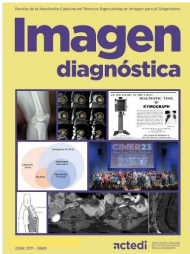

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Artificial Intelligence in Tuberculosis Imaging: Advances, Challenges and Future Directions

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Abstract: Tuberculosis (TB) remains a major global public health challenge, with delayed diagnosis continuing to hinder disease control, particularly in low- and middle-income countries. Chest imaging, especially chest radiography, plays a pivotal role in TB screening and triage; however, its interpretation is often constrained by inter-observer variability, limited radiology expertise and increasing diagnostic workload. Recent advances in Artificial Intelligence (AI), including machine learning, deep learning, convolutional neural networks, foundation models and multimodal AI, have transformed TB imaging by enabling rapid, standardized and highly accurate interpretation of radiological images. AI-assisted computer-aided detection systems have demonstrated diagnostic performance comparable to experienced radiologists and are increasingly being integrated into community screening, active case finding, facility-based diagnosis, treatment monitoring and programme surveillance. This review critically summarizes current evidence on AI applications in chest radiography and computed tomography, digital health integration, population-based screening and implementation within resource-constrained settings, with particular emphasis on the World Health Organization recommendations and the National TB Elimination Programme. It further discusses ethical, regulatory and operational challenges, including algorithmic bias, data privacy, clinical validation and workflow integration, while highlighting emerging innovations such as vision transformers, foundation models, multimodal AI, federated learning, explainable AI and generative AI. Finally, the review identifies key research gaps and future priorities for translating AI into routine clinical practice and national TB programmes. The responsible integration of AI with imaging and digital health technologies has the potential to improve early TB detection, strengthen screening programmes, optimize healthcare resources and accelerate progress toward global tuberculosis elimination.

Key Words: Artificial Intelligence, Tuberculosis, Chest Radiography, Computer-Aided Detection, Deep Learning

INTRODUCTION

Tuberculosis (TB) remains one of the leading infectious causes of morbidity and mortality worldwide, with an estimated 10.8 million new cases and 1.25 million deaths in 2023, despite being a preventable and curable disease. The burden is disproportionately concentrated in Low- and Middle-Income Countries (LMICs), with India contributing the largest share of global TB cases. Delayed diagnosis, limited access to quality healthcare, shortage of trained radiologists and disparities in diagnostic services continue to impede global TB elimination efforts [1,2].

Early diagnosis is fundamental to reducing TB transmission, initiating timely treatment and improving patient outcomes. Although microbiological tests such as smear microscopy, culture and molecular assays remain the diagnostic gold standard, chest imaging, particularly chest radiography (CXR), plays a pivotal role in screening, triaging symptomatic individuals, active case finding and supporting diagnosis in resource-limited settings. Advances in digital radiography, portable X-ray systems and mobile screening units have further expanded the role of imaging in large-scale TB control programmes [3,4].

However, conventional interpretation of chest radiographs is often limited by inter-observer variability, inconsistent reporting, heavy radiologist workload and limited availability of trained experts, particularly in high-burden regions. Subtle radiographic abnormalities may be overlooked, resulting in delayed diagnosis and continued disease transmission.

Recent advances in Artificial Intelligence (AI) have transformed TB imaging by enabling rapid, standardized and automated interpretation of chest radiographs and Computed Tomography (CT) scans. AI technologies, including machine learning, deep learning and computer vision, have demonstrated diagnostic performance comparable to experienced radiologists in several clinical settings, supporting large-scale TB screening and clinical decision-making [5-8].

This review provides a comprehensive overview of current evidence on the application of artificial intelligence in tuberculosis imaging. It critically examines recent technological advances, clinical applications, implementation challenges, ethical considerations and future perspectives, highlighting the potential of AI to strengthen TB screening, diagnosis and global tuberculosis control.

Evolution of Artificial Intelligence in Tuberculosis Imaging

Artificial intelligence has rapidly evolved from simple rule-based image analysis systems to advanced deep learning models capable of detecting complex radiological patterns associated with tuberculosis. The increasing availability of digital imaging datasets, improved computational power and advances in computer vision have accelerated the integration of AI into TB screening and diagnostic workflows, particularly in resource-constrained settings.

