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AI Based Medical Diagnosis for Early Detection of Tuberculosis Using Chest X Ray Images

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Abstract

Tuberculosis (TB) has recently reclaimed its status as the world's leading infectious killer, surpassing COVID-19 mortality rates. A primary obstacle to eradication is the "missing millions" millions of undiagnosed cases that drive community transmission. This research explores the transformative role of Artificial Intelligence (AI) and Deep Learning (DL) in automating the interpretation of chest X-ray (CXR) images to bridge this diagnostic gap. We analyze the evolution of neural network architectures, from Convolutional Neural Networks (CNNs) like ResNet and EfficientNet to Vision Transformers (ViTs) and hybrid models, which have achieved diagnostic accuracies exceeding 99%. The paper further investigates the critical role of precision lung segmentation using U-Net variants and the emergence of multimodal data fusion

Vol. 5 No. 2 (2026)
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3007-2387 3007-2379
Ahmed et al - 2026
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combining CXR with acoustic cough analysis and clinical data to enhance diagnostic robustness. Clinical evidence, such as the Yichang study, demonstrates that AI can increase diagnostic yields by over 230% compared to manual reviews, particularly in resource-constrained primary care settings. Finally, we address deployment challenges, including "black-box" skepticism mitigated by Explainable AI (XAI), domain shift problems, and the potential of Edge AI for real-time inference in remote areas.

1. Introduction

The global landscape of infectious disease management underwent a seismic shift in 2023 and 2024, as tuberculosis (TB), an ancient and persistent pathogen, reclaimed (Feldmann-Jensen et al., 2024). its status as the world's leading infectious killer, surpassing the mortality rates previously attributed to the COVID-19 pandemic (Malik et al., 2020). The *Global Tuberculosis Report 2025* emphasizes that despite significant recovery in essential health services following the peak disruptions of 2020–2021, the absolute burden of the disease remains a formidable public health challenge, with an estimated 10.7 million individuals falling ill annually and approximately 1.25 million succumbing to the infection (Chen et al., 2025). Within this epidemiological context, the primary obstacle to the global eradication of TB is the persistent "missing millions" the estimated 2.4 to 2.6 million individuals who are either undiagnosed or unreported each year, thereby serving as unknown reservoirs for continued community transmission (Biermann, 2021).

The clinical significance of early detection is underscored by the stark mortality statistics associated with untreated tuberculosis, which hovers near 50%, compared to the 85% cure rate achievable through standard anti-TB therapy for drug-susceptible cases (Freitag et al., 2025). The integration of artificial intelligence (AI) and computer-aided detection (CAD) for the analysis of chest X-ray (CXR) images has emerged as a transformative solution to bridge the diagnostic gap, particularly in resource-

Vol. 5 No. 2 (2026)
Pakistan Journal of Medical & Cardiological Review
https://pakjmcr.com/index.php/1/about
Online ISSN 3007-2387
Print ISSN 3007-2379
Ahmed et al - 2026
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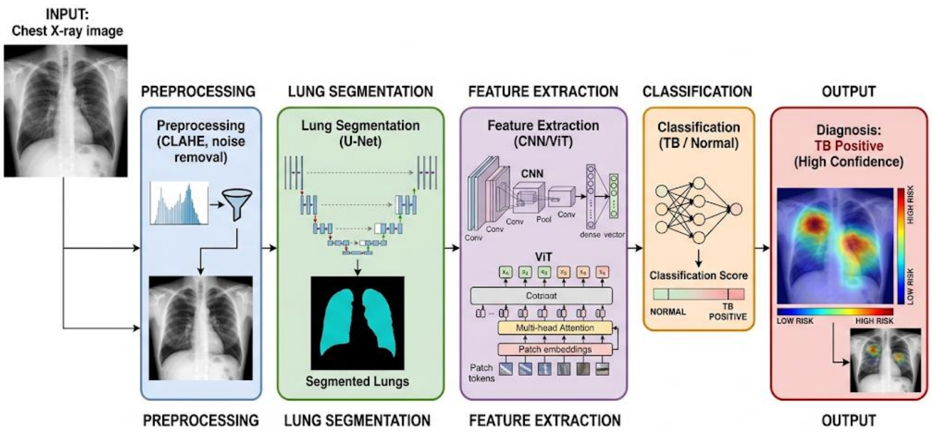
constrained settings where the availability of skilled radiologists is critically insufficient (Rayan et al., 2025). By automating the interpretation of radiographs, AI-based systems offer a scalable, rapid, and objective method for triage and screening, aligning with the primary pillars of the WHO End TB Strategy (Alimiri Dehbaghi & Khoshgard, 2025). The overall workflow of AI-based tuberculosis diagnosis from chest X-ray images is illustrated in Figure 1. This pipeline demonstrates how raw radiographic data are transformed into clinically actionable predictions through sequential deep learning modules.



