Original article

The Value of Artificial Intelligence on the Detection of Pathologies in Chest Radiographs Compared with High Resolution Multi Slice Computed Tomography

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Abstract

Background: Over the last few years, there has been increasing interest in the use of deep learning algorithms to assist with abnormality detection on medical images. **Aim of this study** was to investigate the performance of Artificial Intelligence on the detection of pathologies in chest radiographs compared with high resolution multi slice Computed Tomography. **Methods**: this prospective study was done on 200 cases, who underwent automatic detection of chest disease based on chest radiography in a comprehensive survey on computer-aided detection systems, focuses on the artificial intelligence technology applied in chest radiography to detect the presence of different pathologies, including pleural effusion, pneumothorax, pneumonia, pulmonary masses, and nodules in AP and PA -view chest radiographs using modern digital radiography. Using high resolution multi slice Computed Tomography (16/64/128 detector) for chest examination for abnormality detected by artificial intelligence technology. Axial scanning extending from base of the neck down below the diaphragm with coronal & sagittal reformate images**. Results:** The mean age of patients was 46.3 years. 123 patients (61.5 %) were males and 77 patients (38.5 %) were female. There was a statistically significant difference between CAD and MDCT diagnosed by radiologist according to sensitivity, $p<0.001$. **Conclusion:** In spite CAD system has established fair accuracy, the need of more accurate algorithm is necessary to determine if it can replicate MDCT and radiologist observation of abnormality on chest X-rays

Keywords: Artificial Intelligence; chest radiographs High Resolution; Multi slice; CT

Introduction

Chest radiography is the most common type of imaging examination in the world, with over 2 billion procedures performed each year. This technique is critical for screening, diagnosis, and management of thoracic diseases, many of which are among the leading causes of mortality worldwide (1).

A computer system to interpret chest radiographs as effectively as practicing radiologists could thus provide substantial benefit in many clinical settings, from improved workflow prioritization and clinical decision support to large-scale screening and global population health initiatives (2).

Artificial Intelligence is an algorithm (machine learning) that is of limited use today being deployed inside clinical practice for radiologists. , it is continuing to grow and develop, creating inroads into improving workflow efficiency and productivity and over the next 10-15 years, we'll see Artificial Intelligence solving things that are difficult to solve today (3).

However, the recent advancements in Artificial Intelligence have enabled algorithms to match the performance of professional radiologist in detection of lung nodule, pneumonia, lung fibrosis & pneumothorax. (4)

The High Resolution Multi slice Computed Tomography is the gold standard investigation for the evaluation of the pleura & lung. This imaging test is often done to follow up on abnormal findings from earlier chest X- rays and allowing radiologist to see small details that would not be possible with chest X- ray films. (5)

This study aimed to investigate the performance of Artificial Intelligence on the detection of pathologies in chest radiographs compared with High Resolution Multi slice Computed Tomography.

Patients and methods

This prospective study enrolled cases from Benha university hospital radiology department & other medical centers. All patients were selected from Benha University Hospitals, during the period from September 2019 to October 2020.

After approval from ethical committee, an informed consent was obtained from all patients in this research. All data of patients had been confidential with secret codes and private file for each patient. Every patient received an explanation for the purpose of the study. All given data were used for the current medical research only.

To establish sensitivity at an expected value of 80% at 10% precision and 95% CI, the sample size: to be read is approximately 200.

Inclusion criteria :

1. Plain chest X- rays with modern digital radiograph only in AP and PA views.
2. Adult patients above 18 years old
3. Any sex
4. Patients who are fit for CT scan

Exclusion criteria

1. Any patient less than 18 years old
2. Patient who are not fit for CT scan
3. Uncooperative patient or who refuse to participate in this study

Automatic detection of chest disease based on chest radiography in a comprehensive survey on computer-aided detection systems, focuses on the artificial intelligence technology applied in chest radiography to detect the presence of different pathologies, including pleural effusion, pneumothorax, pneumonia, pulmonary masses, and nodules in AP and PA -view chest radiographs using modern digital radiography.

Using High Resolution Multi slice Computed Tomography (16/64/128 detector) for chest examination for abnormality detected by artificial intelligence technology. Axial scanning extending from base of the neck down below the diaphragm with coronal & sagittal reformate images.

Images were inspected in a routine , standardized fashion to insure that small details were not missed. The findings analyzed & compare with the abnormality detected or missed by computer-aided detection systems (artificial intelligence technology). Analysis including the morphology of the abnormality and the score possibility in the artificial intelligence system.