Evolution of AI

Early Computer-Aided Detection (CAD) systems relied on predefined image-processing rules to identify radiographic abnormalities suggestive of pulmonary tuberculosis. Although these systems improved screening efficiency, their diagnostic accuracy was limited by manually engineered features and poor adaptability.

The introduction of Machine Learning (ML) enabled algorithms to learn from labelled imaging datasets, improving the identification of TB-related abnormalities. This was followed by the widespread adoption of deep learning, particularly Convolutional Neural Networks (CNNs), which automatically extract complex image features and have demonstrated excellent performance in detecting pulmonary infiltrates, cavitation, fibrosis and other TB-related lesions on chest radiographs and CT scans [9-11].

More recently, foundation models trained on massive medical imaging datasets have enabled transfer learning across multiple imaging tasks, reducing the need for extensive disease-specific training. The emergence of generative AI offers new opportunities for automated reporting, image enhancement, clinical documentation and educational support, while multimodal AI integrates imaging with clinical, laboratory and demographic information to improve diagnostic accuracy and clinical decision-making.

Major AI Technologies in Tuberculosis Imaging

Several AI technologies underpin modern TB imaging applications. Machine learning is widely used for disease classification and risk prediction using structured imaging data, whereas deep learning has become the dominant approach for automated image interpretation. Convolutional Neural Networks (CNNs) remain the backbone of most AI-based TB detection systems because of their superior ability to recognize complex radiographic patterns [12-14].

Emerging Vision Transformers (ViTs) have shown promising performance by capturing long-range spatial relationships within medical images and may further improve TB image classification. Computer vision techniques facilitate automated detection, segmentation and quantification of pulmonary lesions, while Natural Language Processing (NLP) extracts clinically relevant information from radiology reports and electronic health records to support integrated decision-making [15,16].

The recent development of Large Language Models (LLMs) has expanded AI applications beyond image analysis by assisting with report generation, literature synthesis and clinical decision support. At the same time, Explainable AI (XAI) has gained increasing importance by improving transparency and helping clinicians understand the reasoning behind AI-generated predictions, thereby enhancing trust and facilitating clinical adoption [17,18] (Table 1-2).

Tuberculosis Imaging: Current Landscape

Medical imaging remains an integral component of tuberculosis (TB) screening, diagnosis and treatment monitoring. Among available modalities, chest X-ray (CXR) is the most widely used owing to its rapid acquisition, low cost and high sensitivity for detecting pulmonary abnormalities. The transition to digital radiography has further improved image quality, storage, transmission and compatibility with AI-based Computer-Aided Detection (CAD) systems, making it the preferred imaging modality for large-scale TB screening.

The development of portable digital X-ray systems and mobile X-ray units has significantly expanded access to TB screening in remote, rural and underserved populations. Combined with AI-assisted interpretation, these technologies facilitate active case finding and community-based screening while reducing dependence on onsite radiologists.

Although Computed Tomography (CT) provides superior visualization of pulmonary lesions-including cavitation, tree-in-bud nodules, lymphadenopathy and subtle parenchymal abnormalities-it is limited by higher

Table 1: Evolution of Artificial Intelligence in Tuberculosis Imaging

Era	AI Technology	Key Characteristics	Major Applications in TB Imaging
Early 2000s	Computer-Aided Detection (CAD)	Rule-based image analysis	Automated TB screening on chest X-rays
2010-2015	Machine Learning	Feature-based predictive models	Abnormality detection and image classification
2015-2020	Deep Learning	Automatic feature extraction	Pulmonary TB detection on CXR and CT
2016-Present	Convolutional Neural Networks (CNNs)	High-performance image recognition	Detection of infiltrates, cavities, fibrosis, pleural disease
2023-Present	Foundation Models	Large pretrained medical imaging models	Transfer learning and multimodal image analysis
Emerging	Generative and Multimodal AI	Integration of imaging, clinical and laboratory data	Automated reporting, decision support and precision TB diagnostics

