Can Artificial Intelligence Reliably Report Chest X-Rays?
Radiologist Validation of an Algorithm trained on 1.2 Million X-Rays

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Abstract

Background and Objectives Chest x-rays are the most commonly performed, cost-effective diagnostic imaging tests ordered by physicians. A clinically validated, automated artificial intelligence system that can reliably separate normal from abnormal would be invaluable in addressing the problem of reporting backlogs and the lack of radiologists in low-resource settings. The aim of this study was to develop and validate a deep learning system to detect chest x-ray abnormalities.

Methods A deep learning system was trained on 1.2 million x-rays and their corresponding radiology reports to identify abnormal x-rays and the following specific abnormalities: blunted costophrenic angle, calcification, cardiomegaly, cavity, consolidation, fibrosis, hilar enlargement, opacity and pleural effusion. The system was tested versus a 3-radiologist majority on an independent, retrospectively collected de-identified set of 2000 x-rays. The primary accuracy measure was area under the ROC curve (AUC), estimated separately for each abnormality as well as for normal versus abnormal reports.

Results The deep learning system demonstrated an AUC of 0.93 (CI 0.92-0.94) for detection of abnormal scans, and AUC (CI) of 0.94(0.92-0.97), 0.88(0.85-0.91), 0.97(0.95-0.99), 0.92(0.82-1), 0.94(0.91-0.97), 0.92(0.88-0.95), 0.89(0.84-0.94), 0.93(0.92-0.95), 0.98(0.97-1), 0.93(0.90-0.99) for the detection of blunted costophrenic angle, calcification, cardiomegaly, cavity, consolidation, fibrosis, hilar enlargement, opacity and pleural effusion respectively.

Conclusions and Relevance Our study shows that a deep learning algorithm trained on a large quantity of well-labelled data can accurately detect abnormalities on chest x-rays. As these systems further increase in accuracy, the feasibility of using artificial intelligence to extend the reach of chest x-ray interpretation and improve reporting efficiency will increase in tandem.

1 Introduction

Chest x-rays are the most commonly ordered diagnostic imaging tests, with millions of x-rays performed globally every year[1]. While the chest x-ray is frequently performed, interpreting a chest x-ray is one of the most subjective and complex of radiology tasks, with inter-reader agreement varying from a kappa value of 0.2 to 0.77, depending on the level of experience of the reader, the abnormality being detected and the clinical setting[2,5]. Due to their wide availability and affordability, chest x-rays are performed all over the world, including remote areas with few or no radiologists. In some parts of the world, digital chest x-ray machines are more widely available than personnel sufficiently trained to report the x-rays they generated[6,7]. If automated detection can be applied in low-resource settings as a disease screening tool, the benefits to population health outcomes globally could be significant. An example of the use of chest x-rays as a screening tool is in tuberculosis screening, where chest x-rays, in the hands of expert readers, are more sensitive than clinical symptoms for the early detection of tuberculosis[8].
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\cite{9,11}. This is a natural consequence of the rapidly growing ability of machines to interpret natural images and detect objects in them. On chest x-rays in particular, there have been a series of studies describing the use of deep learning algorithms to detect various abnormalities\cite{12,14}. Most of these have been limited by the lack of availability of large, high-quality datasets with the largest published work describing an algorithm that has been trained on 112,120 x-rays \cite{13,14}, a relatively small number considering that the majority of chest x-rays are normal, abnormal x-rays are less common and specific abnormalities being rarer still. The previously published work on deep learning for chest x-ray abnormality detection has not made a distinction between the diagnosis of ‘diseases’ and the detection of ‘abnormal findings’. Our approach was to focus on the detection of abnormalities on the x-ray that can be detected visually by an expert without the benefit of the clinical history. This would allow the system to be applied across geographies and differing disease prevalence.

In this paper, we describe the training and radiologist validation of a deep learning system to detect and identify chest x-ray abnormalities. We trained the system on 1.2 million x-rays and tested it against the majority vote of a panel of 3 radiologists on an independent dataset containing 2000 studies. Abnormalities on chest x-rays range from very small lesions to diffuse abnormalities that cover large parts of the lung. The optimal deep learning model architecture differs based on the abnormality being detected; hence, we developed and tested a system that uses an individual algorithm for each abnormality.

