Tuberculosis Detection from Chest X-ray using CNN

A convolutional neural network that screens frontal chest radiographs for TB-suggestive patterns, trained on the Montgomery County and Shenzhen Hospital X-ray collections — an educational prototype with no diagnostic claims.

1. Introduction / Background

Tuberculosis remains one of the world's deadliest infectious diseases, and chest X-ray screening is a frontline triage tool in high-burden regions — but there are far fewer trained radiologists than X-ray machines.

This project builds computer-aided TB screening as an honest educational prototype: a custom CNN trained from scratch on the two classic public TB X-ray collections from the U.S. National Library of Medicine (800 frontal CXRs), evaluated with ROC-AUC, sensitivity and specificity, and presented with a Grad-CAM-style attention overlay. Every page states plainly that this is a teaching build, not a diagnostic device.

2. Problem Statement

Radiologist shortages mean many chest films wait days for reading while TB spreads. An automated second reader that flags TB-suggestive patterns (infiltrates, cavities, upper-lobe consolidation) could prioritize the queue. Students need a project that teaches real medical-imaging methodology — proper metrics, class-imbalance handling, explainability — without pretending a classroom model is a clinical device.

3. Objectives

- Train a custom CNN to distinguish TB-suggestive from normal/clear frontal chest radiographs.
- Evaluate with ROC-AUC, sensitivity, specificity and confusion matrix on a held-out test set.
- Visualize model attention with a Grad-CAM-style overlay for explainability.
- State the educational-prototype limits clearly in all deliverables.

4. Proposed Methodology

The Montgomery (138) and Shenzhen (662) CXR sets are combined (800 images), resized to 224×224 grayscale, histogram-equalized and normalized, with stratified splits. Augmentation (small rotations, flips, contrast jitter) is applied during training. The custom CNN — four conv blocks (32/64/128/256 filters) with batch normalization and max-pooling, global average pooling, Dense(128) with dropout 0.5 and sigmoid output (≈2.1M parameters) — is trained with Adam (lr 1e-4) and weighted binary cross-entropy, with early stopping on validation AUC.

5. System Architecture / Working

- Input: 224×224 grayscale radiograph, histogram-equalized.
- Feature extraction: 4 conv blocks learn texture and opacity patterns across lung fields.

- Classification: global average pooling → Dense(128, dropout 0.5) → sigmoid (TB-suggestive probability).
- Demo: selected radiograph → identical preprocessing → saved weights → probability bars + attention overlay (illustrative).

6. Hardware / Software Requirements

- Python 3, TensorFlow/Keras, NumPy, Matplotlib, scikit-learn, Jupyter Notebook.
- Any modern laptop; training time is modest given the 800-image dataset.
- The web demo runs offline in any modern browser after download.

7. Expected Outcomes

- A trained CNN reaching the design targets of ≈ 0.90 validation ROC-AUC with ≈ 0.85 sensitivity / ≈ 0.88 specificity, reported honestly after the training run.
- An interactive radiograph-analysis demo with attention visualization.
- A complete report, PPT and viva Q&A; covering medical-imaging evaluation and the ethics of medical AI.

8. Applications

- Teaching medical-image classification, ROC analysis and class-imbalance handling.
- Demonstrating Grad-CAM-style explainability for radiology AI.
- A foundation for extended work: lesion localization, multi-disease chest X-ray screening.

9. Future Scope

- Lesion-level localization with bounding-box annotations.
- Multi-disease screening (pneumonia, effusion, nodules) on larger collections.
- Federated training across hospitals (with full regulatory compliance).

10. Conclusion

The project shows how to do medical AI honestly in a classroom: real public data, clinically meaningful metrics, explainability, and limits stated as clearly as results — an educational prototype that teaches the methodology without ever claiming to be a diagnostic device.