Table 2: Major Artificial Intelligence Algorithms Used in Tuberculosis Imaging

AI Technology	Advantages	Limitations	Major Applications
Machine Learning	Simple, efficient, interpretable	Limited performance on complex images	Image classification, risk prediction
Deep Learning	High diagnostic accuracy	Requires large labelled datasets	Automated TB detection
CNN	Excellent feature extraction	Computationally intensive	Chest X-ray and CT interpretation
Vision Transformers (ViT)	Captures global image features	High training requirements	Advanced image classification
Computer Vision	Automated image analysis	Dependent on image quality	Lesion detection and segmentation
NLP	Extracts information from clinical text	Language variability	Radiology report analysis
Large Language Models	Automated reporting and clinical support	Hallucination risk; requires validation	Report generation and decision support
Explainable AI	Improves transparency and clinician trust	May reduce model complexity	Interpretation of AI predictions

costs, greater radiation exposure and reduced accessibility, restricting its routine use to complex or equivocal cases. Magnetic Resonance Imaging (MRI) has a limited role in pulmonary TB because of lower spatial resolution for lung parenchyma but may be useful for evaluating central nervous system, musculoskeletal and cardiac tuberculosis. Ultrasonography serves as a valuable, radiation-free tool for diagnosing extrapulmonary TB, particularly pleural, abdominal and lymph node involvement. Meanwhile, Positron Emission Tomography-Computed Tomography (PET-CT) is primarily used in research and selected clinical situations to assess disease activity, treatment response and residual lesions but is not recommended for routine TB diagnosis due to its high cost and limited availability.

Each imaging modality offers unique strengths and limitations; therefore, selecting the appropriate technique depends on the clinical scenario, resource availability and intended application. Increasingly, AI is enhancing the diagnostic performance and accessibility of these imaging modalities across diverse healthcare settings.

AI Applications Across the Tuberculosis Care Cascade

Artificial intelligence is transforming tuberculosis control by supporting imaging-based decision-making throughout the entire TB care cascade, from community screening to long-term follow-up. By enabling rapid, standardized and automated interpretation of radiological images, AI improves early case detection, reduces diagnostic delays and enhances programme efficiency, particularly in resource-limited settings.

During community screening and active case finding, AI-assisted portable chest radiography facilitates rapid identification of individuals with presumptive TB in high-risk populations such as household contacts, tribal communities, prisons, urban slums, migrants and people living with HIV. Within healthcare facilities, AI supports facility-based screening by triaging symptomatic patients and prioritizing those requiring confirmatory microbiological testing, thereby improving diagnostic efficiency and reducing radiologist workload [19,20].

AI also assists in the diagnosis of pulmonary TB by detecting characteristic radiographic abnormalities and estimating disease severity. Emerging evidence suggests potential applications in identifying imaging features associated with drug-resistant tuberculosis, although microbiological confirmation remains essential. Beyond diagnosis, AI supports treatment monitoring by objectively quantifying radiographic changes, assessing disease progression and evaluating therapeutic response over time. During follow-up, AI enables standardized comparison of serial images, facilitating early detection of relapse or residual disease [5,6,13,21].

At the programme level, AI contributes to public health surveillance by analysing large imaging datasets to monitor screening performance, identify geographical hotspots, evaluate programme effectiveness and support evidence-based resource allocation. These applications position AI as an important tool for strengthening TB elimination efforts through faster diagnosis, improved efficiency and data-driven decision-making (Table 3).

AI in Chest X-ray Interpretation

Chest radiography remains the primary imaging modality for tuberculosis (TB) screening and artificial intelligence has substantially enhanced its diagnostic utility through rapid, automated and standardized image interpretation. Deep learning-based Computer-Aided Detection (CAD) systems can identify radiographic abnormalities

Table 3: Artificial Intelligence Applications Across the Tuberculosis Care Cascade

