Artificial Intelligence based Chest X-ray (CXR) Screening for Pulmonary Tuberculosis: A Phase 2

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Abstract

Introduction: Chest-Xray is the simplest and the most important step in diagnosis of pulmonary tuberculosis. However, interpretation of radiographs requires expertise, is time-consuming, and is prone to human error.

Artificial intelligence (AI) based CXR screening has the potential to overcome these limitations, especially in resource-limited settings. Sevamob provides artificial intelligence enabled healthcare platform to organizations and developed *XrayAI*, an AI system for TB screening from chest X-rays. It uses foundation models for image recognition. To determine the accuracy of AI based point-of-care screening solution for CXR, following were used. Android Smartphone / tablet with Sevamob app. The system was operated by a nurse or a technician with minimal training.

Methods: A total of 100 CXRs images from clinically suspected TB patients were included. We conducted a Phase 2 clinical study to evaluate the diagnostic performance of XrayAI compared with consensus readings of a panel of radiologists.

Results: Compared to expert panel consensus, XrayAI achieved a sensitivity of 100%, negative predictive value (NPV) of 100%, and balanced accuracy of 81.25%. Out of 100 cases, XrayAI correctly identified all 28 TB-positive cases (sensitivity 100%) and 45 TB-negative cases, but misclassified 27 non-TB cases as TB (specificity 62.5%).

Conclusion: The high sensitivity and NPV demonstrate that XrayAI is a reliable screening tool for ruling out tuberculosis on CXR. This makes it particularly suitable for mass screening programs, though its moderate specificity may necessitate confirmatory testing.

Index terms: Tuberculosis, artificial intelligence, CXR

I. Introduction

Tuberculosis remains a leading cause of morbidity and mortality worldwide, particularly in resource-constrained countries .Chest X-ray (CXR) is first and foremost step in the diagnosis of tubercular infections. but interpretation requires trained radiologists , which are often unavailable in remote and rural settings. Errors in radiographic interpretation may delay diagnosis and treatment initiation. [1]. Also, in remote areas, due to lack of expert radiologist, timely diagnosis at initial level is not possible, which may lead to increased morbidity. Artificial intelligence (AI)based chest xray diagnosis can be an answer to overcome this problem. AI can be used even in the remotest areas where expert radiologists are not available. [3] The use of artificial intelligence in medicine is currently of great interest.[2,4,5,6] The diagnostic and predictive analysis of medicalphotos, for instance, photographs of retina[8] and skin lesions, microscopicpathological images[10-12] and radiological images. are one of the clinicalpractice fields where artificial intelligence is expected to have a majorinfluence.[7-15]. This potential usefulness is largely due to advances in deep learning with artificial deep neural networks (NN),which consist of a stack of multiple layers of artificial neuronal links that loosely simulates the brain's neuronal connections, and methods specialized for analysis of images, such as the convolution neural network, a particular form of deep neural network that conceptually mimics the visual pathway [13,16,18]. Adoption of artificial intelligence tools in clinical practice requires careful, meticulous confirmation of their clinical performance and utility before the adoption.□17] Based on the urgent need for data standardization and interoperability in digital radiology, we launched a cross-departmental prospective quality improvement project to incorporate artificial intelligence digital radiology technology and outline the resource requirements for implementation. The solutions presented here empower radiologists to gain an appreciation of and enable the assessment of the appropriateness of the AI system for screening. We have also shown that current AI systems can aid in the timely diagnosis of infections in resource constraint setting of developing countries like India. The use of artificial intelligence-based diagnosis and data regarding the same is scarce to our best knowledge.

Sevamob provides artificial intelligence enabled healthcare platform to organizations. It uses deep learning for image recognition, machine learning for triaging and computer vision for object counting. AI models of various medical conditions are first trained in the software from anonymized image data procured from various sources. The software can then be used to screen for these medical conditions in new samples. The system can work in low resource settings. .

Therefore Sevamob has developed *XrayAI*, a deep learning–based tool that automatically analyses chest radiographs for features consistent with TB. The present study was conducted to evaluate its diagnostic performance in comparison with expert radiologists. .□26]

II. Methods

This was a retrospective, observational Phase 2 clinical study conducted using 100 anonymized CXRs images of clinically suspected pulmonary tuberculosis cases.

III. Data Collection and Reference Standard

The dataset consisted of 28 radiographically confirmed TB cases and 72 non-TB cases. Consensus diagnosis from a panel of radiologists served as the gold standard.

IV. AI Model and Workflow

The AI system (*XrayAI*) was developed using the foundation models and optimized for TB detection. For each CXR , the AI outputted a binary classification (TB positive or negative).

V. Performance Evaluation

Diagnostic performance was assessed by calculating sensitivity, specificity, accuracy, positive predictive value (PPV), negative predictive value (NPV), F1 score, false positive rate (FPR), false negative rate (FNR), and balanced accuracy.

VI. III. Results

Confusion Matrix (N = 100)

- True Positive (TP): 28
- True Negative (TN): 45
- False Positive (FP): 27

- False Negative (FN): 0

Performance Metrics

- Sensitivity (Recall): 100%
- NPV: 100%
- Specificity: 62.5%
- Precision (PPV): 50.9%
- F1 Score: 67.5%
- FPR: 37.5%
- FNR: 0%
- Accuracy: 73.0%
- Balanced Accuracy: 81.25%

VII. Interpretation

The system correctly detected all TB cases (sensitivity 100%, FNR 0%), making it an excellent screening tool. However, 27 non-TB cases were incorrectly labeled as TB, resulting in moderate specificity (62.5%).

VIII. IV. Discussion

This Phase 2 study demonstrates that *XrayAI* provides highly sensitive screening for tuberculosis on CXRs. The AI detected all true positive cases with an NPV of 100%, which is crucial for ruling out TB in large-scale screening. These findings are consistent with prior work that has shown AI can achieve expert-level performance in CXR interpretation.

The moderate specificity (62.5%) indicates that the system tends to over-diagnose TB, leading to false positives. While this reduces precision, it is acceptable in a screening context, where the primary goal is to ensure no TB- positive cases are missed. Individuals flagged positive by XrayAI can undergo confirmatory testing (e.g., sputum microscopy, molecular diagnostics).

Strengths of this study include the use of expert consensus as reference and the demonstration of AI utility in TB screening. Limitations include the relatively small sample size and retrospective design. Larger, prospective studies across diverse populations are needed to further validate the system.

IX. Conclusion

XrayAI demonstrates excellent sensitivity and negative predictive value for TB detection from CXRs. These findings support its role as a reliable AI-based screening tool, particularly in resource-limited and high-burden settings. Its deployment could aid early case finding and timely initiation of treatment, thereby contributing to TB control efforts globally.

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