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AI-Based Chest X-Ray Tool to Detect Lung Nodule in a Tuberculosis Endemic Population: A Screening Clinical Series Study

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ABSTRACT

Introduction: In countries with high tuberculosis prevalence, early lung cancer (LC) detection can be confounded by nodules from latent TB (LTB), delaying diagnosis. Limited evidence exists on TB and LC in integrated screening, and AI performance in TB-endemic settings remains unknown. This study evaluates AI's effectiveness in screening LC in such settings.

Methods: This is a screening clinical series where qXR Lung Nodule, Lung Nodule Malignancy Score (LNMS), and TB algorithm were used. Patients who were flagged for nodule (high or low-risk by LNMS) and gave consent were enrolled. Overall, AI processed CXR of 25166 patients. 1683 were flagged for nodules; 318 gave consent. 36

patients who had other cancer were excluded. Agreement between AI and radiologist is reported. For patients who underwent CT, the positive and negative predictive value of AI is reported with Lung-RADS as reference standard (>=4A as high-risk).

Results: 282 (180 high-risk and 102 low-risk) were included. Mean age was 54.4 and 145 (51.4%) were females. 155 (55%) were also flagged as TB presumptive by AI. The proportion agreement between radiologist and AI for nodule was 53.5% (47.7-59.3). 94 (54 high-risk and 40 low-risk) underwent CT scan. PPV of high-LNMS was 44.4% (32.0-57.6). NPV of low-LNMS was 77.5% (62.5-87.7). PPV/NPV in those with concurrent AI's TB flag 46/73 and for those with TB negative it was 42/100. 36 patients underwent biopsy and 14 (9 high-LNMS, 5 low-LNMS) were confirmed as cancer. Six of the 14 cancer cases were confirmed TB negatives and in four of these patients AI detected high-risk nodule.

Conclusions: There is considerable overlap in AI prediction of TB and nodules. PPV was comparable when analyzed by AI's TB results. However, NPV was higher when there is no concurrent TB prediction. LC investigations may benefit high-risk LNMS patients once TB is ruled out.

Keywords: Integrated Screening; AI; Tuberculosis; Lung Cancer

INTRODUCTION

Lung cancer remains one of the leading causes of cancer-related mortality globally, with low- and middle-income countries (LMICs) bearing a disproportionate burden due to inadequate access to early diagnostic technologies and limited health infrastructure.[1] In addition, tuberculosis (TB) continues to be endemic in many of these geographies, particularly in Southeast Asia, sub- Saharan Africa and parts of Latin America. These challenges are demonstrated in the Philippines, a high TB-burden country, where the overlap of TB and lung cancer risks presents significant diagnostic uncertainty. Radiographic similarities between TB-related lesions and early-stage lung cancer can obscure timely and accurate diagnosis, delaying appropriate clinical interventions.[2,3]

In TB-endemic and resource-limited settings like the Philippines, access to advanced imaging such as CT scans and specialist consultations is often limited. Chest x-rays (CXRs) remain the most widely accessible imaging modality for initial pulmonary evaluation. However, there can be challenges in interpretation of CXRs due to shortage of radiologists as well as inter-reader variability. Even for experienced clinicians, distinguishing between granulomatous TB lesions and malignant lung nodules can be difficult, especially in patients with subtle or non-specific findings.[4,5] As a result, patients may face delayed diagnosis and treatment, often being detected as cancer at more advanced stages of disease.[5]

Artificial intelligence (AI)-based CXR interpretation tools have shown increasing potential in streamlining radiologic workflows, by improving consistency, triaging abnormalities, and aiding early detection of diseases such as TB and lung cancer.[6,7] One such tool is qXR, developed by Qure.ai, which incorporates TB and lung nodule detection algorithms and has been validated for TB and Lung Cancer identification in different types of deployments.[8] The Lung Nodule Malignancy Score (LNMS), categorizes detected nodules into high- or low-risk classes using radiographic features, thereby helping prioritize patients for CT evaluation.