Stage of TB Care Cascade	Primary Objective	Major AI Applications
Community Screening	Early identification of presumptive TB	AI-assisted portable chest X-ray, automated triage, mass screening
Active Case Finding	Detect TB among high-risk populations	Mobile digital X-ray, CAD software, targeted community screening
Facility-Based Screening	Prioritize patients for confirmatory testing	Automated chest X-ray interpretation, triage support
Diagnosis	Detect radiological features suggestive of TB	AI-based lesion detection, severity assessment, decision support
Drug-Resistant TB	Support identification of advanced disease patterns	Imaging pattern recognition, treatment response assessment*
Treatment Monitoring	Evaluate disease progression and response	Serial image comparison, lesion quantification
Follow-up	Detect residual disease or relapse	Automated longitudinal image analysis
Programme Surveillance	Strengthen TB control programmes	Screening analytics, hotspot identification, programme monitoring

*AI supports imaging assessment but does not replace microbiological diagnosis of drug-resistant tuberculosis

Table 4: Comparison of Major AI Software for Tuberculosis Chest X-ray Interpretation

AI Software	Developer	Primary Modality	Major Strengths	Typical Applications
CAD4TB	Delft Imaging (Netherlands)	Chest X-ray	WHO-endorsed, widely validated	Community screening, active case finding
qXR	Qure.ai (India)	Chest X-ray	High sensitivity, cloud integration	Screening, triage, tele-radiology
Lunit INSIGHT CXR	Lunit (South Korea)	Chest X-ray	High diagnostic accuracy, multiple thoracic abnormalities	Hospital and screening programmes
InferRead DR	Infervision (China)	Chest X-ray	Automated lesion detection	Clinical decision support
JF CXR-1	Fujifilm (Japan)	Chest X-ray	Rapid automated interpretation	Screening and workflow optimization

suggestive of pulmonary TB, including pulmonary infiltrates, cavitation, fibrosis, pleural effusion, miliary nodules and other characteristic lesions, while also generating severity scores that assist in patient triage, referral and treatment prioritization.

Several commercially available CAD platforms have demonstrated excellent diagnostic performance. CAD4TB, qXR, Lunit INSIGHT CXR, InferRead DR and JF CXR-1 are among the most extensively validated systems for automated TB screening. These software solutions analyse digital chest radiographs within seconds and generate abnormality scores that help identify individuals requiring confirmatory microbiological testing. Numerous studies have reported diagnostic performance comparable to experienced radiologists, particularly in high-burden settings, while substantially reducing reporting time and improving access to expert interpretation where radiologists are scarce [22-24].

Recognizing the growing evidence base, the World Health Organization (WHO) recommends the use of AI-based computer-aided detection software as an alternative to human interpretation for digital chest radiographs in TB screening among individuals aged 15 years and older. Although diagnostic performance varies depending on the software, study population, disease prevalence and threshold values, most validated CAD systems consistently demonstrate high sensitivity with acceptable specificity, making them valuable triage tools rather than standalone diagnostic tests. Consequently, AI-assisted chest radiography has emerged as an important component of modern TB screening programmes, particularly in resource-constrained settings where rapid, scalable and standardized interpretation is essential (Table 4).

AI in CT Imaging for Tuberculosis

Although chest radiography remains the primary imaging modality for TB screening, Computed Tomography (CT) provides superior visualization of pulmonary abnormalities and is particularly valuable in complex or diagnostically challenging cases. Artificial intelligence has further enhanced CT interpretation by enabling automated detection, segmentation and quantitative assessment of tuberculosis-related lesions.

Deep learning algorithms accurately identify subtle pulmonary lesions, including small nodules, tree-in-bud opacities, cavities, consolidation and bronchogenic spread that may not be readily visible on conventional chest radiographs. AI also facilitates automated assessment of mediastinal lymphadenopathy, an important feature of primary tuberculosis, particularly in children and immunocompromised individuals.

Beyond diagnosis, AI-based CT analysis supports disease quantification by measuring lesion volume, extent of pulmonary involvement and cavity burden, providing objective biomarkers for disease severity. Serial AI-assisted CT assessments also enable standardized evaluation of treatment response, helping clinicians monitor disease progression, assess therapeutic effectiveness and identify persistent or recurrent disease. Although CT-based AI applications demonstrate high diagnostic accuracy, their routine use remains limited by higher costs, radiation exposure and restricted availability. Consequently, AI-assisted CT is best viewed as a complementary tool for selected clinical indications rather than a replacement for AI-enabled chest radiography in large-scale TB screening programmes [25-28].

