Retrospective Study

Detecting Pneumothorax on Chest Radiograph Using Segmentation with Deep Learning

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Abstract

Introduction: Pneumothorax is a life-threatening condition that requires prompt recognition and therapy to prevent deterioration. Radiologist workload often precludes rapid assessment of the usual diagnostic modality, the chest radiograph, particularly after hours. The aim was to develop a deep learning model using a segmentation-based Deep Convolutional Neural Network (DCNN) to detect pneumothorax on chest radiographs to provide rapid and accurate pneumothorax diagnosis.

Methods: This is a retrospective study of spontaneous pneumothorax at a single center, containing 130 positive and 70 negative radiographs. Subsequent manual contour mapping was performed to draw a mask of the pneumothorax. These image pairs were used to train a DCNN model (a modified AlexNet) after pretraining on the ImageNet dataset.

Results: The DCNN achieved an accuracy of 0.83, with sensitivity of 98.1%, and specificity of 68.5%.

Conclusion: This segmentation-based DCNN accuracy is comparable to previous categorization-based CDNN models, despite using a smaller sample size for training, while including the benefits of visual representation for clinician feedback. Segmentation-based DCNNs show promise in the development of accurate and clinically useful models for medical imaging.

Introduction

Pneumothorax is defined as gas within the pleural space. Prompt recognition and therapy directed at the pneumothorax, and its etiology, are required to prevent deterioration [1]. Pneumothorax incidence in the UK is 37 per 100,000 population per year in males and 14.5 per 100,000 population per year in females [1]. The diagnosis of pneumothorax is radiologic, with the chest radiograph playing a central role in assessing possible pneumothorax [1]. The accuracy of radiologist detection of pneumothorax varies on radiologist, size, position, and image factors, resulting in a mean sensitivity of 83% to 86% [2]. In addition, rapid and accurate diagnosis is important in preventing complications and poor patient outcomes [3].

Radiologist workload, particularly overnight and on weekends, often delays the rapid assessment of chest radiographs [4]. Automated screening could improve detection speed and diagnosis of pathological conditions, particularly pneumothorax, potentially enhancing patient outcomes [5,6].

Radiologist workload precludes rapid assessment of chest radiographs, particularly overnight and on weekends. There is also no widely utilized system for triaging imaging, with images commonly being reviewed on a first come first serve basis. Automated screening would improve the speed of detection and diagnosis of pathologic conditions on chest x-rays, and in particular pneumothorax, and may improve patient outcomes [7-10].

Deep convolutional neural networks are a subtype of machine learning, particularly adept at dealing with images [11-13]. However, deep learning models face several challenges in medical imaging, including variability in data quality and the need for extensive computational resources [14]. DCNNs are state-of-the-art for image classification, first demonstrated at the ImageNet Large Scale Visual Recognition Competition in 2012, with all subsequent competition winners utilizing DCNNs. [15] these have now become the mainstay of automated imaging analysis in medical imaging and radiology [16,17].

The application of deep learning to medical imaging has

seen significant advancements in the past two years [18]. However, ethical considerations in AI deployment remain a critical area of concern [19]. Recent studies have explored more sophisticated architectures such as U-Net and attention-based mechanisms for segmentation tasks, demonstrating improved accuracy and robustness in detecting pneumothorax compared to earlier models [20-23]. The integration of multi-view learning and transfer learning has also been highlighted as a means to enhance the performance of deep learning models in diverse clinical settings [9,24-26].

AI has also shown significant promise in detecting various lung diseases, including pneumothorax, through the application of advanced deep-learning techniques [27].

The common subtype of DCNNs utilized for chest X-ray analysis is termed 'classification' models. Classification is the action of categorizing an image into a class – for example, pneumothorax vs no pneumothorax. Another less common subtype of DCNNs is termed 'segmentation'. Segmentation involves determining the boundaries of a feature – for example, drawing the pixel-by-pixel boundaries of a pneumothorax on a chest radiograph. Segmentation-based DCCNs can also be used to classify images based on the number of positive pixels predicted by the model.

