automatic Diagnosis of Pneumothorax Using Class-Imbalanced Chest X-Rays Dataset. IEEE Access, 2022; 10: 27670-27683.

16. Feng S, Liu Q, Patel A, et al. Automated pneumothorax triaging in chest X-rays in the New Zealand population using deep-learning algorithms. J Med Imaging Radiat Oncol, 2022.

17. Thian YL, Ng DW, Hallinan J, et al. Effect of Training Data Volume on Performance of Convolutional Neural Network Pneumothorax Classifiers. J Digit Imaging, 2022; 35(4): 881-892.

18. Lee CC, Lin CS, Tsai CS, et al. A deep learning-based system capable of detecting pneumothorax via electrocardiogram. Eur J Trauma Emerg Surg, 2022; 48(4): 3317-3326.

19. Tian Y, Wang J, Yang W, et al. Deep multi-instance transfer learning for pneumothorax classification in chest X-ray images. Med Phys, 2022; 49(1): 231-243.

20. Seah J, Tang C, Buchlak QD, et al. Do comprehensive deep learning algorithms suffer from hidden stratification? A retrospective study on pneumothorax detection in chest radiography. BMJ Open, 2021; 11(12): e053024.

21. Kuo PC, Tsai CC, López DM, et al. Recalibration of deep learning models for abnormality detection in smartphone-captured chest radiograph. NPJ Digit Med, 2021; 4(1): 25.

22. Hong M, Rim B, Lee H, et al. Multi-Class Classification of Lung Diseases Using CNN Models. Applied Sciences, 2021; 11(19): 9289.

23. Rueckel J, Huemmer C, Fieselmann A, et al. Pneumothorax detection in chest radiographs: optimizing artificial intelligence system for accuracy and confounding bias reduction using in-image annotations in algorithm training. Eur Radiol, 2021; 31(10): 7888-7900.

24. Cho Y, Park B, Lee SM, et al. Optimal number of strong labels for curriculum learning with convolutional neural network to classify pulmonary abnormalities in chest radiographs. Comput Biol Med, 2021; 136: 104750.

25. Niehues SM, Adams LC, Gaudin RA, et al. Deep-Learning-Based Diagnosis of Bedside Chest X-ray in Intensive Care and Emergency Medicine. Invest Radiol, 2021; 56(8): 525-534.

26. Kao CY, Lin CY, Chao CC, et al. Automated Radiology Alert System for Pneumothorax Detection on Chest Radiographs Improves Efficiency and Diagnostic Performance. Diagnostics (Basel), 2021; 11(7).

27. Mosquera C, Diaz FN, Binder F, et al. Chest x-ray automated triage: A semiologic approach designed for clinical implementation, exploiting different types of labels through a combination of four Deep Learning architectures. Comput Methods Programs Biomed, 2021; 206: 106130.

28. Wang Y, Sun L, Jin Q. Enhanced Diagnosis of Pneumothorax with an Improved Real-Time Augmentation for Imbalanced Chest X-rays Data Based on DCNN. IEEE/ACM Trans Comput Biol Bioinform, 2021; 18(3): 951-962.

29. Nam JG, Kim M, Park J, et al. Development and validation of a deep learning algorithm detecting 10 common abnormalities on chest radiographs. Eur Respir J, 2021; 57(5).

30. Choi SY, Park S, Kim M, et al. Evaluation of a deep learning-based computer-aided detection algorithm on chest radiographs: Case-control study. Medicine (Baltimore), 2021; 100(16): e25663.

31. Lyu W, Xia F, Zhou C, et al. Application of deep learning-based chest CT auxiliary diagnosis system in emergency trauma patients. Zhonghua yi xue za zhi, 2021; 101(7): 481-486.

32. Kim EY, Kim YJ, Choi WJ, et al. Performance of a deep-learning algorithm for referable thoracic abnormalities on chest radiographs: A multicenter study of a health screening cohort. PLoS One, 2021; 16(2): e0246472.

33. Li F, Shi JX, Yan L, et al. Lesion-aware convolutional neural network for chest radiograph classification. Clin Radiol, 2021; 76(2): 155.e151-155.e114.

34. Thian YL, Ng D, Hallinan J, et al. Deep Learning Systems for Pneumothorax Detection on Chest Radiographs: A Multicenter External Validation Study. Radiol Artif Intell, 2021; 3(4): e200190.

35. Abedalla A, Abdullah M, Al-Ayyoub M, et al. Chest X-ray pneumothorax segmentation using U-Net with EfficientNet and ResNet architectures. PeerJ Comput Sci, 2021; 7: e607.