Nett: AI-Based Diagnostic Pipeline for Tuberculosis Detection at Chest X-Ray Images
Figure 1: AI-Based Diagnostic Pipeline for Tuberculosis Detection Using Chest X-Ray Images

2. Epidemiological Dynamics and the Impetus for Automated Screening

The 2024 and 2025 WHO reports highlight a disconcerting resurgence in TB incidence, with a 4.6% increase noted between 2020 and 2023, effectively reversing the previous decade's trend of a 2% annual decline (Raj et al., 2025). This resurgence is concentrated geographically, with 87% of cases occurring in 30 high-burden countries. Just eight nations account for two-thirds of the global total: India (25%), Indonesia (10%), the Philippines (6.8%), China (6.5%), Pakistan (6.3%), Nigeria (4.8%), the Democratic Republic of the Congo (3.9%), and Bangladesh (3.6%) (Gurung, 2023). In these regions, the diagnostic pathway is frequently hampered by a reliance on passive case-finding

Vol. 5 No. 2 (2026)
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https://pakjmcr.com/index.php/1/about
Online ISSN Print ISSN
3007-2387 3007-2379

DOI: http://doi.org/10.5281/zenodo.20233537

strategies symptom-dependent healthcare access which often result in significant delays, with pooled mean total delays reaching 87.6 days from symptom onset to treatment initiation (Asres et al., 2018).

Chest X-ray remains the frontline screening tool due to its sensitivity, speed, and widespread digital availability (Eneogu et al., 2024). However, the efficacy of CXR is fundamentally constrained by human interpretation. Moderate inter-observer and intra-observer agreement rates, even among trained clinicians, lead to substantial discrepancies in radiological assessment (McLaughlin et al., 2022). In sub-Saharan Africa and Southeast Asia, the chronic shortage of radiologists means that films are either interpreted by non-specialists or left unread, directly contributing to missed diagnoses and the continued spread of *Mycobacterium tuberculosis* (Heffernan et al., 2021).

Table 1. Global Tuberculosis Burden and Detection Gaps (2022–2024)

Metric	**2022 Estimate**	**2023 Estimate**	**2024 Estimate**	**Change/Trend**
Global TB Incidence	10.7 Million	10.8 Million	10.7 Million	Stabilizing at high levels (Andrade, 2025)
Annual TB Deaths	1.13 Million	1.25 Million	1.20 Million	Reclaimed #1 killer status (Andrade, 2025)
Undiagnosed/Unreported Cases	~2.5 Million	2.6 Million	~2.4 Million	Major transmission driver (World

Vol. 5 No. 2 (2026)
Pakistan Journal of Medical & Cardiological Review
https://pakjmcr.com/index.php/1/about
Online ISSN 3007-2387 Print ISSN 3007-2379
Ahmed et al - 2026
DOI: http://doi.org/10.5281/zenodo.20233537

				Health Organization, 2024)
MDR/RR-TB Diagnosis Coverage	44 %	46 %	48 %	Slow improvement (World Health Organization, 2025)
Domestic Funding vs. Needs	~20% of target	~20% of target	~20% of target	Stagnant at 1B of 5B needed (Andrade, 2025)

3. Foundational Neural Network Architectures for Image Analysis

The rapid maturation of deep learning (DL) has provided the technical foundation for modern AI-based medical diagnosis (Fujita, 2020). Unlike traditional computer-aided detection, which relied on hand-crafted features such as shape descriptors, deep learning models, particularly Convolutional Neural Networks (CNNs), automatically learn hierarchical representations of pulmonary abnormalities directly from raw pixel data (Attallah, 2023).