2 Methods

2.1 Algorithm Development

We used 1.2 million chest x-rays and their corresponding radiology reports to train convolutional neural networks (CNNs) to identify chest x-ray abnormality. We developed natural language processing (NLP) algorithms to parse unstructured radiology reports and extract information about the presence and nature of chest x-ray abnormality. These extracted findings were used as labels when training CNNs. Individual networks were trained to identify normal x-rays, and the following chest x-ray findings: ‘blunted CP angle’, ‘calcification’, ‘cardiomegaly’, ‘cavity’, ‘consolidation’, ‘fibrosis’, ‘hilar enlargement’, ‘opacity’ and ‘pleural effusion’.

2.1.1 Pre-processing and Data Augmentation

The training dataset was obtained from 27 centers, and contained chest x-rays that varied considerably in size, resolution and quality. All x-rays were down-sampled and resized to a standard size. A set of image normalization techniques was applied to these images to reduce source-dependent variation. Additionally, a number of abnormality-specific data augmentation techniques were applied. The aim of data augmentation is to generate a dataset that can be used to train models so they are unaffected by variability in x-ray machine manufacturer, model, voltage, exposure and other parameters that vary from center to center.

2.1.2 Architecture and Training

The basic blocks in the systems that detect individual abnormalities are versions of densenets\cite{15} or resnests\cite{16} that are modified to process information at a significantly higher resolution than their vanilla versions. All the classification models that build up the individual abnormality detection systems are pre-trained on the task of separating chest x-rays from x-rays of other body parts rather than the popular ImageNet pre-training. This step is aimed at making use of the super-set consisting of all the x-rays. We observed improved model convergence and incremental gains in generalization performance when compared to ImageNet pre-training.

2.1.3 Use of Model Ensembles

Ensembling is a simple way of improving generalization performance by combining the predictions produced by a set of models. Multiple models are trained to detect each abnormality. These models differ with respect to the architecture used, model initialization conditions and the distribution of the training dataset. A subset of these models is selected using various heuristics\cite{17} and a majority
Table 1: Source of x-rays used for the study

| Pool  | Center          | Date               |
|-------|-----------------|--------------------|
| Pool 1| CAH-Salt Lake   | 16-08-2017 to 31-08-2017 |
|       | CAH-Pune        | 07-09-2017 to 23-09-2017 |
|       | CAH-Mysore      | 10-07-2017 to 25-07-2017 |
| Pool 2| CAH-Pune        | 01-02-2013 to 31-07-2013 |

ensembling scheme is used to combine the predictions of these selected models to make a decision about the presence or absence of a particular abnormality.

2.2 Study Design

2.2.1 Data selection

A combination of out-patient and in-hospital x-rays from three Columbia Asia Hospitals (CAH) in India at Kolkata, Pune and Mysore were used to create two databases for the study, as described in Table 1. There was no overlap between these centers or the centers from where training data was obtained.

All data were de-identified before use in this study. Radiologist validation was performed in 2 phases, using a separate set of 1000 x-rays for each phase. Sample size calculations are explained in section 2.4.1 Chest x-rays were filtered as follows: all PA and AP view chest x-rays where a corresponding radiologist report was available were selected. From this set, x-rays from pediatric patients (< 14 years of age) and x-rays taken with the patient in the supine position (bedside/portable x-rays) were excluded. A set of 1000 x-rays (Set 1) was then selected randomly from Pool 1, with no enrichment of x-rays containing the abnormalities of interest. A second set of 1000 x-rays (Set 2) were sampled from Pool 2 to include a minimum of 80 examples of each abnormality and a random sample of the remaining x-rays. We used an NLP tool that parsed the x-ray radiology reports to implement the exclusions listed above, and to automate the sampling for phase 2. The study design is illustrated in Figure 1.

2.2.2 Inclusion and Exclusion criteria

PA and AP view chest x-rays from ambulatory adult patients taken in the standing position were included in the study. x-rays from patients under 14 years of age, x-rays taken in the supine position - from bedside or portable x-ray machines - were excluded. As a result, the datasets did not contain any x-rays with visible intravenous lines, tubes, catheters, ECG leads or any implanted medical devices such as pacemakers.

2.2.3 Abnormality definitions

To ensure that reviewing radiologists and the algorithm were using the same frame of reference for defining abnormalities, the definitions in Table 2.2 were used to extract tags from reports during the algorithm development phase and by the radiologists during the validation phase.