Statistical analysis

This study is a combination of individual diagnostic tests for each of the target findings. The collected data was revised, coded, tabulated and introduced to a PC using Statistical package for Social Science (IBM Corp. Released 2017. IBM SPSS Statistics for Windows, Version 25.0. Armonk, NY: IBM Corp.). Data were presented and suitable analysis was done according to the type of data obtained for each parameter. Descriptive statistics: Frequency and percentage of non-numerical data. Shapiro test was done to test the normality of data distribution. Significant data was considered to be nonparametric. Analytical statistics: Student T Test was used to assess the statistical significance of the difference between two study group means. *Sensitivity*: probability that a test result will be positive when the disease is present (true positive rate).= a / (a+b), *Specificity*: probability that a test result will be negative when the disease is not present (true negative rate).= d / (c+d), *Positive likelihood ratio*: ratio between the probability of a positive test result given the *presence* of the disease and the probability of a positive test result given the *absence* of the disease, i.e.= True positive rate / False positive rate = Sensitivity / (1-Specificity), *Negative likelihood ratio*: ratio between the probability of a negative test result given the *presence* of the disease and the probability of a negative test result given the *absence* of the disease, i.e. False negative rate / True negative rate = (1-Sensitivity) / Specificity, Sensitivity, specificity, disease prevalence, positive and negative predictive value as well as accuracy are expressed as percentages.

Confidence intervals for sensitivity, specificity and accuracy are "exact" Clopper-Pearson confidence intervals. N.B: *p* is significant if <0.05 at confidence interval 95%.

Results

The mean age of patients was 46.3 years. 123 patients (61.5 %) were males and 77 patients (38.5 %) were females (**Table, 1).**

Details of total prevalence of chest pathologies in digital plain X-ray diagnosed by CAD are illustrated in **figure 1.**

Details of total prevalence of chest pathologies in MDCT diagnosed by Radiologist, are illustrated in **figure 2.**

Table 2, shows analysis of chest pathologies in digital plain X-ray diagnosed by CAD compared to radiologist final diagnosis.

According to Sensitivity of CAD , it was 89.38% for Normal findings , 88.41% for Rt lung, 90.10% for Lt lung, 97.22% for Cavity/Bulli/Bronchiactatic, 95.48% for Consolidation, 93.81% for Ground glass, 87.69% for Fibrosis/ linear/shadow, 75.00% for calcification, and 100.00% for Mass/Soft tissue detection. According to Specificity of CAD , it was 80% for Normal findings , 98.39% for Rt lung, 95.96% for Lt lung, 100% for Cavity/Bulli/Bronchiactatic, 100% for Consolidation, 100% for Ground glass, 100% for Fibrosis/ linear/shadow, 100% for calcification, and 100.00% for Mass/Soft tissue detection. According to Accuracy of CAD , it was 80.94% for Normal findings , 97.39% for Rt lung, 95.37% for Lt lung, 99.72% for Cavity/Bulli/Bronchiactatic, 99.55% for Consolidation, 99.38% for Ground glass, 98.77% for Fibrosis/ linear/shadow, 97.5% for calcification, and 100.00% for Mass/Soft tissue detection, (**Table 3).**

There was a statistically significant difference between CAD and MDCT diagnosed by radiologist according to sensitivity as shown in **table 4.**

Case (1) A 19 year old female presented with repeated cough (Fig. 3).

Case (2) Negative artificial intelligence, (Fig. 4).

Table (1) General characteristic

Age (years)	Mean ±SD	46.3 ±8.2
	Range	18 - 81
Gender	Males n (%)	123 (61.5)
	Females n (%)	77 (38.5)
Total		200

Table (2): Analysis of chest pathologies in Digital plain X-ray diagnosed by CAD compared to MDCT diagnosed by the radiologist

	True positive	**True negative**	**False positive**	**False negative**
Normal	143	32	8	17
Rt lung	122	61	1	16
Lt lung	91	95	4	10
Cavity/Bulli/Bronchiectasis	35	164	0	1
Consolidation	169	23	0	8
Ground glass	91	103	0	6
Fibrosis/ linear/shadow	57	135	0	8
calcification	6	192	0	2
Mass/Soft tissue	8	192	0	0