3.1. Convolutional Neural Networks (CNNs) and Feature Extraction

The evolution of CNN architectures from AlexNet to ResNet and EfficientNet has progressively improved the accuracy of TB detection. ResNet (Residual Network) introduced skip connections, enabling the training of extremely deep networks by mitigating the vanishing gradient problem, which has enabled AUC values as high as 0.9944 for active TB identification (Malwade et al., 2025). DenseNet (Densely

Vol. 5 No. 2 (2026)
Pakistan Journal of Medical & Cardiological Review
https://pakjmcr.com/index.php/1/about
Online ISSN 3007-2387
Print ISSN 3007-2379
Ahmed et al - 2026
DOI: http://doi.org/10.5281/zenodo.20233537

Connected Network) further refined this by connecting each layer to every subsequent layer, enhancing feature reuse and proving particularly effective in medical imaging where datasets may be smaller (Huang et al., 2019).

EfficientNet has emerged as a preferred architecture for real-world clinical deployment due to its use of compound scaling, which balances depth, width, and resolution to optimize performance while maintaining a low computational footprint (Verma & Bohat, 2025). In integrated diagnostic pipelines, EfficientNetB0 is frequently utilized as a backbone for classification after a lung segmentation stage, achieving 99.76% accuracy on standard TB benchmarks (Metwally, 2022).

3.2. Vision Transformers and Global Contextual Awareness

A significant architectural shift has occurred with the introduction of Vision Transformers (ViTs) for radiographic analysis. While CNNs focus on local neighborhoods of pixels, ViTs utilize self-attention mechanisms to capture global dependencies across the entire thoracic cavity (Aburass et al., 2025). A typical ViT architecture for TB detection involves partitioning the CXR into patches, which are then flattened and embedded into a sequence of tokens (Kotei & Thirunavukarasu, 2024).

The Vision Transformer encoder blocks, consisting of multi-headed self-attention (MHSA) and position-wise feed-forward networks, allow the model to weight the importance of different lung regions relative to one another. This global context is critical for detecting subtle patterns like miliary TB or for identifying hilar lymphadenopathy (Singh et al., 2024).

3.3. Hybrid Modeling and Computational Efficiency

To address the limitations of both CNNs and Transformers, researchers have developed hybrid models that combine the spatial inductive bias of convolutions with the global contextual reach of Transformers. For instance, a hybrid model utilizing GhostNet (a lightweight CNN) and MobileViT has been evaluated for resource-limited

Vol. 5 No. 2 (2026)
Pakistan Journal of Medical & Cardiological Review
https://pakjmcr.com/index.php/1/about
Online ISSN 3007-2387 Print ISSN 3007-2379
Ahmed et al - 2026
DOI: http://doi.org/10.5281/zenodo.20233537

environments, achieving accuracy levels of 99.52% with only 7.73 million parameters (Lu et al., 2022). This balance between accuracy and computational cost is vital for deployment in clinics that lack access to high-end GPU servers (Babu et al., 2025).