2.3 Validation of NLP algorithm and deep learning algorithms

2.3.1 Abnormality extraction from reports

We used a custom NLP to extract relevant findings from the original radiology reports. The NLP algorithm was constructed using a thoracic imaging glossary [18], curated by a panel of radiologists and combined with standard NLP tools to manage typographic errors, detect negations and identify synonyms. The custom NLP algorithm was iterated through trial and error and its accuracy checked on an independent dataset of 1000 chest x-rays against an expert reader who was provided with the tag definitions [2], original reports and the corresponding x-rays. These expert readers were blinded to the algorithm output.
2.3.2 Validation of deep learning algorithm: accuracy of abnormality detection

The x-rays were randomly divided among six certified radiologists (three pairs), with 3-15 years of radiology experience. A third read was available in the form of the original radiology report accompanying each chest x-ray. A custom validation portal was used for radiologist validation and contained the original resolution DICOM file. Radiologists marked ‘present’ or ‘absent’ for each abnormality. A pen tool was used to mark out the area affected and a text field was available for comments. The gold standard for this study was the majority opinion on the presence or absence of each abnormality between three radiologists’ reads. Algorithm accuracy on detecting abnormal x-rays and on each individual abnormality is reported versus this gold standard. Algorithm output was generated on both datasets and placed in a locked database, until completion of the radiologist validation. Radiologists were blinded to the original x-ray report and the algorithm output when reviewing the x-rays for the validation study.

2.4 Statistical Analysis

2.4.1 Sample size calculation

Calculating sensitivity and specificity precisely with a 95% confidence interval would require a sample size of approximately 20,000 in an un-enriched dataset randomly sampled from the population. We therefore used the enrichment strategy detailed in Section 2.2.1. The sample size required for estimating 80% sensitivity with 90% accuracy and 95% confidence interval is 951. Therefore, 2000 x-rays were considered sufficient to evaluate the classification of x-rays as normal or abnormal. Sensitivity was chosen over specificity for this sample size calculation as a false negative result is considered a worse outcome than a false positive in preliminary diagnostic investigations [19].

Figure 1: Study Design.
abnormalities we studied have a prevalence of less than 5\% in the typical outpatient setting. A sample size of 951 x-rays would give 3\% precision for estimating 80\% specificity at 95\% confidence interval. Given a prevalence of less than 10\% for each of the specific conditions listed above, at least 77 true cases per condition would give a sensitivity of 80\% with 10\% precision and 95\% confidence interval. Therefore, we used a minimum of 80 true cases per condition for Set 2.

### 2.4.2 Algorithm performance measurements versus radiologists

When calculating AUC for a particular abnormality, we used Set 1 in its entirety and all x-rays positive for that abnormality from Set 2. This allowed us to use a sufficiently large number of ‘abnormality-positive’ cases for sensitivity calculation, while keeping the ratio of normal to abnormal x-rays close to the natural distribution. This also enabled a fairer estimation of specificity than using both sets combined and was equivalent to evaluating the accuracy of detection for each abnormality separately. The entire dataset \((n = 2000)\) was used when calculating AUC for detection of abnormal x-rays. We calculated AUC confidence intervals using the ‘distribution-based’ method described by Hanley and McNeil [20]. We measured the concordance between paired readers for each abnormality with percentage of agreement and the Cohen’s kappa(\(\kappa\)) statistic[21]. In addition, we measured concordance between all three readers for each finding using Fleiss’ kappa(\(\kappa\)) statistic[22]. Since readers were grouped into three pairs, each reported measure of inter-reader agreement is the average of three estimates.

### 3 Results

Basic demographics and the number of scans containing each abnormality are summarized in table 4. 658 out of 2000 x-rays were abnormal, with the most frequent abnormalities being ‘opacity’,
Table 3: Demographics of the study population