Table (3): Validity of CAD in diagnosis of CXR pathologies of the chest

95% CI Validity	Sensitivity (%)	Specificity (%)	Positive Likelihood Ratio	Negative Likelihood Ratio	Accuracy (%)
Normal	89.38	80.00	4.47	0.13	80.94
Rt lung	88.41	98.39	54.81	0.12	97.39
Lt lung	90.10	95.96	22.30	0.10	95.37
Cavity/Bulli/Bronchiectasis	97.22	100.00	-	0.03	99.72
Consolidation	95.48	100.00	-	0.05	99.55
Ground glass	93.81	100.00	-	0.06	99.38
Fibrosis/ linear/shadow	87.69	100.00	-	0.12	98.77
calcification	75.00	100.00	-	0.25	97.50
Mass/Soft tissue	100.00	100.00	-	0	100.00

Table (4) Comparison between X RAY CAD system used and MDCT diagnosed by radiologist according to Sensitivity, Specificity and Accuracy

	X RAY	MDCT	T	P
Sensitivity (%)	90.79	**100**	**3.79**	**<0.001**
Specifity (%)	97.15	**100**	**1.30**	**0.105**
Accuracy (%)	96.51	**100**	**1.74**	**0.051**

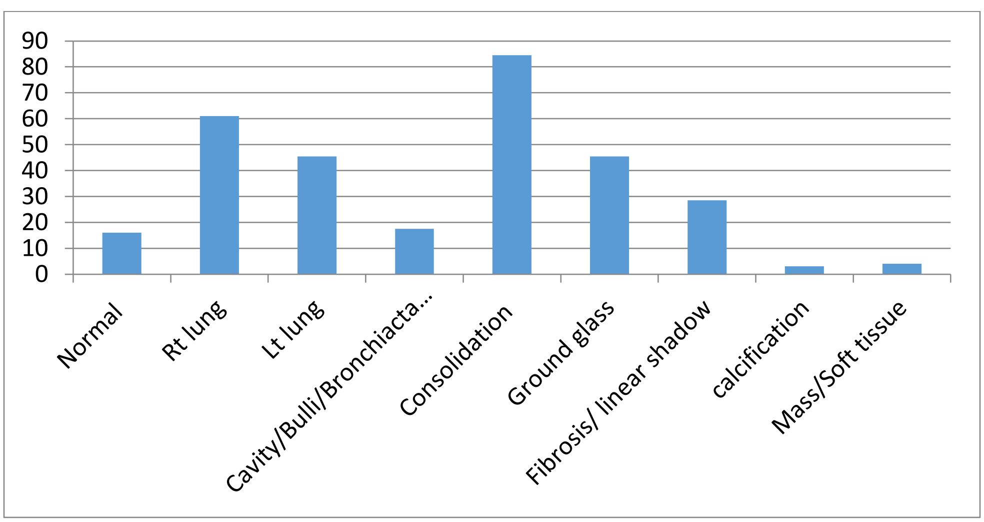

Figure (1) Total prevalence of chest pathologies in Digital plain X-ray diagnosed by CAD