Table 2. Benchmarking of Prominent Deep Learning Architectures in TB Detection

Architecture Type	Specific Model	Accuracy	Sensitivity	Key Advantage
CNN (Residual)	ResNet-101	99.01%	98.40%	Robust gradient flow (Nijiati et al., 2022)
CNN (Dense)	DenseNet-201	98.60%	97.50%	High feature reuse (Beyer, 2025)
CNN (Scaled)	EfficientNetB4	99.79%	99.00%	Optimal resolution scaling (EfficientNet Study, 2025)
Transformer	ViT (Standard)	92.60%	91.50%	Global spatial awareness (Sindhushre

Vol. 5 No. 2 (2026)
Pakistan Journal of Medical & Cardiological Review
https://pakjmcr.com/index.php/1/about
Online ISSN 3007-2387
Print ISSN 3007-2379
Ahmed et al - 2026
DOI: http://doi.org/10.5281/zenodo.20233537

				e et al., 2025)
Hybrid	GhostNet-MobileViT	99.52 %	99.10%	Low inference overhead (Beyer, 2025)

4. Precision Lung Segmentation and Pre-processing Workflows

The accuracy of an AI diagnostic system is heavily dependent on the quality of the input data and the isolation of the Region of Interest (ROI). In chest radiography, the lung fields must be accurately segmented to prevent the classifier from focusing on irrelevant anatomical features (Khalifa & Albadawy, 2024).

4.1. Semantic Segmentation with U-Net and Its Variants

The U-Net architecture, characterized by its symmetric contracting and expanding paths, remains the gold standard for medical image segmentation. By utilizing skip connections between the encoder and decoder, U-Net preserves high-resolution spatial information (Siddique et al., 2021). Advanced iterations like UNet++ and TASPP-UNet (Triple Atrous Spatial Pyramid Pooling) have further refined this, achieving Intersection over Union (IoU) scores exceeding 0.92 (Mukasheva et al., 2024). A novel architecture named CXR-Seg, which integrates an EfficientNet encoder with a transformer attention module at the bottleneck layer, has demonstrated superior performance in segmenting lungs from TB-infected images, reaching a Dice coefficient of 96.32% on the Shenzhen Tuberculosis dataset (Din et al., 2025). This precise segmentation ensures that the subsequent classification model focuses solely on

Vol. 5 No. 2 (2026)

Pakistan Journal of Medical & Cardiological Review

https://pakjmcr.com/index.php/1/about

Online ISSN 3007-2387

Print ISSN 3007-2379

Ahmed et al - 2026

DOI: http://doi.org/10.5281/zenodo.20233537

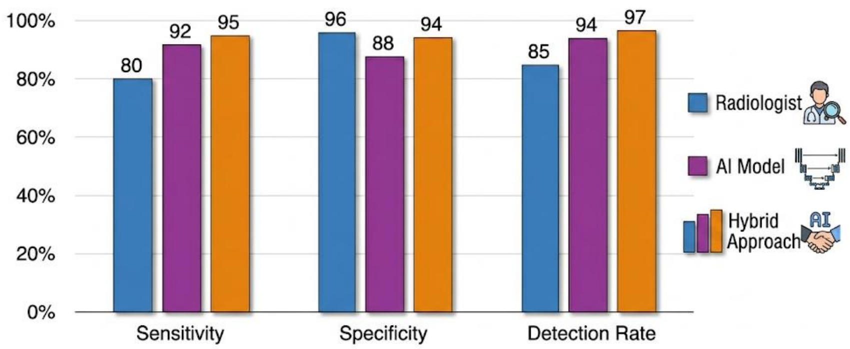
pulmonary manifestations like consolidations and cavities (Marinakis et al., 2024).

4.2. Image Enhancement and Feature Saliency

Radiographic images in high-burden settings are often produced using older equipment, leading to inconsistent exposure and noise. Pre-processing techniques such as Contrast Limited Adaptive Histogram Equalization (CLAHE) and Gamma Correction have been shown to significantly enhance the visibility of TB lesions (Akdemir et al., 2025). By improving the signal-to-noise ratio, these techniques allow the neural network to identify subtle pattern fluctuations, thereby increasing both precision and recall (Zangane et al., 2025).