| Characteristic                     | Set1 (n = 1000) | Set2 (n = 1000) | Combined (n = 2000) |
|-----------------------------------|-----------------|-----------------|---------------------|
| **Patient Demographics**          |                 |                 |                     |
| Age                               |                 |                 |                     |
| No. of scans for which age was known | 803             | 1000            | 1803                |
| Mean                              | 48.04           | 50.61           | 49.32               |
| Standard deviation                | 18.69           | 17.93           | 18.36               |
| Range                             | 16 – 95         | 16 – 100        | 16 – 100            |
| No. of females / No. of scans for which sex was known (percentage) | 324/803 (40.3%) | 265/1000 (26.5%) | 589/1803 (32.6%) |
| **Prevalence**                    |                 |                 |                     |
| No. of scans (percentage) with    |                 |                 |                     |
| No abnormality detected (Normal)  | 440             | 218             | 658                 |
| Blunted CP angle                  | 35              | 121             | 156                 |
| Calcification                     | 57              | 244             | 301                 |
| Cardiomegaly                      | 61              | 116             | 177                 |
| Cavity                            | 1               | 15              | 16                  |
| Consolidation                     | 13              | 92              | 105                 |
| Fibrosis                          | 13              | 97              | 110                 |
| Hilar enlargement                 | 15              | 49              | 64                  |
| Opacity                           | 104             | 341             | 445                 |
| Pleural Effusion                  | 36              | 122             | 158                 |

Table 4: Demographics of the study population Based on a 3-reader consensus ground truth derived from original radiology report plus consensus of radiologists, as defined in section 2.2.3.

Table 4: Demographics of the study population

Achieving a high accuracy on report parsing enabled the use of a large number of x-rays to train the deep learning algorithms. Abnormality extraction accuracy from radiology reports versus manual extraction by a single reader is summarized in Table 5a. The algorithm was able to detect normal x-ray reports with a sensitivity of 0.94 and a specificity of 1 versus the expert reader. For detection of individual abnormalities from reports, sensitivity varied from 0.93 for pleural effusion to 1 for calcification and cavity; specificity varied from 0.92 for opacity to 0.99 for fibrosis.

3.1 Interradiologist Concordance

Inter-reader concordance is described in Table 5b. Concordance was highest on detection of abnormal x-rays (inter-reader agreement 85%, Cohen’s kappa 0.6, Fleiss’ kappa 0.56) and on the specific abnormalities pleural effusion (inter-reader agreement 85%, Cohen’s kappa 0.6, Fleiss’ kappa 0.56), cardiomegaly (inter-reader agreement 85%, Cohen’s kappa 0.6, Fleiss’ kappa 0.56), and calcification (inter-reader agreement 85%, Cohen’s kappa 0.6, Fleiss’ kappa 0.56).

3.2 Algorithm accuracy versus the majority opinion of 3 radiologists

The deep learning system accuracy at identifying each of the 12 abnormalities is listed in Table 6. The algorithm was able to detect normal x-ray reports with a sensitivity of 0.94 and a specificity of 1 versus the expert reader. For detection of individual abnormalities from reports, sensitivity varied from 0.93 for pleural effusion to 1 for calcification and cavity; specificity varied from 0.92 for opacity to 0.99 for fibrosis.

Table 6: Demographics of the study population

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| Finding                      | #Positives | Sensitivity (95% CI) | Specificity (95% CI) |
|-----------------------------|------------|----------------------|---------------------|
| Normal(No abnormality detected) | 105        | 0.9429 (0.8798-0.9787) | 1.0000 (0.9591-1.0000) |
| Blunted CP angle            | 146        | 0.9795 (0.9411-0.9957)  | 0.9824 (0.9712-0.9901) |
| Calcification               | 116        | 1.0000 (0.9687-1.0000)  | 0.9660 (0.9519-0.9770)  |
| Cardiomegaly                | 125        | 0.9920 (0.9562-0.9998)  | 0.9760 (0.9635-0.9851)  |
| Cavity                      | 30         | 1.0000 (0.8843-1.0000)  | 0.9856 (0.9709-0.9921)  |
| Consolidation               | 161        | 0.9876 (0.9558-0.9985)  | 0.9761 (0.9654-0.9854)  |
| Fibrosis                    | 124        | 0.9839 (0.9430-0.9980)  | 0.9931 (0.9851-0.9975)  |
| Hilar Enlargement           | 289        | 0.9689 (0.9417-0.9857)  | 0.9732 (0.9585-0.9838)  |
| Opacity                     | 612        | 0.9608 (0.9422-0.9747)  | 0.9251 (0.9142-0.9492)  |
| Pleural Effusion            | 246        | 0.9309 (0.8917-0.9592)  | 0.9602 (0.9436-0.9730)  |
| Total(all findings)         | 1954       | 0.9672 (0.9584-0.9747)  | 0.9771 (0.9736-0.9803)  |