While previous studies have demonstrated the utility of AI tools in general populations, their real-world performance in TB-endemic settings remains underexplored. In TB-prevalent contexts, where health systems are strained and diagnostic resources limited, effective early identification of lung cancer could dramatically improve survival and reduce late-stage treatment costs. If proven accurate and reliable, AI-enabled tools could serve as valuable adjuncts to routine radiographic workflows, enabling more efficient triage and referral.

To address this gap, we looked at a screening clinical series on the real-world performance of the qXR AI tool in a TB-endemic setting for detecting lung nodules. Specifically, we assessed how the tool performs in terms of agreement with radiologists, diagnostic value validated by CT and biopsy, and whether its predictions are influenced by concurrent TB detection. We hypothesized that AI predictions, especially when TB is ruled out, could support better triage patient particularly with high-risk lung nodules for downstream investigations such as CT.

This study described the performance of AI-based Computer Aided Detection (CAD) device in detecting lung nodules and or TB lesions in chest X-rays and the proportion agreement between the radiologist’s clinical eye versus AI-based CAD device in reading CXRs for TB lesions and lung nodule lesions.

METHODS

Study Design and Setting: This is a screening clinical series study conducted at the Asian Hospital and Medical Center (AHMC), a tertiary care hospital in Metro Manila, Philippines. The study looked at the performance of an AI-based chest X-ray interpretation system in detecting lung nodules suspicious for malignancy in the TB-endemic population of the Philippines.

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Figure 1: Study Workflow

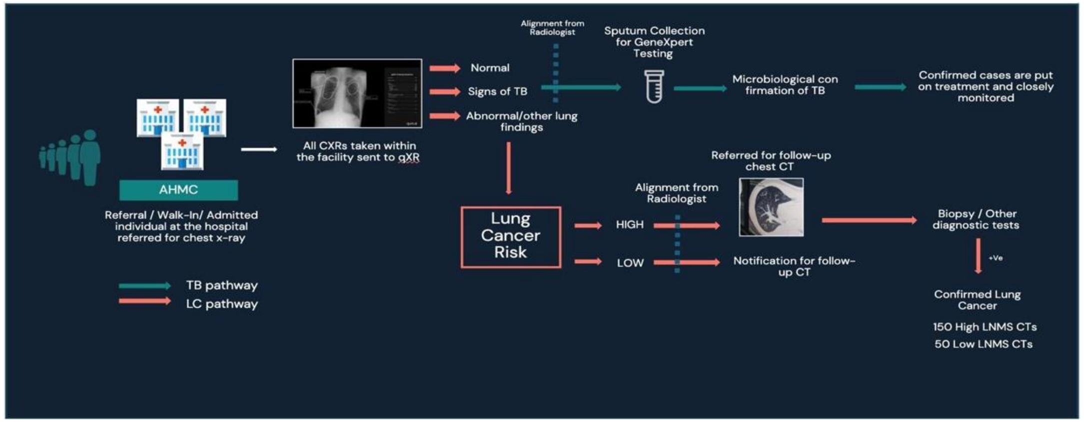


Diagram Participants: The study reviewed AI-analyzed chest radiographs of 25,166 patients (from study period years 2023 to early 2024). From these, 1,683 were flagged by the AI (qXR) for the presence of nodules (209 were high risk).

A total of 318 patients consented to share their medical data in the research cohort for next steps. After excluding 36 patients for various reasons (including prior history of other cancers or incomplete data), 282 patients were included in the final analysis. Among 282 patients, 180 were flagged as high-risk and 102 as low-risk by AI, however only 94 had CT scan done and 36 biopsies done, with 14 confirmed cancer cases.