5. Comparative Clinical Performance: AI vs. Radiologist

The true value of AI in tuberculosis diagnosis is measured by its performance relative to the current clinical standard of manual radiographic review. Extensive comparative studies have demonstrated that contemporary CAD systems frequently exceed the diagnostic capabilities of human readers, particularly in high-volume triage settings (Hua et al., 2023). A comparative analysis of diagnostic performance is presented in Figure 2. The results highlight the superiority of AI-assisted and hybrid approaches over manual interpretation.



(Illustrative Data on a Tuberculosis Screening Dataset)

Figure 2: AI vs Radiologist Diagnostic Performance Comparison

Vol. 5 No. 2 (2026)
Pakistan Journal of Medical & Cardiological Review
https://pakjmcr.com/index.php/1/about
Online ISSN Print ISSN
3007-2387 3007-2379
Ahmed et al - 2026
DOI: http://doi.org/10.5281/zenodo.20233537

5.1. The Yichang Diagnostic Yield Study

A large-scale retrospective study conducted across 39 healthcare facilities in Yichang, China, analyzed radiographs from over 93,000 patients to compare the JF CXR-1 CAD software against original radiologist interpretations (Yang et al., 2023). The study found that CAD identified 83.9% (229/273) of bacteriologically confirmed cases, whereas radiologists had only identified 25.6% (70/273) during the initial clinical encounter (Magitta, 2024). This 230% increase in diagnostic yield underscores the potential for AI to find the "missing" cases overlooked in routine practice (Chircop, 2025).

Crucially, the performance of CAD was significantly higher in township-level primary care facilities (DYD 86.7%) compared to county-level hospitals (DYD 62.5%), suggesting that AI is most impactful where radiologist availability is lowest (Jiang et al., 2025).

5.2. Target Product Profiles and WHO Standards

The WHO established a Target Product Profile (TPP) for TB triage tests, requiring a minimum sensitivity of 90% and a minimum specificity of 70% (MacLean et al., 2023). Benchmarking of commercially available algorithms revealed that multiple models reach the sensitivity threshold, though only a few consistently meet the specificity target (Hallgren et al., 2019).

Table 3. Performance of Evaluated Systems against WHO TPP

Evaluated System	Sensitivity	Specificity	AUC	Meeting WHO TPP?
qXR (version 3)	90.0%	74.3%	0.908	Yes (Banu & Creswell, 2021)
CAD4TB	90.0%	72.9%	0.90	Yes

Vol. 5 No. 2 (2026)
Pakistan Journal of Medical & Cardiological Review
https://pakjmcr.com/index.php/1/about
Online ISSN Print ISSN
Ahmed et al - 2026
3007-2387 3007-2379
DOI: http://doi.org/10.5281/zenodo.20233537

(version 6)			3	(Banu & Creswell, 2021)
JF CXR-1	83.9%	1.7% (PPV)	0.84 9	Sensitivity focus (Banu & Creswell, 2021; Jiang et al., 2025)
Lunit INSIGHT	88.0%	68.0%	0.88 6	Borderline (Banu & Creswell, 2021)
AI-Generated Report	95.2%	86.7%	0.90 8	Yes (Internal) (Reader Acceptance Study, 2025)

Despite high standalone accuracy, clinical evidence suggests that a "human-in-the-loop" strategy is currently optimal. Radiologists using AI as a second reader have shown sensitivity improvements of up to 11%–26%, while simultaneously reducing reading times by approximately one-third (Nation & Macalister, 2020).

6. Explainable AI (XAI) and the Trust Frontier

One of the primary barriers to the widespread clinical adoption of AI is the "black-box" nature of deep neural networks. For healthcare providers, understanding the *why* behind a TB diagnosis is critical for treatment decisions (Ennab, 2025).

6.1. Visual Interpretability via Saliency Maps

Gradient-weighted Class Activation Mapping (Grad-CAM) generates visual heatmaps highlighting the regions of the CXR that most influenced the model's prediction (Bates,

Vol. 5 No. 2 (2026)
Pakistan Journal of Medical & Cardiological Review
https://pakjmcr.com/index.php/1/about
Online ISSN Print ISSN
Ahmed et al - 2026
3007-2387 3007-2379
DOI: http://doi.org/10.5281/zenodo.20233537

2024). The mathematical basis involves computing the gradients of the output score with respect to the feature maps of the final convolutional layer (Chattopadhay et al., 2018). While Grad-CAM is intuitive, newer techniques like Pixel-level Interpretability (PLI) have been shown to significantly outperform Grad-CAM in granularity (Dhore et al., 2024).