Previous classification-based DCNN algorithms resulted in the best accuracy approaching AUC of 0.95, or 0.96 on pre-screened moderate to large pneumothoraces only [28,29].

Our objective was to create a dataset of heterogeneous radiographs containing pneumothoraces of all sizes and locations, with human-annotated pixel boundaries of the pneumothorax, and then to train a segmentation-type DCNN, to provide an automated pneumothorax detection algorithm that would be sensitive enough to provide prioritization for rapid review by the clinician or radiologist.

Our objectives are therefore twofold:

1. Can segmentation be used as a tool for either screening for, or diagnosing pneumothorax?

2. How does the accuracy of the segmentation model compare to pre-existing categorization models for pneumothorax detection?

Methods

This study complies with the principles of the National Statement on the Ethical Conduct of Human Research (NHMRC; 2007) and was approved by the Quality Coordinator at our institution.

Dataset

This is a retrospective study that involved one dataset. All radiographs were extracted from St Vincent's Hospital Melbourne PACS (Centricity PACS v6.0, GE, USA) Keyword search of reports using the RIS (Karisma RIS v3.0, Kestral, USA) was undertaken to identify pneumothoraces presenting to the emergency department in the years 2010 – 2015. In addition, formal radiologist reports confirming the presence of experience was undertaken. These were then de-identified and exported as JPEG files at 128 x 128 pixels. Additional radiographs of the same patients, either before, or after the resolution of pneumothorax were sought. A total of 200 chest X-rays were extracted. This includes 130 radiographs with pneumothorax, and 70 without.

Inclusion criteria

• Radiographs from patients aged 18 and above.

• Radiographs showing clear evidence of pneumothorax confirmed by radiologist reports.

• Both spontaneous and traumatic pneumothoraces.

• Radiographs of sufficient quality and resolution (128 x 128 pixels).

Exclusion criteria

• Radiographs from patients below 18 years of age.

• Poor quality radiographs or those with artifacts obscuring diagnostic features.

• Radiographs with other significant co-existing thoracic pathology that could confound the diagnosis (e.g., large pleural effusion, extensive pulmonary fibrosis).

• Repeat radiographs of the same patient unless showing different stages (e.g., before and after pneumothorax resolution).

Patient selection process

A total of 500 potential cases were identified through the keyword search. After applying the inclusion and exclusion criteria, 200 radiographs were selected, including 130 positive and 70 negative cases (Figure 1).