(a) Tag extraction accuracy: performance of the NLP algorithm in inferring findings from the reports.

| Finding                      | Radiologist 1 & 2 Agreement % | Cohen’s $\kappa$ | All reads Fleiss’ $\kappa$ |
|-----------------------------|--------------------------------|------------------|-----------------------------|
| Normal(No abnormality detected) | 85.00                          | 0.6049           | 0.5618                       |
| Blunted CP angle            | 83.58                          | 0.2968           | 0.3054                       |
| Calcification               | 83.00                          | 0.5803           | 0.5821                       |
| Cardiomegaly                | 91.60                          | 0.5333           | 0.5284                       |
| Cavity                      | 97.50                          | 0.3824           | 0.4047                       |
| Consolidation               | 88.28                          | 0.3529           | 0.3397                       |
| Fibrosis                    | 89.40                          | 0.3781           | 0.3495                       |
| Hilar Enlargement           | 89.38                          | 0.2630           | 0.2101                       |
| Opacity                     | 70.70                          | 0.2306           | 0.1733                       |
| Pleural Effusion            | 90.69                          | 0.5341           | 0.5305                       |

(b) Concordance between the readers.

Table 5: Reliability of the gold standard: Abnormality extraction accuracy from radiology reports versus manual extraction by a single reader is summarized in table 5a. Inter-reader concordance is described in table 5b.
Figure 2: AUC curves for all abnormalities versus a 3-radiologist majority, with reader performance marked.
### Table 6: Performance of the algorithms

| Finding                  | AUC (95% CI)                          | High sensitivity operating point | High specificity operating point |
|--------------------------|---------------------------------------|-----------------------------------|-----------------------------------|
|                          |                                       | Sensitivity | Specificity | Sensitivity | Specificity |
| Normal (No Abnormality Detected) | 0.9278 (0.9162-0.9394) | 0.9100     | 0.7519      | 0.8192      | 0.9086      |
| Blunted CP angle         | 0.9434 (0.9179-0.9690) | 0.9487     | 0.7692      | 0.8461      | 0.9100      |
| Calcification            | 0.8812 (0.8550-0.9073) | 0.9069     | 0.6550      | 0.6511      | 0.8912      |
| Cardiomegaly             | 0.9670 (0.9484-0.9856) | 0.9717     | 0.8636      | 0.8474      | 0.9284      |
| Cavity                   | 0.9351 (0.8511-1.0000) | 0.9375     | 0.7528      | 0.8125      | 0.9850      |
| Consolidation            | 0.9394 (0.9074-0.9714) | 0.9047     | 0.7921      | 0.8285      | 0.9049      |
| Fibrosis                 | 0.9171 (0.8810-0.9532) | 0.9000     | 0.7072      | 0.7818      | 0.9011      |
| Hilar Enlargement        | 0.8908 (0.8379-0.9437) | 0.9218     | 0.7509      | 0.6718      | 0.8907      |
| Opacity                  | 0.9324 (0.9155-0.9493) | 0.9033     | 0.7836      | 0.8000      | 0.9011      |
| Pleural Effusion         | 0.9841 (0.9703-0.9979) | 0.9810     | 0.8355      | 0.8797      | 0.9660      |

### 4 Discussion

Long before deep learning, automated chest x-ray interpretation using traditional image processing methods have been used to identify chest-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\([23, 28]\). With the advent of convolutional neural networks and deep learning, there has been a resurgence of interest in automated chest x-ray interpretation with many research groups leveraging convolutional neural networks to detect pneumonia, tuberculosis and other chest diseases\([12, 14, 29, 31]\).

In 2017, Shin et al.\([12]\) used a combination of convolutional neural networks and recurrent neural networks to identify, caption and describe the context of chest x-ray abnormalities, but were limited by the small size of training datasets that were publicly available. Subsequently, Lakhani and Sundaram\([29]\) trained convolutional neural networks to detect tuberculosis and reported an AUC of 0.99 that was achieved with a small training dataset of 857 x-rays and a test dataset of 150 x-rays. This exceptionally high accuracy has not been replicated by any other group. In 2017, Wang et al.\([30]\) used the Chestx-ray14 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. They 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\([13, 14, 30, 31]\). Using the same Chestx-ray14 dataset, Rajapurkar et al trained their algorithm ‘CheXNet’ to detect pneumonia and validated it against a dataset of 420 x-rays independently reported by Stanford Radiologists. They found that the algorithm outperformed Radiologists in detecting pneumonia\([13]\). The lack of large, reliable, openly available chest x-ray datasets with radiologist-confirmed ground truth makes it difficult to benchmark deep learning algorithms.