6.2. Mathematical Feature Contribution: SHAP and LIME

SHapley Additive exPlanations (SHAP) and Local Interpretable Model-Agnostic Explanations (LIME) provide transparency by quantifying the contribution of each feature to the final probability (Parisineni & Pal, 2024). While computationally expensive, SHAP offers the most mathematically sound explanation for complex diagnostic decisions (Khalyasmaa et al., 2025). LIME has proven effective in identifying specific pathologies like edema, though it can sometimes be inconsistent (Vimbi et al., 2024).

7. Multimodal Data Fusion: Beyond the Radiograph

Modern AI research is shifting toward multimodal fusion, integrating heterogeneous data sources such as imaging, symptoms, and laboratory findings to improve diagnostic robustness (Al-Zoghby et al., 2025).

7.1. Integrated Clinical and Acoustic Biomarkers

Innovative frameworks now combine digital radiographs with acoustic analysis of cough sounds and clinical electronic health records (EHR). Research demonstrates that intermediate fusion models achieve an accuracy of 98%, compared to 94% for CXR-only models (Rashid et al., 2025). Cough audio analysis, specifically utilizing Capsule Networks, has emerged as a low-cost triage method capable of identifying unique respiratory patterns (Serrurier et al., 2022).

7.2. Integrating Molecular Diagnostics and AI

AI acts as a high-sensitivity triage tool to filter the patient population, significantly

Vol. 5 No. 2 (2026)
Pakistan Journal of Medical & Cardiological Review
https://pakjmcr.com/index.php/1/about
Online ISSN Print ISSN
Ahmed et al - 2026
3007-2387 3007-2379
DOI: http://doi.org/10.5281/zenodo.20233537

reducing the number of expensive molecular tests like GeneXpert required (Chakraborty, 2024). Data from triage programs indicate that AI can reduce GeneXpert testing volume by 50% while maintaining a sensitivity above 90% (Nsengiyumva et al., 2021).

Table 4. Multimodal Diagnostic Performance Comparison

Modality Combination	Accuracy	Sensitivity	AUC	Clinical Utility
CXR Only	94.0%	93.0%	0.940	Standard screening (Hayat et al., 2025)
Cough Only	79.0%	76.0%	0.810	Remote triage (Hayat et al., 2025)
CXR + CT + Cough	98.0%	97.5%	0.990	Comprehensive assessment (Hayat et al., 2025)
CXR + Symptom Survey	92.4%	91.1%	0.950	Primary care integration (Mapari et al., 2025)

8. Challenges in Generalization: The Domain Shift Problem

A critical hurdle in AI deployment is the performance degradation observed when a model is applied to a demographic setting different from its training data (Rather et al., 2024). This domain shift is often caused by variations in patient anatomy and X-ray machine manufacturer artifacts (Eslami et al., 2024).

Vol. 5 No. 2 (2026)
Pakistan Journal of Medical & Cardiological Review
https://pakjmcr.com/index.php/1/about
Online ISSN 3007-2387
Print ISSN 3007-2379
Ahmed et al - 2026
DOI: http://doi.org/10.5281/zenodo.20233537

To counter this, supervised adversarial domain adaptation (ADA) techniques are used to train the feature extractor alongside a domain discriminator, making features from both domains indistinguishable (Saleem et al., 2024). This technique has improved accuracy on target populations, such as Nigerian cohorts, to over 90% (Onovo et al., 2023).