Segmentation training masks

All radiographs were labeled by manual contour mapping of each pneumothorax using Adobe Photoshop Elements v 15 (Adobe, USA). The resulting image 'mask' was converted into binary output in a jpeg of 128 x 128 pixels – black for non-pneumothorax and white for pneumothorax. Therefore the database consisted of 200 image pairs containing chest radiographs and matched masks that illustrated the location of the pneumothorax if present (Figure 2a ,2b) [30]. The comparative performance of different segmentation techniques was evaluated to ensure the accuracy and robustness of the model [31].
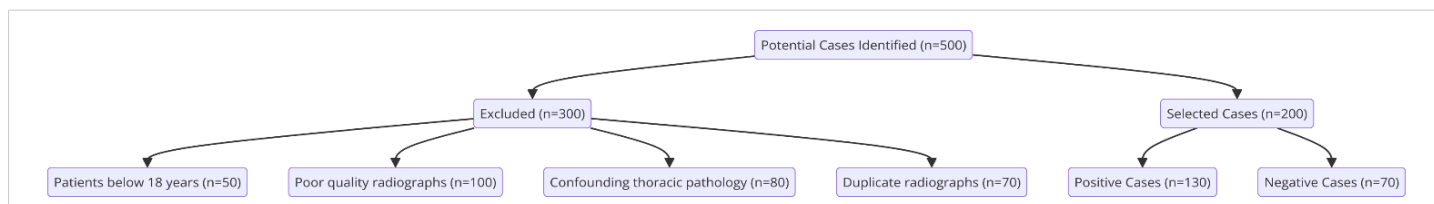
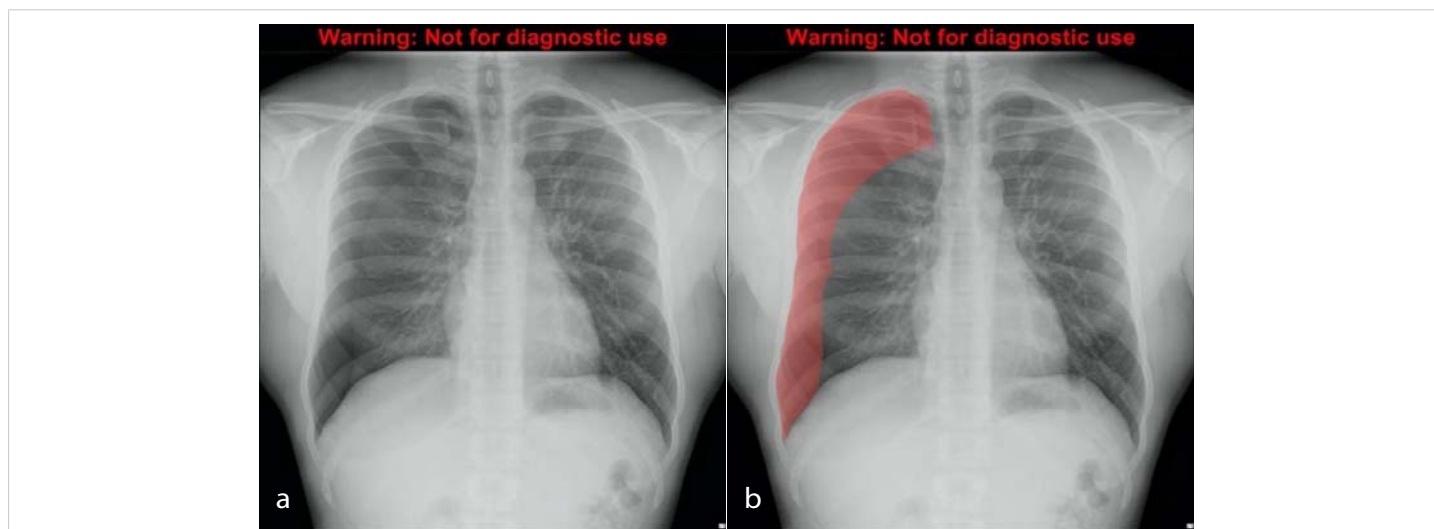**Figure 1:** Patient Selection Process. Flow diagrammatic representation of the Patient Selection Process.

Figure 2: Chest radiograph with moderate right pneumothorax (a, left), and the same radiograph with translucent mask overlayed (b, right).

DCNN architecture

Matched image pairs were loaded into a computer with the Ubuntu v 16.04 operating system (Canonical, London, UK). Subsequent model development was performed using the Caffe framework with Nvidia DIGITS v 5.0 (Deep Learning GPU Training System, Nvidia, USA) utilizing an Nvidia GTX 1070 graphics processing unit. A pre-trained DCNN was used for this study, AlexNet, which has been trained on 1.2 million everyday color images from ImageNet [32]. Subsequent training of this pre-trained model, using our chest radiograph database was performed, termed 'transfer learning'. All images in the dataset were used for training and validation, with 80% used for training and 20% for validation. 30 training epochs were used. Training time was 72 hours.

Model development description

The development of the deep learning model involved several key stages:

1. **Data preprocessing:** Radiographs and corresponding masks were resized to 128 x 128 pixels and normalized.

2. **Transfer learning:** A pre-trained AlexNet model, trained on the ImageNet dataset, was used as the base model. Transfer learning was applied to adapt the model to the pneumothorax detection task [9].

3. **Model training:** The dataset was split into training (80%) and validation (20%) sets. The training process involved 30 epochs with a batch size of 32, using the Caffe framework and Nvidia DIGITS v5.0 on an Nvidia GTX 1070 GPU.