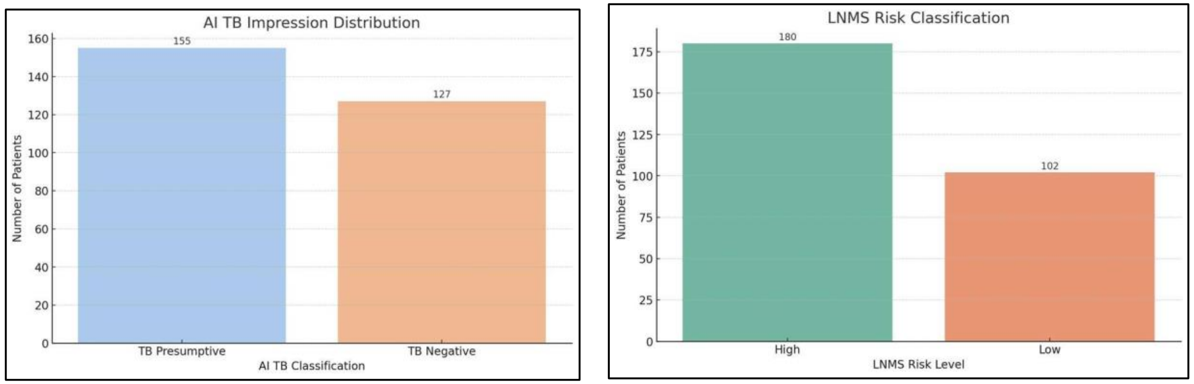
AI Algorithms Used: The AI platform used in this study included:

1. qXR for automated detection of pulmonary TB.
2. qXR's Lung Nodule Malignancy Score (LNMS) to risk-stratify nodules as either "High" or "Low" probability of malignancy.

Reference Standards and Validation: Patients who underwent chest CT scans were classified using Lung-RADS, with scores ≥4A considered high-risk as reference standard. In cases where biopsies were performed, histopathology results served as the gold standard for confirming malignancy.

Data Collection and Definitions: Key variables included age, gender, AI impression (TB and LNMS), radiologist report, CT scan findings, biopsy results, and final diagnosis. Data were collected from electronic medical records and radiology archives.

Figure 2: AI TB Impression Distribution and LNMS Risk



Classification Statistical Analysis: Descriptive statistics were calculated for baseline demographics. Agreement between AI and radiologists was measured using proportion agreement. Diagnostic performance (PPV, NPV) was evaluated with CT scan findings as the reference for nodules, and subgroup analysis was performed based on TB status.

Ethical considerations: The study was approved by the Institutional Ethics Committee before initiation. Informed consent was obtained from all patients and their attending physicians. Confidentiality was exercised. Data were anonymized, with access limited to the principal investigator and co-investigators.

RESULTS

Baseline Characteristics: Of the 282 patients included in the final analysis, the mean age was 54.4 years, with 145 females (51.4%) and 137 males (48.6%). The AI tool flagged 155 patients (55%) as TB presumptive, while 127 (45%) were TB negative. Based on LNMS, 180 were high-risk and 102 were low-risk for malignancy. See Table 1.

Table 1: Study population

Variable	Category	Number of patients	Percentage
Age group	>= 50	172	60.99
	< 50	110	39.01
Sex	Female	145	51.42
	Male	137	48.58
AI TB Impression	TB Negative	127	45.04
	TB Presumptive	155	54.96
Lung Nodule Malignancy Score	High Risk	180	63.83
	Low Risk	102	36.17

Summary AI vs Radiologist

Agreement (Table 2): Agreement between AI and radiologist impressions was 53.5% (95% CI: 47.7–59.3). Lower concordance was noted in TB-flagged patients, suggesting a confounding effect of TB-related changes. Agreement was higher in patients aged 50 years or older at 57.0% (95% CI: 49.5%– 64.1%), compared to 48.2% (95% CI: 39.1%–57.4%) in those younger than 50 years. Males demonstrated greater agreement at 59.9% (95% CI: 51.5%–67.7%), while agreement among females was 47.6% (95% CI: 39.6%–55.7%).