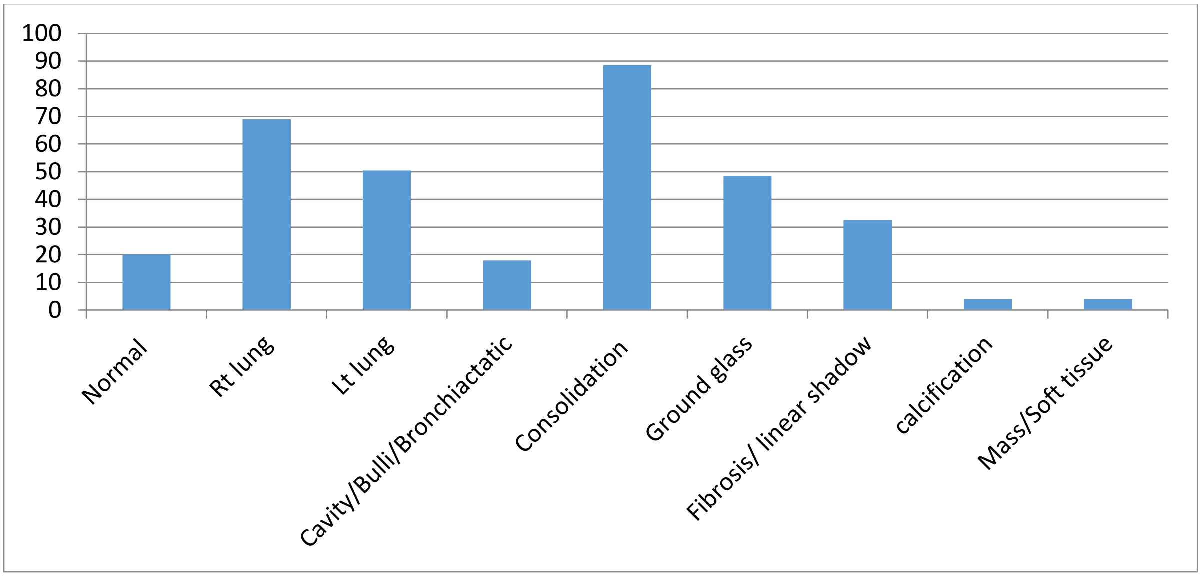

Figure (2) Total prevalence of chest pathologies in MDCT diagnosed by Radiologist

Figure 3: Case (1) A 19 years old female presented with repeated cough. Figure 3

Chest X Ray erect PA view shows linear shadows with bronchiectasis at the RT. lower zone.

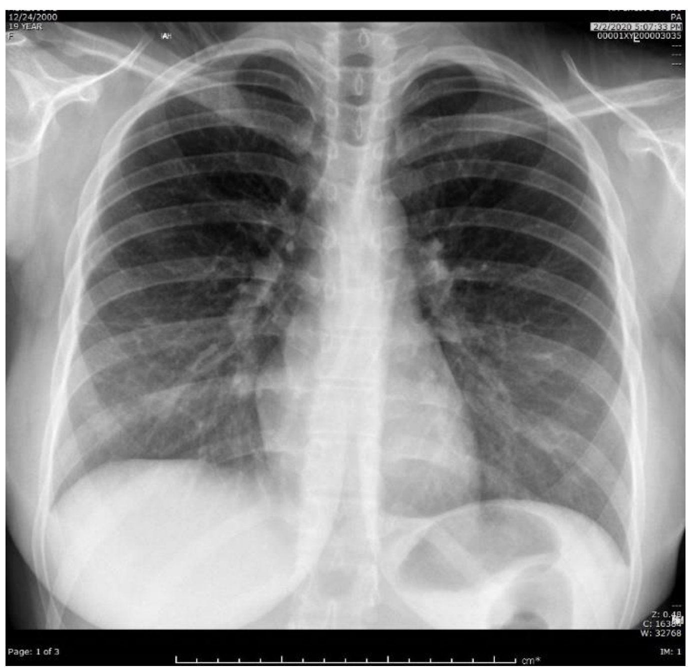

Figure 3a: chest X Ray in erect PA view

AI image mark abnormality at the RT. Mid /lower zones peripherally located. (Figure 3b)

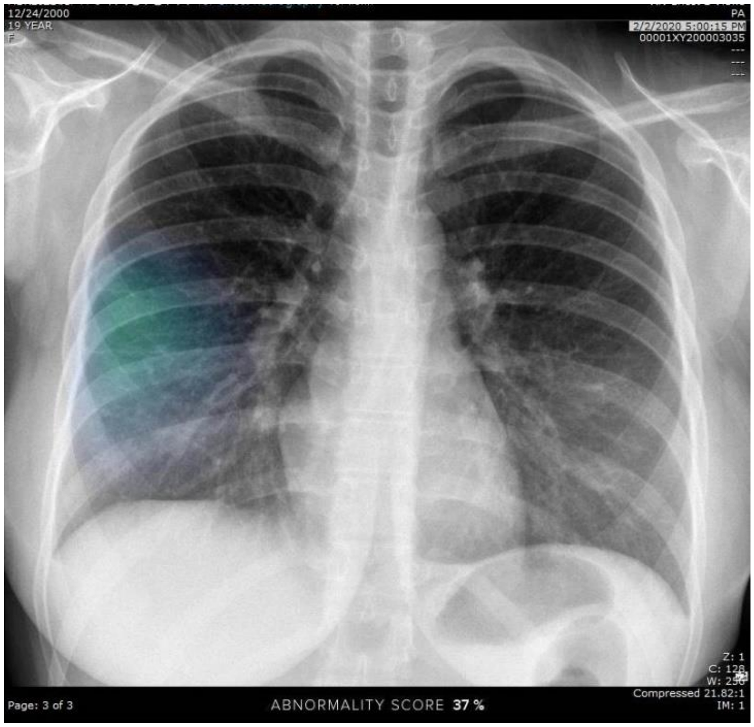

Figure 3b: Film in AI system.