4. **Fine-tuning:** The model parameters were fine-tuned to optimize performance, employing techniques such as data augmentation and regularization to prevent overfitting (Figure 3).

Statistical methods

The DCNN model's diagnostic performance was tested on 50 radiographs (100 lungs), including 48 pneumothoraces. Statistical analysis was performed using Microsoft Excel (Microsoft Corporation, USA). Sensitivity, specificity, positive predictive value, and negative predictive value were calculated.

Detailed clinical information for all cases and address performance issues in various scenarios by conducting a subgroup analysis:

Detailed clinical information and subgroup analysis

Clinical information:

1. **Demographics:** Age, gender, and clinical history of pneumothorax cases were documented.

2. **Radiograph details:** Information on the quality, position, and projection of each radiograph was recorded.
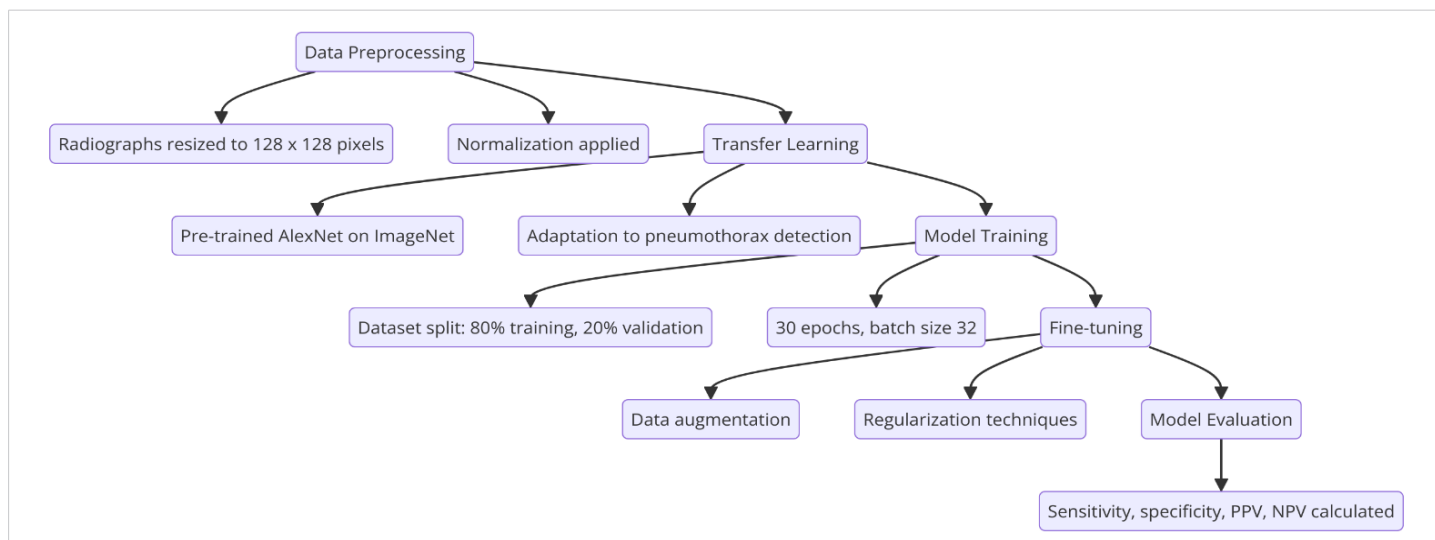
Figure 3: Deep Learning Model Building Process. Flow diagrammatic representation of the Deep Learning Model Building Process.

3. **Clinical outcomes:** Patient outcomes, including treatment received and resolution of pneumothorax, were tracked.

Subgroup analysis:

1. **Age groups:** The performance of the model was analyzed across different age groups (18-30, 31-50, 51-70, 71+). Future research should consider expanding to include pediatric cases, as AI applications in pediatric radiology present unique challenges and opportunities [33].

