Supplementary Material

Training strategies: The training strategies included the following steps.

Training configuration
The model was trained with a batch size of 8 and utilized a optimizer with a momentum value of 0.9. The learning rate followed a cosine decay schedule starting from 0.005, included a warm-up phase spanning 25,000 steps. An ensemble of artificial intelligence (AI) models has been developed to enhance the trained model's sensitivity.

Segmentation model:

Lung region extraction– First model extracts lung regions from chest X-ray (CXR) images, isolating region of interest for further analysis.

Abnormality detection:

- Base model for region of interest' detection–The second model predicts whether an image is normal or abnormal.
- Subclassification model for pleural abnormalities–The third model detected regions like pleural effusion or thickening.
- Early detection model for infiltrations and small nodules–The fourth model identifies various early-stage lesions like infiltration/nodules.
- Grouped classification model for TB *vs*. non-TB cases –The fifth model distinguishes between TB and non-TB-specific regions.
- Model for cardiac lesions–The final model specifically identifies cardiomegaly.

All aforementioned steps with post-processing algorithms are targeted for classifying images as normal or abnormal.

Lung region segmentation and model framework

This model identifies left and right lung regions using image segmentation technique.

Data for lung region segmentation

A total of 453 adult and paediatric CXR images, with an equal distribution (50-50 ratio) of normal and abnormal images were used to train the AI model for segmentation. Software was used to label lung regions using polygon annotation. After data preparation, training was performed on images of varying sizes to extract the lung boundaries accurately (**Supplementary Figure 2**).

Model training and benefits

After segmentation, the model was then trained and tested on test datasets in order to achieve precise coordinates for bilateral costophrenic angles, BB extraction for bilateral lung apices and comprehensive lung region mapping using minimum and maximum coordinates along different axes (**Supplementary Figure 3**).

Application in dextrocardia and other conditions

The model recognizes reversed heart shadow seen in dextrocardia, hyperinflation and other abnormalities by analysing lung height-to-width ratios, and structurally distorted images.

Abnormality detection using AI models
For abnormality detection, five individual AI models, each designed for a specific purpose, were trained.

Subclassification model for pleural abnormalities

A sub-classification model was developed to detect pleural thickening and effusion, integrating costophrenic-angle measurements for greater precision. As illustrated in **Supplementary Figure 3C and D**, the base ROI detector flagged a secondary lesion in the left lower field, which the pleural model subsequently validated.

- Early detection model for infiltrations and small nodules
- This model was trained exclusively on infiltration and small-nodule to boost sensitivity for subtle, often variably interpreted findings. Lesion likelihood is determined by a cutoff rule: if AI-generated bounding box extends beyond one-third of either lung's lateral half, the presence of pathology is deemed highly probable (Supplementary Figure 3E and F).
- Grouped classification model detects lesion based on patterns of certain TB and non-TB disease conditions that may have been missed by base model. It applies a threshold value of 75%, ensuring detection of missed lesions.
- Model for cardiac lesions: Last model was developed to detect cardiomegaly by calculating cardiothoracic ratio (CTR); with CTR>0.55 as cardiomegaly. **Supplementary Figure 3G and H** shows bounding boxes around heart conforming to CTR of~0.56 and ~0.48 respectively.
- Criteria for exclusion of false positive cases

The following criteria must be clinically correlated before classifying as abnormal:

(a) Costochondral junction: Calcification of costochondral junction is common feature in older patient. Such predictions need to be confirmed clinically in absence of age as input parameter (**Supplementary Figure 4A**).
(b) X-ray rotations: The rotation in CXR may make hilum and lymph node to appear enlarged and dense in CXRs. Such predictions are marked as prominent and need clinical correlation (**Supplementary Figure 4B**).
(c) Variations in diaphragm: The variations in the shape of diaphragm pose a major challenge in identifying abnormality. A depressed diaphragm (**Supplementary Figure 4C**), need to be confirmed by other models or in post-processing analysis before concluding it as abnormal.