Table 2: Proportion Agreement between AI and Radiologist Impressions: Overall and by Patient Demographics

Patient Demographics	Category	N	Overall Agreement (95% CI)
Overall	All patients	282	53.5% (47.7% - 59.3%)
Age group	Greater than or equal to 50	172	57% (49.5% - 64.1%)
	Less than 50	110	48.2% (39.1% - 57.4%)
Sex	Male	137	59.9% (51.5% - 67.7%)
	Female	145	47.6% (39.6% - 55.7%)

CT and Biopsy Results: Overall, the AI tool demonstrated a PPV of 44.4% (95% CI: 32.0%–57.6%) and an NPV of 77.5% (95% CI: 62.5%–87.7%) among patients who underwent CT imaging. Radiologist performance was slightly lower, with a PPV of 38.7% (95% CI: 27.6%–51.2%) and an NPV of 71.9% (95% CI: 54.6%–84.4%).

Subgroup Analysis (Table 3): Among patients aged 50 years or older, the AI's PPV increased to 50%, while the NPV was 74.3%. In contrast, for those younger than 50, the AI's PPV was 31.2% (95% CI: 14.2%–55.6%), but the NPV reached 100%. Radiologist values followed a similar trend.

When stratified by sex, the AI's PPV was 41.7% and NPV was 82.6% in males, compared to a PPV of 32.3% and NPV of 75% for radiologists. In females, the AI's PPV was 46.7% and NPV was 70.6%, while radiologists had a PPV of 45.2% and NPV of 68.8%.

For AI TB impression subgroups, the PPV for TB-presumptive patients was 45.7% and the NPV was 72.7% for AI, compared to 38.1% and 65.4% for radiologists. In TB-negative patients, the AI's PPV was 42.1% and NPV was 100%, while radiologist performance showed a PPV of 40% and NPV of 100%.

Table 3: PPV & NPV of AI and Radiologist against Lung RADS

Variable	Category	Predictor	PPV (95% CI)	NPV (95% CI)	N
	All	AI	44.4% (32% - 57.6%)	77.5% (62.5% - 87.7%)	94
Overall	All	Radiologist	38.7% (27.6% - 51.2%)	71.9% (54.6% - 84.4%)	94
	Greater than or equal to 50	AI	50% (34.8% - 65.2%)	74.3% (57.9% - 85.8%)	73
	Greater than or equal to 50	Radiologist	42.2% (29% - 56.7%)	67.9% (49.3% - 82.1%)	73
Age group	Less than 50	AI	31.2% (14.2% - 55.6%)	100% (56.6% - 100%)	21
	Less than 50	Radiologist	29.4% (13.3% - 53.1%)	100% (51% - 100%)	21
	Male	AI	41.7% (24.5% - 61.2%)	82.6% (62.9% - 93%)	47
	Male	Radiologist	32.3% (18.6% - 49.9%)	75% (50.5% - 89.8%)	47
	Female	AI	46.7% (30.2% - 63.9%)	70.6% (46.9% - 86.7%)	47
Sex	Female	Radiologist	45.2% (29.2% - 62.2%)	68.8% (44.4% - 85.8%)	47
	TB Presumptive	AI	45.7% (30.5% - 61.8%)	72.7% (55.8% - 84.9%)	68
	TB Presumptive	Radiologist	38.1% (25% - 53.2%)	65.4% (46.2% - 80.6%)	68
AI TB	TB Negative	AI	42.1% (23.1% - 63.7%)	100% (64.6% - 100%)	26
Impression	TB Negative	Radiologist	40% (21.9% - 61.3%)	100% (61% - 100%)	26

DISCUSSION

This study evaluated the real-world performance of an AI-based chest X-ray interpretation tool in a TB-endemic and resource-limited setting, focusing on its ability to detect lung nodules suspicious for malignancy. The results demonstrate both the promise and the complexity of using AI tools in TB-endemic regions for integrated screening for lung cancer and TB.