AI and Digital Health Integration

The integration of artificial intelligence with digital health technologies has expanded the reach and efficiency of tuberculosis (TB) imaging, particularly in resource-limited settings. AI-enabled portable digital X-ray systems and mobile screening vans facilitate rapid community-based screening by bringing diagnostic services closer to underserved populations. Automated image analysis at the point of care reduces dependence on onsite radiologists and enables immediate identification of individuals requiring confirmatory testing.

Advances in cloud-based reporting and tele-radiology allow chest radiographs acquired in remote areas to be securely analysed by AI algorithms and reviewed by specialists in real time, improving diagnostic accuracy and reducing reporting delays. Smartphone-based reporting further enhances accessibility by enabling healthcare workers to upload images, receive AI-generated abnormality scores and coordinate referrals through mobile applications [29,30].

The integration of AI with Electronic Health Records (EHRs) and national TB information systems, such as India's Ni-kshay platform, supports automated data capture, patient tracking, treatment monitoring and programme evaluation. Looking ahead, wearable technologies may complement imaging by enabling continuous monitoring of physiological parameters, treatment adherence and symptom progression, although their role in TB care remains largely investigational. Together, AI and digital health technologies are creating an integrated ecosystem that enhances early diagnosis, continuity of care and programme efficiency [31-33].

AI for Population-Based Tuberculosis Screening

Artificial intelligence has emerged as a powerful tool for population-based tuberculosis screening, enabling rapid interpretation of chest radiographs and supporting large-scale active case finding in high-burden settings. AI-assisted screening is particularly valuable in mass screening programmes, where it can efficiently identify individuals with radiographic abnormalities suggestive of TB and prioritize them for confirmatory microbiological testing.

The greatest public health impact is observed when AI is deployed among high-risk populations, including household contacts, prison inmates, tribal and remote communities, residents of urban slums, migrant workers, people living with HIV and individuals attending diabetes clinics, all of whom have an increased risk of developing tuberculosis. By reducing dependence on expert radiologists and enabling standardized interpretation, AI facilitates timely diagnosis in settings where specialist resources are limited.[34,35]

Several implementation studies have demonstrated that AI-supported chest radiography can improve screening efficiency, increase case detection, reduce diagnostic delays and optimize the utilization of confirmatory molecular tests. Emerging evidence also suggests favourable cost-effectiveness, particularly in high-burden settings where AI can reduce unnecessary investigations while improving diagnostic yield. From a public health perspective, AI-enabled screening has the potential to strengthen active case finding, interrupt community transmission, improve programme performance and accelerate progress toward global tuberculosis elimination targets.

AI in Low- and Middle-Income Countries

Artificial intelligence has enormous potential to strengthen tuberculosis control in low- and middle-income countries (LMICs), where the burden of TB is highest and access to radiologists and advanced diagnostic services is often limited. By providing rapid, standardized interpretation of digital chest radiographs, AI can improve early case detection, reduce diagnostic delays and support decentralized TB screening in resource-constrained settings.

In India, AI is increasingly being integrated into the National TB Elimination Programme (NTEP) through digital chest radiography, computer-aided detection (CAD) software and active case-finding initiatives. Consistent with World Health Organization (WHO) recommendations, AI-assisted interpretation of digital chest X-rays is being adopted as a triage tool to support TB screening among individuals aged 15 years and above. These technologies are particularly valuable in rural and underserved areas where radiology expertise is scarce [20,36].

Despite these advances, implementation remains constrained by inadequate digital infrastructure, unreliable internet connectivity, equipment maintenance and shortages of trained personnel. The digital divide may further limit equitable access, particularly among remote and socioeconomically disadvantaged populations. Addressing these challenges requires sustained investment in digital infrastructure, standardized imaging systems, workforce training and capacity building to ensure responsible, equitable and sustainable adoption of AI within national TB programmes.

Ethical, Legal and Regulatory Issues

The expanding use of artificial intelligence in tuberculosis imaging necessitates careful attention to ethical, legal and regulatory considerations. AI models trained on non-representative datasets may exhibit algorithmic bias, resulting in variable diagnostic performance across different populations, age groups or healthcare settings. Ensuring fairness and equitable model performance is therefore essential, particularly in high-burden LMICs.