8.1. Vulnerable Sub-populations: HIV and Pediatrics

Generalization is particularly difficult in pediatric patients and people living with HIV (PLWH). Pediatric TB is typically paucibacillary, often lacking the classic cavitary lesions seen in adults (Buthelezi, 2020). AI models like qXR-pTB, specifically cleared for children aged 0–3, focus on identifying these "occult" findings, achieving sensitivities up to 98.2% (Emegano et al., 2026).

In PLWH, tuberculosis often presents with atypical features (Kacprzak et al., 2022). While AI models generally outperform human readers in HIV-positive cohorts (AUC 0.79 vs 0.65 for physicians), the presence of co-morbidities can increase false-positive rates (Sun et al., 2025).

9. Edge AI and Hardware Optimization for Rural Deployment

The development of Edge AI where inference occurs locally on low-cost hardware is essential for clinics in remote areas that lack internet connectivity (Jain et al., 2026).

Hardware accelerators such as the NVIDIA Jetson Nano, Google Coral Edge TPU, and the Raspberry Pi 5 (integrated with the Hailo-8 NPU) have demonstrated the capability to run TB detection models in real-time (Ariodito Hermanto, 2025). Tiny Machine Learning (TinyML) focuses on deploying these models on microcontrollers using techniques like 8-bit quantization and knowledge distillation, which can reduce model sizes by up to 98% while retaining performance (Somvanshi et al., 2025).

10. Economic Impact and Public Health Policy

The programmatic value of AI depends on its integration into a functioning diagnostic

Vol. 5 No. 2 (2026)

Pakistan Journal of Medical & Cardiological Review

https://pakjmcr.com/index.php/1/about

Online ISSN 3007-2387 Print ISSN 3007-2379

Ahmed et al - 2026

DOI: http://doi.org/10.5281/zenodo.20233537

cascade (Najjar, 2023). Modeling studies in Pakistan have demonstrated that AI-based CXR triage can avert 3%–4% of additional DALYs compared to smear microscopy alone (Aurangzeb et al., 2025). From a fiscal screened individuals by 37% compared to upfront GeneXpert testing (Miglietta et al., 2025). perspective, AI-based triage reduces the cost per 1,000).

Table 5. Summary of Implementation Barriers and Mitigation Strategies

Level	Key Barrier	Proposed Mitigation Strategy
Technical	Domain/Covariate Shift	Adversarial training and local fine-tuning (Nigerian Health Information Study, 2025)
Hardware	Lack of connectivity/power	Deployment of Edge AI on NPU-enabled devices (Kumar Gupta, 2025)
Clinical	Black-box skepticism	Integration of XAI (Grad-CAM/SHAP) (Bhandari et al., 2025)
Economic	High cost of PCR/GeneXpert	Using AI as a high-sensitivity triage filter (Banu & Creswell, 2021)
Policy	Funding deficits (4B gap)	Increased domestic funding coordination (Andrade, 2025)
Social	Stigma and remoteness	Mobile outreach with ultra-portable AI (Vijayan et al., 2025)

Conclusion

The integration of AI-based medical diagnosis represents a seismic shift in the global strategy to end tuberculosis. By providing a scalable, rapid, and highly sensitive triage tool, AI effectively addresses the critical shortage of radiologists in high-burden nations. Technical advancements in hybrid modeling and multimodal fusion have pushed diagnostic performance beyond human capabilities, while XAI frameworks like Grad-CAM and SHAP are beginning to bridge the "trust frontier" for clinicians. Despite these gains, the successful eradication of TB depends on overcoming the domain shift problem across diverse populations and ensuring that these models can operate on low-cost Edge AI hardware in regions without internet connectivity. Ultimately, AI-based triage not only improves patient outcomes by enabling early detection but also offers significant economic benefits, reducing the reliance on expensive molecular testing by up to 50%. To realize the full potential of these technologies, future efforts must focus on integrating AI into a cohesive diagnostic cascade supported by increased domestic funding and policy coordination

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Online ISSN 3007-2387
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Online ISSN 3007-2387
Print ISSN 3007-2379
Ahmed et al - 2026
DOI: http://doi.org/10.5281/zenodo.20233537

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