The AI model showed an overall agreement of 53.5% with radiologist interpretations, with some variations by demographic factors. Among patients who underwent CT imaging, the AI demonstrated encouraging PPV and NPV values of 44.4% and 77.5%, respectively. Notably, NPV was higher when there is no concurrent TB prediction. LC investigations may benefit high-risk LNMS patients once TB is ruled out.

These results suggest that AI tools can have a valuable role in supporting diagnostic decision-making in settings with limited radiology resources, especially when integrated with existing TB screening programs that use chest radiography. The integration approach could leverage existing healthcare infrastructure while providing dual screening benefits for both infectious and neoplastic diseases.

In the Philippines, chest x-rays are included as a subsidized diagnostic tool within the PhilHealth's *Konsulta/ Yakap* Package, a program that aims to provide Filipinos with access to primary care services, primarily as a screening tool for TB.[9] The *Konsulta/ Yakap* package does not include any screen tool for lung cancer, primarily since LDCT is unaffordable and inaccessible in the community, but the 2025 PhilHealth Cancer Screening package includes LDCT for lung cancer screen.[10] It can be thus advocated that early detection of lung cancer can be implemented along with the national TB screening program, using AI-assisted chest x-ray. [11]

Our study adds to the literature by evaluating AI performance in a real-world setting, particularly one with overlapping infectious and neoplastic lung disease burdens. However, several limitations must be acknowledged. First, this is a screening clinical series study and the sample size of patients who underwent confirmatory testing (CT or biopsy) was modest, limiting the statistical power to assess diagnostic performance robustly. Second, the selection of patients for downstream testing may have introduced verification bias, as higher-risk individuals were more likely to undergo CT or biopsy. Albeit given these limitations, it can be explored that out of the 25,166 who underwent chest-xray 1,683 were AI-flagged with nodules in this study. These 1,683 cases would just be the ones triaged for LDCT lung cancer screen and not 25,166, lowering lung cancer screen cost for the health department.

In clinical terms, the study implies that the AI-assisted chest x-ray can moderately rule in lung nodules with a 44% (PPV) certainty and rule out nodules with 77% (NPV) certainty. While the NPV is better than chance, it leaves room for missed nodules (false negatives), and the PPV indicates a considerable number of false alarms (false positives). Higher PPV and NPV values would be more desirable to confidently confirm or exclude nodules. These values emphasize that while AI tools can aid lung nodule detection, their results should be integrated with clinical judgment and possibly follow-up low dose Ct scan imaging, especially given the consequences of missed or misclassified lung nodules in lung cancer screening.

NPV of LDCT is around 98-99.9% meaning LDCT is very reliable in ruling out lung nodules if the scan is negative. PPV varies widely but is often low (<50%), indicating many positive findings on LDCT may not be cancerous or true nodules and require further evaluation (usually a biopsy).[12]

Future research should focus on prospective, larger-scale studies with longitudinal follow-up to track AI-flagged nodules over time, incorporating multi-modal imaging and perhaps biomarkers. Additional calibration of the AI model for endemic settings where healed TB lesions are more common might further improve its specificity for malignancy. Finally, cost-effectiveness analyses and health system readiness assessments will be important for informing policy decisions around AI integration in screening programs.

SUMMARY

AI-based tools for chest X-ray interpretation, particularly those offering integrated TB and lung nodule assessments, may help bridge the diagnostic delay in detecting lung cancer in TB-endemic regions. While not flawless, these systems provide actionable insights, especially when TB is ruled out, making them valuable allies in population-scale screening efforts. With careful clinical integration, they could meaningfully support overburdened health systems in resource-limited environments.

DECLARATION

Ethical Approval:

Ethical approval was given.

Availability of supporting data:

The patients' medical record is available at the hospital for review.

Competing interests:

There is no competing interest on behalf of the authors in reporting this study.

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Authors' information and contributions:

All authors are doctors of Asian Hospital and Medical Center and members of the research team who conducted the study and wrote this report.

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