The use of digital imaging and clinical data also raises concerns regarding data privacy, confidentiality and cybersecurity. Robust governance mechanisms are required to protect patient information and ensure responsible data sharing. Equally important is explainability, enabling clinicians to understand the basis of AI-generated predictions and increasing confidence in clinical decision-making. Clear accountability and rigorous validation are necessary to ensure that AI systems complement, rather than replace, clinical judgment.

International regulatory frameworks continue to evolve. The World Health Organization (WHO) has issued guidance supporting the ethical implementation of AI in healthcare and recommends AI-based CAD software for digital chest radiograph interpretation in TB screening under defined conditions. Several AI imaging systems

Table 5: WHO Recommendations and Current International Guidance on AI in Tuberculosis Imaging

Organization	Guidance/Recommendation
WHO	Recommends AI-based CAD software as an alternative to human interpretation for digital chest radiographs in TB screening among individuals aged ≥15 years
WHO Consolidated TB Guidelines	AI should be used as a triage tool and complemented by microbiological confirmation
FDA	Several AI-based chest imaging software have received regulatory clearance for clinical use
CE Certification (European Union)	Multiple CAD platforms approved for clinical implementation
India (NTEP/NTEP guidance)	Increasing adoption of AI-enabled chest radiography within active case-finding and TB screening initiatives

Table 6: Major Challenges and Proposed Solutions for AI in Tuberculosis Imaging

Challenge	Proposed Solution
False-positive findings	Optimize threshold values and combine with microbiological confirmation
False-negative findings	Continuous model refinement using diverse datasets
Limited external validation	Multicentre prospective validation studies
Poor generalizability	Development of geographically diverse training datasets
Variable image quality	Standardized imaging protocols and quality assurance
Limited performance in pediatric/HIV-associated TB	Disease-specific algorithm development
High implementation costs	Affordable digital infrastructure and scalable deployment
Workflow integration	Integration with PACS, EHRs and national TB information systems

have also received U.S. Food and Drug Administration (FDA) clearance or CE certification for clinical use. In India, the implementation of AI is supported by evolving digital health policies and data protection regulations, emphasizing the need for robust governance, quality assurance and continuous post-deployment evaluation (Table 5).

Current Challenges

Despite significant progress, several challenges continue to limit the widespread implementation of AI in tuberculosis imaging. AI algorithms may generate false-positive findings that increase unnecessary confirmatory testing or false-negative results that delay diagnosis and contribute to ongoing disease transmission. Maintaining an appropriate balance between sensitivity and specificity remains critical for effective screening programmes.

Many AI models also lack robust external validation across geographically diverse populations, raising concerns regarding generalizability and real-world performance. Variability in image quality, differences in imaging equipment and inconsistent acquisition protocols may further affect diagnostic accuracy. Additionally, evidence remains limited for challenging clinical scenarios such as pediatric tuberculosis, HIV-associated TB and extrapulmonary tuberculosis, where radiological manifestations are often atypical.

Other barriers include the cost of digital imaging infrastructure, software licensing, maintenance and integration into existing healthcare systems. Successful implementation also requires seamless incorporation of AI into routine clinical workflows without increasing the workload of healthcare professionals. Addressing these technical, operational and clinical challenges through multicentre validation studies, standardized reporting, continuous quality assurance and implementation research will be essential for maximizing the public health impact of AI-enabled tuberculosis imaging (Table 6).

Future Perspectives

The future of artificial intelligence in tuberculosis imaging extends beyond automated image interpretation toward integrated, intelligent and patient-centred diagnostic systems. Foundation models and Vision Transformers (ViTs) are expected to further improve image recognition by learning from large-scale medical imaging datasets and capturing complex radiological patterns with greater accuracy. The development of multimodal AI, integrating imaging with clinical, laboratory, genomic and epidemiological data, will enable more comprehensive and personalized diagnostic decision-making.