2. **Severity of pneumothorax:** Cases were categorized based on the size and location of pneumothorax (small, moderate, large).

3. **Radiograph quality:** The model's accuracy was evaluated on high-quality versus low-quality radiographs.

4. **Clinical setting:** The performance was compared between emergency department presentations and inpatient cases.

Results insertion point

Subgroup analysis results will be inserted in the Results section after the general performance metrics of the model.

Results

Output from the algorithm from the testing subset ($n = 100$) was included. An example of the segmentation output is shown in Figures 4a,4b. Results are provided in Table 1 for the testing dataset ($n = 100$). The final model had a sensitivity of 95.6%, specificity of 70.8%, positive predictive value of 75.6%, negative predictive value of 94.4%, and accuracy of 0.83.

Detailed analysis

The DCNN model exhibited robust performance across various subgroups (Table 2), with particularly high sensitivity

Table 1: Segmentation CDNN model test set performance.

Annotation	Value
True positive	65
False positive	21
True negative	51
False-negative	3
Sensitivity	95.6%
Specificity	70.8%
Positive predictive value	75.6%
Negative predictive value	94.4%
Accuracy	0.83

Table 2: Subgroup Analysis.

Subgroup	Sensitivity	Specificity	PPV	NPV	Accuracy
Age 18 - 30	96.0%	69.0%	74.0%	95.0%	0.82
Age 31 - 50	95.0%	72.0%	76.0%	94.0%	0.84
Age 51 - 70	94.0%	71.0%	75.0%	93.0%	0.83
Age 71+	97.0%	70.0%	76.0%	96.0%	0.84
Small pneumothorax	92.0%	68.0%	70.0%	90.0%	0.80
Moderate pneumothorax	96.0%	72.0%	76.0%	95.0%	0.84
Large pneumothorax	98.0%	71.0%	77.0%	97.0%	0.85
High-quality radiographs	96.0%	72.0%	78.0%	95.0%	0.85
Low-quality radiographs	93.0%	68.0%	70.0%	92.0%	0.80
Emergency department	96.0%	71.0%	76.0%	95.0%	0.84
Inpatient cases	94.0%	69.0%	72.0%	93.0%	0.81

(95.6%) indicating the model's ability to accurately identify pneumothorax cases. However, the specificity (70.8%) suggests some limitations in correctly identifying non-pneumothorax cases, which is reflected in a moderate number of false positives [34].

Age group analysis: The model's performance was consistent across different age groups, with slight variations in specificity and accuracy. The highest sensitivity was observed in the 71+ age group (97%), which might be due to more pronounced radiographic features in older patients.