Ours is the largest chest x-ray training and testing dataset reported in the literature: we trained a deep learning algorithm on 1.2 million chest x-rays, and validated it against 2000 chest x-rays labelled by a 3-radiologist majority. For determining algorithm accuracy, the 2000 chest x-ray dataset was used, separate from the training dataset and sourced from a separate centre. The algorithm
achieved an AUC of 0.93 for differentiating normal from abnormal chest x-rays, while the AUC for detection of individual abnormalities varied from 0.86 to 0.98. AUCs were higher for abnormalities with higher prevalence in the dataset, greater inter-reader agreement and consistency of reporting terminology. The highest accuracy was achieved for findings that were unambiguously defined and reported with consistent terminology, such as pleural effusion or cardiomegaly. Unlike previous algorithms trained to make a diagnosis, our chest x-ray algorithm was trained to identify abnormal findings and differentiate normal from abnormal. We did this to facilitate clinical use of the algorithm across geographies, independent of local disease prevalence.

Physician concordance, sensitivity and specificity of chest x-ray interpretations are known to vary widely depending on the abnormality being detected, reader expertise, and clinical setting. Inter-radiologist agreement on interpretation of adult chest x-rays with pneumonia ranges from a kappa value(κ) of 0.43 to 0.53 [2,3]. For asbestos-related abnormalities on chest x-rays, inter-reader agreement was fair (κ=0.36), with the highest agreement on pleural calcification (κ=0.63) [32]. Studies on the radiological assessment of tuberculosis showed moderate intra-observer concordance with κ=0.55 on average, increasing to 0.64 for abnormalities requiring urgent attention [33]; similar concordance was observed for TB screening in patients with HIV κ=0.63 [34]. In contrast, inter-reader agreement on pediatric hilar lymphadenopathy ranged from values of 0.05 to 0.55 [35]. The inter-reader variability we encountered in our study is similar to that previously documented. However, for the detection of blunted CP angle, we found lower agreement rate (κ=0.3) than previously been reported (κ=0.7) [36]. Agreement rates for opacity are also low in our study, likely related to differences in reader definition of ‘opacity’. Our readers were blinded to clinical history, a factor that might have impacted both accuracy and inter-reader variance. Experience did not reduce inter-reader variance, suggesting that the high inter-reader variance is due to the inherent difficulty in interpreting a 2D greyscale display of a 3D complex body part containing tissue densities that range from air to bone.

Radiologist opinion is not the ground truth for chest x-rays but is only a precursor to the final clinical and histopathology diagnosis. We tested the algorithm to determine if it can replicate radiologist observation of abnormality on chest x-rays rather than diagnose chest pathology. Although reader consensus is the customary mode of establishing ground truth in radiology, it does not provide information on inter-reader variability [37,38]. We used a 3-reader majority opinion, without consensus, as ground truth. Our results demonstrate that manually curated, but fully automated NLP methods can be used to reliably detect abnormal findings in radiology reports at the scale required for training deep learning algorithms [5a]. However, chest x-ray reports are inherently subjective to differing reporting styles and are not optimized for automated extraction. The main limitation to sample size when using a 3-reader validation is radiologist time. We used an enriched data subset in an attempt to achieve adequate representation of each abnormality. This was achieved for all abnormalities except for ‘cavity’, where we could not reliably estimate algorithm accuracy. In our study, we did not exclude multiple x-rays from the same patient; however given that bedside and portable x-rays were excluded, the probability that repeated x-rays from the same patient occurred in the validation dataset is very low.

5 Conclusion

Our study demonstrates that deep learning algorithms trained on large datasets can accurately detect abnormalities on chest x-rays, with close to radiologist-level accuracy. Apart from providing automated chest x-ray interpretations in under-served and remote locations, automated draft or preliminary reports of abnormal chest x-rays can improve turnaround and clear backlogs. Further research is required to assess the clinical acceptance of artificial intelligence in the real-world and quantify the benefit of such automation to physicians and their patients.

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