Emerging technologies such as federated learning will facilitate collaborative AI model development while preserving patient privacy, whereas edge AI will enable real-time image analysis directly on portable X-ray devices, reducing dependence on internet connectivity. Digital twins may offer opportunities to simulate disease progression and evaluate treatment response, while generative AI could support automated reporting, clinical documentation, education and workflow optimization. Increasing emphasis on Explainable AI (XAI) will improve transparency and clinician confidence, supporting responsible adoption in routine practice. Collectively, these innovations are expected to enable real-time reporting and AI-assisted clinical decision support, strengthening TB screening, diagnosis and programme implementation [37-39] (Table 7).

Research Gaps

Despite encouraging evidence, important research gaps remain before AI can be widely integrated into tuberculosis control programmes. Most available studies are retrospective and focus primarily on algorithm development, highlighting the need for large prospective multicentre studies evaluating clinical effectiveness and patient outcomes. Evidence from low- and middle-income countries (LMICs) remains limited despite bearing the highest global TB burden.

Further research is needed to establish the cost-effectiveness of AI-assisted imaging within national TB programmes and to identify optimal implementation strategies across different healthcare settings. Implementation research should evaluate workflow integration, clinician acceptance, operational feasibility and long-term sustainability. Additional evidence is also

Table 7: Emerging Artificial Intelligence Technologies in Tuberculosis Imaging

Technology	Potential Applications in TB Imaging
Foundation Models	Generalizable image interpretation across multiple imaging tasks
Vision Transformers (ViT)	Advanced chest X-ray and CT image classification
Multimodal AI	Integration of imaging, laboratory and clinical data
Federated Learning	Collaborative AI model development while preserving data privacy
Edge AI	Real-time analysis on portable X-ray devices without continuous internet connectivity
Explainable AI	Transparent and interpretable diagnostic predictions
Generative AI	Automated reporting, education and clinical documentation
Digital Twins	Simulation of disease progression and treatment response
AI-Assisted Decision Support	Integrated clinical and imaging-based decision-making
Real-Time Cloud Analytics	Remote screening, surveillance and programme monitoring

required for challenging clinical scenarios, including pediatric tuberculosis, drug-resistant TB, HIV-associated TB and extrapulmonary disease. Finally, robust programmatic evidence demonstrating the impact of AI on case detection, treatment outcomes, transmission reduction and progress toward TB elimination goals remains limited and should be prioritized.

Practical Recommendations

Successful implementation of AI in tuberculosis imaging requires coordinated efforts across multiple stakeholders. Radiologists, pulmonologists and TB physicians should use AI as a clinical decision-support tool that complements expert interpretation while maintaining microbiological confirmation as the diagnostic standard. Public health professionals should integrate AI-assisted imaging into active case-finding strategies, screening programmes and surveillance systems to improve early detection and programme efficiency.

The National TB Elimination Programme (NTEP) should promote standardized AI implementation, strengthen digital infrastructure, ensure quality assurance and support workforce training for AI-enabled TB screening. Researchers should prioritize prospective validation studies, implementation research and evaluation of AI performance across diverse populations and healthcare settings. Policymakers should establish clear regulatory frameworks, promote equitable access to validated AI technologies and invest in digital health systems that support sustainable integration into routine TB care.

CONCLUSIONS

Artificial intelligence is rapidly transforming tuberculosis imaging by enabling faster, more accurate and standardized interpretation of radiological images across diverse healthcare settings. From community screening and early diagnosis to treatment monitoring and programme surveillance, AI has the potential to improve diagnostic efficiency, expand access to expert interpretation and strengthen tuberculosis control, particularly in resource-constrained countries.

However, successful implementation requires rigorous clinical validation, ethical governance, robust regulatory oversight and seamless integration into existing healthcare systems. Addressing challenges related to algorithmic bias, data quality, infrastructure and equitable access will be essential to ensure responsible and sustainable adoption.

As AI technologies continue to evolve, their greatest contribution may lie not only in improving image interpretation but also in supporting integrated, data-driven tuberculosis control programmes. When combined with strong public health systems, digital health infrastructure and evidence-based implementation strategies, AI has the potential to accelerate progress toward the global goal of tuberculosis elimination while improving the quality, efficiency and equity of TB care.

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