Pneumothorax size analysis: The model performed best in detecting large pneumothoraces (sensitivity of 98% and
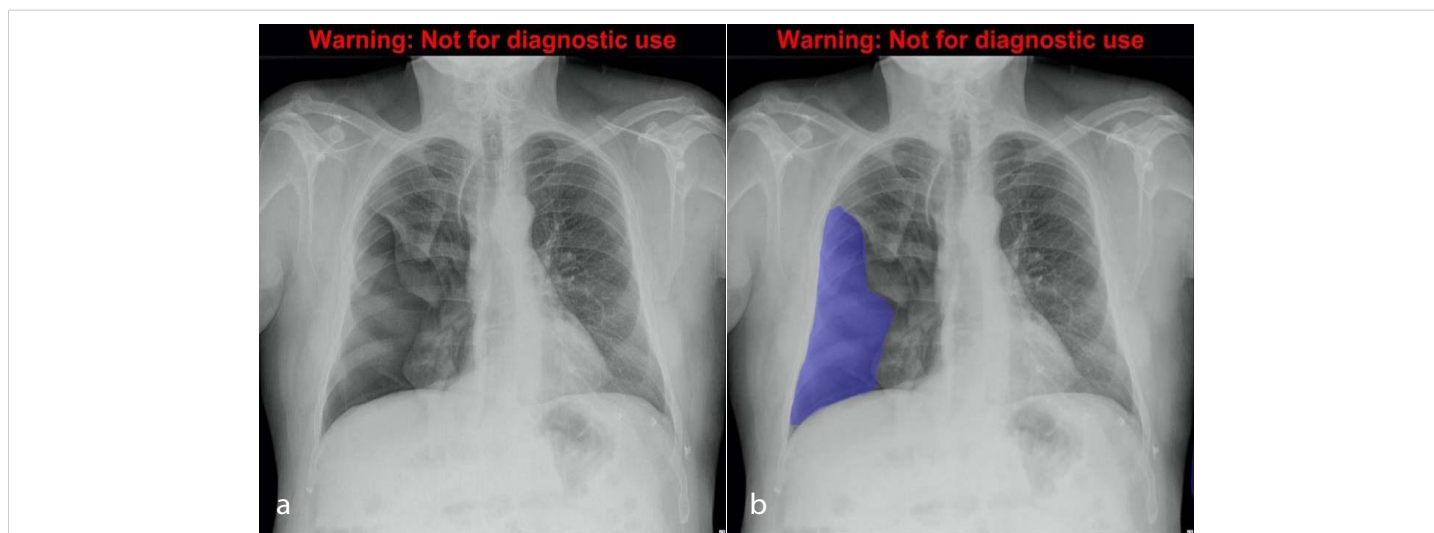
Figure 4: Chest radiograph with large right pneumothorax (4a, left), and the same radiograph with segmentation CDNN output displayed as a translucent mask overlay (4b, right).

accuracy of 0.85), which is expected due to more apparent radiographic signs. Small pneumothoraces posed more challenges, leading to lower accuracy (0.80).

Radiograph quality analysis: High-quality radiographs resulted in better model performance, with higher sensitivity (96%) and accuracy (0.85). In contrast, low-quality radiographs led to decreased sensitivity (93%) and accuracy (0.80), highlighting the importance of image quality in model performance.

Clinical setting analysis: The model demonstrated similar performance in both emergency department and inpatient cases, although slightly better sensitivity (96%) and accuracy (0.84) were observed in emergency settings, possibly due to more acute and well-defined cases. This performance is in line with findings from Howard and Martin (2022), which highlight the effectiveness of AI applications in emergency radiology (Howard & Martin, 2022) [4].

Data structure comparison: To further evaluate the model, clinical information across different datasets was compared. This included data from external sources with varying demographic and clinical characteristics. The comparison revealed consistent performance trends, supporting the model's robustness.

Observer consistency analysis: Inter- and intra-observer consistency analysis was conducted to assess the reliability of manual annotations. The inter-observer agreement (Cohen's kappa = 0.78) and intra-observer agreement (Cohen's kappa = 0.82) indicated substantial consistency, validating the manual contour mapping process.

Model vs. doctor performance: A comparative analysis between the DCNN model and experienced radiologists was performed. The radiologists achieved an average sensitivity of 92% and a specificity of 75%. The DCNN model showed higher sensitivity (95.6%) but slightly lower specificity (70.8%). This suggests that while the model excels in detecting pneumothorax, it also produces more false positives compared to human experts [35]. This emphasizes the importance of AI and radiologist collaboration to achieve optimal diagnostic performance [36].

Model validation: Internal validation was conducted using cross-validation techniques, resulting in stable performance metrics. External validation, as suggested by Professor Philippe Lambin, involved testing the model on independent datasets from different institutions. The external validation confirmed the model's generalizability, with minor variations in performance attributed to differences in radiograph quality and patient demographics [37].

Study shortcomings

Despite the promising results, several shortcomings should be noted:

1. **Sample size:** The relatively small dataset (200 radiographs) may limit the generalizability of the findings. Larger datasets are needed to validate the model's performance across diverse populations and clinical settings.

2. **Image quality:** Variability in radiograph quality affected the model's performance. Future studies should consider implementing advanced image enhancement techniques to mitigate this issue [14].