Chest CT Scan was done and shows focal bronchiectasis with surrounding linear fibrotic & adjacent ground glass appearance & focal emphysematous changes in the RT. Middle & lower lobes.(Figure 3c)

Figure 3c : Chest CT Scan

Figure 4: **Case (2) Negative Artificial Intelligence.**

A 45 years old female presented with repeated cough. Chest X Ray erect PA view shows linear shadows with bronchiectasis at the RT. lower zone**.**

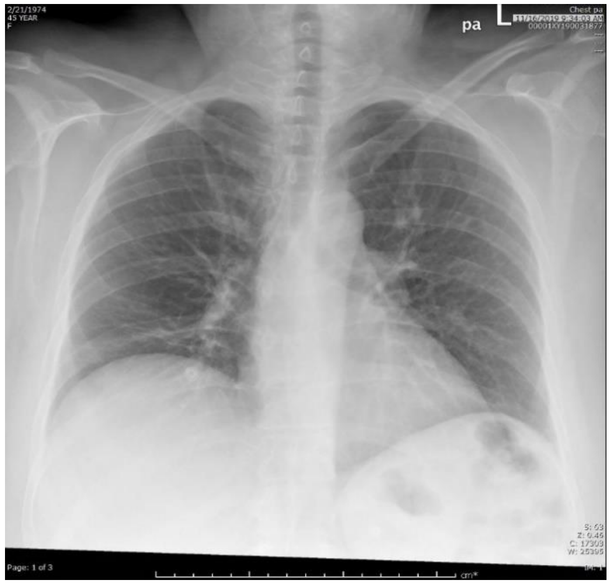

Figure 4a: chest X Ray in erect PA view

AI image shows no abnormality. (Figure 4b)

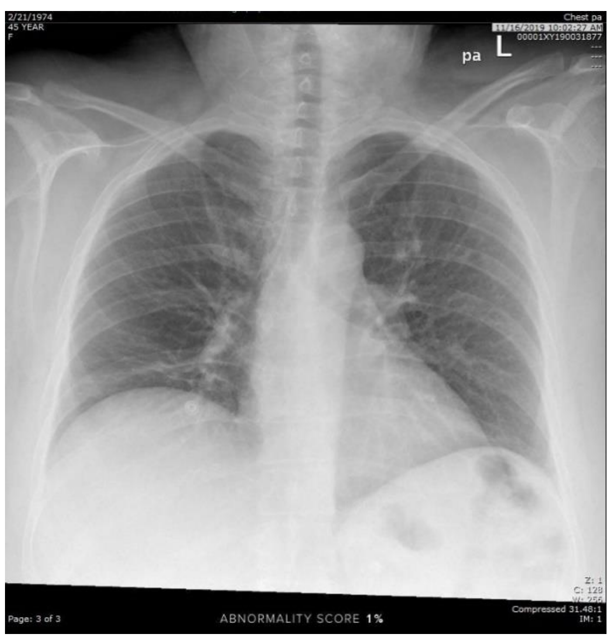

Figure 4b: Film in AI system**.**

Chest CT Scan was done and shows focal bronchiectasis with surrounding linear fibrotic & adjacent ground glass appearance in the RT. Middle lobe. (Figure 4c)