36. Sung J, Park S, Lee SM, et al. Added Value of Deep Learning-based Detection System for Multiple Major Findings on Chest Radiographs: A Randomized Crossover Study. Radiology, 2021; 299(2): 450-459.
37. Draelos RL, Dov D, Mazurowski MA, et al. Machine-learning-based multiple abnormality prediction with large-scale chest computed tomography volumes. Med Image Anal, 2021; 67: 101857.
38. Wang H, Wang S, Qin Z, et al. Triple attention learning for classification of 14 thoracic diseases using chest radiography. Med Image Anal, 2021; 67: 101846.
39. Rueckel J, Trappmann L, Schachtner B, et al. Impact of Confounding Thoracic Tubes and Pleural Dehiscence Extent on Artificial Intelligence Pneumothorax Detection in Chest Radiographs. Invest Radiol, 2020; 55(12): 792-798.
40. Chen KC, Yu HR, Chen WS, et al. Diagnosis of common pulmonary diseases in children by X-ray images and deep learning. Sci Rep, 2020; 10(1): 17374.
41. Röhrich S, Schlegl T, Bardach C, et al. Deep learning detection and quantification of pneumothorax in heterogeneous routine chest computed tomography. Eur Radiol Exp, 2020; 4(1): 26.
42. Wang H, Gu H, Qin P, et al. CheXLocNet: Automatic localization of pneumothorax in chest radiographs using deep convolutional neural networks. PLoS One, 2020; 15(11): e0242013.
43. Yi PH, Kim TK, Yu AC, et al. Can AI outperform a junior resident? Comparison of deep neural network to first-year radiology residents for identification of pneumothorax. Emerg Radiol, 2020; 27(4): 367-375.
44. Hwang EJ, Hong JH, Lee KH, et al. Deep learning algorithm for surveillance of pneumothorax after lung biopsy: a multicenter diagnostic cohort study. Eur Radiol, 2020; 30(7): 3660-3671.
45. Kitamura G, Deible C. Retraining an open-source pneumothorax detecting machine learning algorithm for improved performance to medical images. Clin Imaging, 2020; 61: 15-19.
46. Park S, Lee SM, Lee KH, et al. Deep learning-based detection system for multiclass lesions on chest radiographs: comparison with observer readings. Eur Radiol, 2020; 30(3): 1359-1368.
47. Wang H, Jia H, Lu L, et al. Thorax-Net: An Attention Regularized Deep Neural Network for Classification of Thoracic Diseases on Chest Radiography. IEEE J Biomed Health Inform, 2020; 24(2): 475-485.
48. Elkins A, Freitas FF, Sanz V. Developing an app to interpret chest X-rays to support the diagnosis of respiratory pathology with artificial intelligence. Journal of Medical Artificial Intelligence, 2020; 3.

49. Lai KHA, Ma SK. Sensitivity and specificity of artificial intelligence with Microsoft Azure in detecting pneumothorax in emergency department: A pilot study. Hong Kong Journal of Emergency Medicine, 2020; 0(0): 1024907920948994.

50. Majkowska A, Mittal S, Steiner DF, et al. Chest Radiograph Interpretation with Deep Learning Models: Assessment with Radiologist-adjudicated Reference Standards and Population-adjusted Evaluation. Radiology, 2020; 294(2): 421-431.

51. Li X, Thrall JH, Digumarthy SR, et al. Deep learning-enabled system for rapid pneumothorax screening on chest CT. Eur J Radiol, 2019; 120: 108692.

52. Park S, Lee SM, Kim N, et al. Application of deep learning-based computer-aided detection system: detecting pneumothorax on chest radiograph after biopsy. Eur Radiol, 2019; 29(10): 5341-5348.

53. Liang X, Peng C, Qiu B, et al. Dense networks with relative location awareness for thorax disease identification. Med Phys, 2019; 46(5): 2064-2073.

54. Hwang EJ, Park S, Jin KN, et al. Development and Validation of a Deep Learning-Based Automated Detection Algorithm for Major Thoracic Diseases on Chest Radiographs. JAMA Netw Open, 2019; 2(3): e191095.

55. Taylor AG, Mielke C, Mongan J. Automated detection of moderate and large pneumothorax on frontal chest X-rays using deep convolutional neural networks: A retrospective study. PLoS Med, 2018; 15(11): e1002697.

56. Rajpurkar P, Irvin J, Ball RL, et al. Deep learning for chest radiograph diagnosis: A retrospective comparison of the CheXNeXt algorithm to practicing radiologists. PLoS Med, 2018; 15(11): e1002686.

57. Cicero M, Bilbily A, Colak E, et al. Training and Validating a Deep Convolutional Neural Network for Computer-Aided Detection and Classification of Abnormalities on Frontal Chest Radiographs. Invest Radiol, 2017; 52(5): 281-287.

58. Chen B, Li J, Guo X, et al. DualCheXNet: dual asymmetric feature learning for thoracic disease classification in chest X-rays. Biomedical Signal Processing and Control, 2019; 53: 101554.

59. Zhou Y, Zhou T, Zhou T, et al. Contrast-Attentive Thoracic Disease Recognition With Dual-Weighting Graph Reasoning. IEEE Trans Med Imaging, 2021; 40(4): 1196-1206.

60. Luo JX, Liu WF, Yu L. Pneumothorax Recognition Neural Network Based on Feature Fusion of Frontal and Lateral Chest X-Ray Images. IEEE Access, 2022; 10: 53175-53187.

61. Lin CH, Wu JX, Li CM, et al. Enhancement of Chest X-Ray Images to Improve Screening Accuracy Rate Using Iterated Function System and Multilayer Fractional-Order Machine Learning Classifier. IEEE Photonics Journal, 2020; 12(4): 1-18.

62. Haq NF, Moradi M, Wang ZJ. A deep community based approach for large scale content based X-ray image retrieval. Med Image Anal, 2021; 68: 101847.

63. Wang Q, Liu Q, Luo G, et al. Automated segmentation and diagnosis of pneumothorax on chest X-rays with fully convolutional multi-scale ScSE-DenseNet: a retrospective study. BMC Med Inform Decis Mak, 2020; 20(Suppl 14): 317.