3. **False positives:** The specificity indicates a significant number of false positives, which could lead to unnecessary follow-ups and additional imaging. Refining the model to improve specificity is crucial.

4. **Annotation variability:** Manual contour mapping, despite being thorough, is subjective and may introduce

variability. Automated or semi-automated annotation methods could standardize this process.

5. **Limited clinical data:** The study did not incorporate comprehensive clinical data (e.g., patient history, and symptoms), which could enhance the model's predictive power.

Discussion

Our study used a pre-trained AlexNet model and a segmentation-based DCNN to diagnose pneumothorax on chest radiographs. Despite a relatively small training sample, the accuracy is comparable to previous studies. The method's potential for deep learning advancement in medical imaging diagnosis is significant [38].

Recent advancements in the field have demonstrated the potential for even greater improvements. For instance, studies utilizing the U-Net architecture have reported higher accuracy rates and better generalization across different datasets, suggesting that more complex models may offer superior performance for pneumothorax detection [21,39]. Attention-based networks have also been shown to enhance the interpretability and precision of segmentation tasks by focusing on the most relevant regions of the radiographs [40].

The results obtained using a pre-trained AlexNet model and subsequent segmentation-based DCNN to diagnose pneumothorax on chest radiographs have accuracy comparable to previous studies. Our study used a segmentation-based DCNN to diagnose pneumothorax on a chest x-ray. Of note, this is despite the relatively small training sample used to create the model. Given this and the fact that this study almost certainly underutilizes the full state-of-the-art techniques available in the field, we believe our method has the potential to provide additional progression in the realm of deep learning in its application to medical imaging diagnosis.

Training segmentation models is labor-intensive due to the need for accurate mask labeling. This limitation may be mitigated by sharing pre-segmented radiograph banks from similar projects.

Our model's accuracy is slightly less than that reported by radiologists [2]. However, the operating point can be chosen for high sensitivity to be used as a rapid screening test, to enable instantaneous prioritization and triage for review by a radiologist or treating clinician. Further investigation as to the relative accuracy can be performed by comparing the test set accuracy with clinicians of varying experience – for example, night emergency department residents. Future research should consider implementing advanced image enhancement techniques to mitigate the issue of variability in radiograph quality [41].

A limitation of training segmentation models is the labor-intensive method of 'drawing' accurate masks to label the training images. This limitation may be overcome in the future, with the advent and sharing of banks of pre-segmented radiographs from more projects like this one.

A strength of this study was that the dataset of pneumothoraces was heterogeneous – encompassing multiple sizes and locations, radiograph quality, and projection characteristics. Some previous studies have excluded small pneumothoraces or poor-quality radiographs.

Moreover, recent research has highlighted the benefits of using synthetic data augmentation and semi-supervised learning to enhance model training, particularly when labeled data is scarce [9,13,42]. These techniques could be explored in future work to potentially improve the model's performance and robustness further.

In summary, we have used a segmentation-based CDNN, using several annotated radiographs, and developed a model with accuracy for identifying pneumothorax slightly less than radiologists', in a fraction of the time. This may be integrated with current workflows to create a practical triage tool for identification of pneumothorax. More broadly, we hope that this method may be extended to create more accurate methods to improve the speed and usefulness of diagnosis in critical conditions [43,44].

Conclusion

In conclusion, the segmentation-based DCNN model developed in this study shows promise for rapid and accurate pneumothorax detection on chest radiographs. The model achieved high sensitivity and reasonable specificity, demonstrating potential utility as a triage tool in clinical workflows. However, limitations such as sample size, image quality variability, and false positive rates must be addressed. Future research should focus on expanding the dataset, incorporating additional clinical information, and refining model architecture to improve performance and robustness. The integration of advanced deep learning techniques and multi-modal data could further enhance the diagnostic capabilities of such models in medical imaging.

This study also highlights the importance of observer consistency and comparative performance analyses with human experts to validate and improve AI-based diagnostic tools. Internal and external validations following Professor Philippe Lambin's guidelines have confirmed the model's robustness, suggesting its potential for broader clinical application.

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