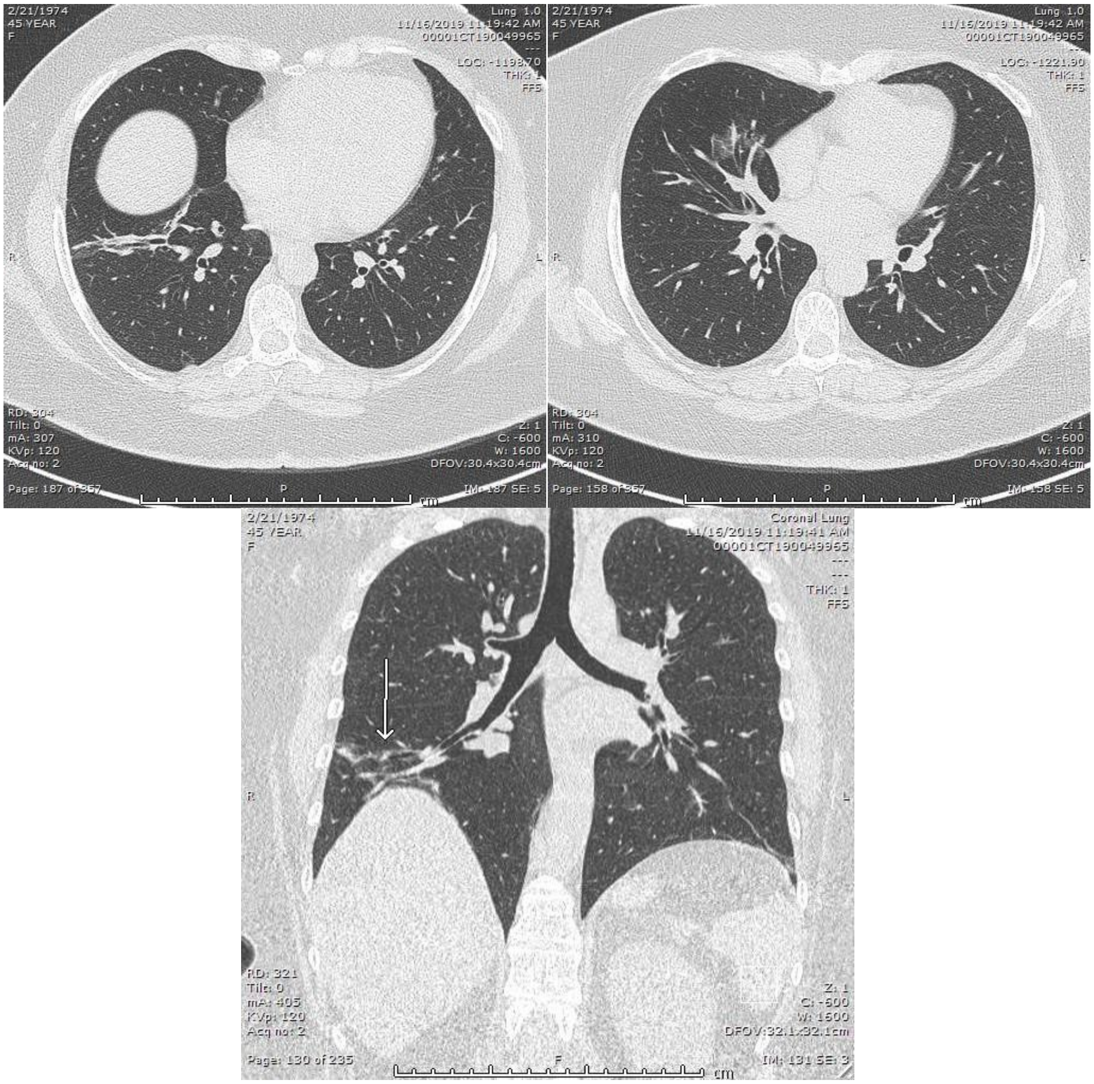

Figure 4c: Chest CT Scan

Discussion

Since the widespread developments of artificial intelligence (AI) in various fields, it is now used in hospitals. Together with advancements in computer vision, the combination of AI and computer vision provide interesting opportunities for the radiology department. In 1985, the term computer-aided detection (CAD) for the detection of pulmonary nodules was introduced (6). Current advances in computer vision for medical imaging show that combining AI with radiologists is beneficial (7).

For the evaluated combination scenarios of CAD plus readers, we observed a trade-off between specificity and sensitivity, or a trade-off between specificity – sensitivity. This study was established to investigate the performance of artificial intelligence on the detection of pathologies in chest radiographs compared with high resolution multi slice Computed Tomography. The mean age of patients was 46.3 years. 123 patients (61.5 %) were males and 77 patients (38.5 %) were females. There was a statistically significant difference between CAD and MDCT diagnosed by radiologist according to sensitivity, $p<0.001$.

Long before deep learning, automated chest X-ray interpretation using traditional image processing methods have been used to identify chest X-ray views, segment parts of the lung, identify cardiomegaly or lung nodules and diagnose tuberculosis. However, these traditional methods did not come into routine clinical use because of their need for standardized X-ray quality, machine model and images free of artefacts (8).

In 2017, two studies (9,10), bought attention to the use of deep learning to interpret chest X-ray images. Other researchers (11) used the chest X-ray 14 dataset, a single-source dataset containing 112,120 X-rays and NLP-generated labels for 14 thoracic diseases that was made publicly available by the NIH. Several groups used this dataset to train and validate deep learning algorithms with NLP-generated labels as ground truth and reported AUCs ranging from 0.69 to 0.91 for various abnormalities (12)**.**

Conclusion

In spite CAD system has established fair accuracy, the need of more accurate algorithm is necessary to determine if it can replicate MDCT and radiologist observation of abnormality on chest X-rays

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