REVIEW

Artificial intelligence and diagnosis and management of tuberculosis disease in children

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Purpose of review

The literature review is pertinent because diagnosing pediatric tuberculosis (PdTB) remains quite challenging, especially in areas with limited resources, due to complications caused by variable generalized symptoms, paucibacillary characteristics, vague clinical manifestations, and challenges associated with pediatric sputum sample production. Recent developments in artificial intelligence have the potential to enhance the accuracy of diagnoses and the effectiveness of treatments.

Recent findings

Nineteen published studies between January 2024 and July 2025 were examined, which focused on artificial intelligence driven chest X-ray (CXR) examination and medical prediction. The reviewed studies utilized convolutional neural networks (CNN), transfer learning, and stacked ensemble machine learning (SEML) to achieve sensitivity values ranging from 76.0 to 98.2%, specificity of 70.0 to 98.0%, and area under the curve (AUC) values of as high as 0.98 in AI-CXR diagnosis for the detection of PdTB. Through continuous experiments and use of the AI-CXR triage in Ethiopia (2025), successfully identifying over 30% of patients, while prediction models indicate 82% hepatotoxicity concerns in Nigerian cohorts. Plasma proteomics and exhaled breath analysis are emerging methodologies that exhibit potential; however, pediatric datasets are limited, necessitating multicenter validation.

Summary

Artificial intelligence enhances the diagnosis and treatment prediction of PdTB in resource-constrained settings. The integration of artificial intelligence with existing diagnostic tools like GeneXpert and telemedicine strategies can significantly improve the efficiency of screening processes. Future research efforts should prioritize the expansion of pediatric datasets and the evaluation of multimodal AI-PdTB approaches.

Keywords

artificial intelligence, chest X-ray, diagnostics, machine learning, pediatric tuberculosis

INTRODUCTION

Tuberculosis (TB) is the most predominant communicable disease with a severe mortality rate in children, with about 1.2 million pediatric cases annually [1]. Primarily, TB is caused by a gram-positive bacterium, *Mycobacterium tuberculosis*, which is spread through inhalation of aerosols as droplets from an infected individual, usually adults who are infected with active pulmonary tuberculosis (APTB) [2]. Pediatric tuberculosis (PdTB) pathophysiology is different compared to adults because of age-related immunological response. Children below the age of 5 years are highly susceptible to PdTB because of their underdeveloped immune system. This also increases the risk of latent TB infection to active TB, with about a 40–50% newborn progression rate compared to that of adults (10–15%) [3]. Again, about 30% of PdTB are

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KEY POINTS

- Artificial intelligence-driven chest-X-ray analysis using convolution neural network and transfer learning achieves high diagnostic accuracy for pediatric tuberculosis, with a sensitivity of 98.2% and an area under the curve value of 0.98.
- Innovative methods, including plasma proteomics and exhaled breath analysis, show promise as noninvasive biomarkers for pediatric tuberculosis, where machine learning models accurately identify unique signatures for each child using proteomic panels and leverage the high-sensitivity values of volatile organic chemicals for triage, although these require multicenter validation
- Artificial intelligence, when integrated with GeneXpert and telemedicine, enhances the efficacy of pediatric tuberculosis screening, addressing challenges such as paucibacillary disease and sputum collection difficulties.

also characterized by extra-pulmonary forms, such as meningitis TB, and osteoarticular TB, which could lead to neurological and skeletal disorders [4].

Meanwhile, the detrimental effects of PdTb are numerous during active PbTB disease, such as but not limited to chronic (persistent) coughs, fever, and chills, and in severe conditions, life-threatening meningitis, resulting in 96% pediatric mortality if not treated [5]. Other effects occurred as post-TB effects, including abnormal development, chronic pulmonary impairment resulting in diminished respiratory capacity, and complications. The diagnosis of PdTB is complicated because of variable generalized symptoms, paucibacillary characteristics, vague clinical manifestations, and, above all, challenges associated with producing sputum from the children. The diagnostic process includes chest X-ray (CXR), tuberculin skin test (TST), interferon gamma release assay (IGRA), and sputum or gastric lavage for microbial confirmation. Despite the advancement in technology and modification, the aforementioned techniques are not sensitive or specific, especially in children [6].

Given the ongoing diagnostic challenges and epidemiological issues, such as significant under-diagnosis, increasing incidence rates, elevated risk factors, and mortality rates, and disparities across scarce resources and high-burden areas, pose significant challenges in PdTB, artificial intelligence presents a possible solution. Artificial intelligence is a broad field in computer science that focuses on or is engineered to execute activities that conventionally necessitate the cognitive ability of humans. These tasks include pattern identification, recognition, and decision-making, thus acquiring knowledge from the data instead of adhering to clearly defined programming. Clinically, prominent artificial intelligence methodologies encompass convolutional neural networks (CNNs), which analyze images by emulating the visual cortex of humans to identify attributes such as pulmonary opaqueness [7]. Other important artificial intelligence methods are transfer learning, which modifies pretrained models from extensive datasets like the CXRs for application to limited PdTB datasets, thereby mitigating data scarcity [8], and the stacked ensemble machine learning (SEML), which integrates different methods to enhance predictive accuracy, such as therapeutic results, by minimizing errors through voting mechanisms [9].

Relatedly, artificial intelligence has demonstrated potential characteristics by overcoming the aforementioned diagnostic challenges in modeling and interpreting chest X-ray (CXR). Artificial intelligence methodology can augment the identification of TB-specific radiographic characteristics and then predict the treatment result, thus presenting an opportunity for a better therapeutic result, especially in a resource-constrained environment [10].

In this review, we therefore evaluate the studies that apply artificial intelligence in PdTB within the last 18 months (January 2024 to July 2025) to assess the diagnostic effectiveness relating to children's health and then explore artificial inetlligence's capacity to address enduring diagnostic difficulties in resource-limited environments. The included reviewed studies are represented in the Table 1.

Artificial intelligence and chest X-ray diagnostics for pediatric tuberculosis

CXR is the frontline and crucial diagnostic method for the assessment of PdTB. Its interpretation is critically important in evaluating PdTB; this can be challenging due to abnormalities such as lymphadenopathy found in children, which can mimic pneumonia. Because of this, in recent years, there has been an increasing trend of interest in artificial intelligence driven CXR analysis, focusing on multiple views [8], which utilizes deep learning frameworks plus a generative algorithm to improve specificity and detection efficacy, especially in paucibacillary cases with occult radiographic findings. These methods, when incorporated into clinical workflow, use convolutional neural networks (CNNs) that have already been trained on large adult TB datasets and then fine-tuned using the PdTB dataset. This recorded 0.90, 0.99, and 0.98 as sensitivity, specificity, and AUCs values [8] for artificial intelligence assisted CXR diagnosis of PdTB. The technique also uses an automatic feature extraction technique that reduces inter-observer disagreement. The AUC is a reliable value that rules out decisions by

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Table 1. The characteristics of the 18 reviewed studies

Ref.	AI technique	Modality	Focus area	Key results	Study cohort
Capellán-Martín *et al.*[11■■]	CNN and Ensemble	CXR multiple view	AI, CXR-based diagnosis	Accurate for zero TB detection	PbTB CXR datasets validated globally
Lan *et al.*[12■■]	DL models	CXR	Pneumonia and pediatric TB diagnosis	Achieved >90% accuracy value	PbTB CXR/ pneumonia
Yilmaz [13■]	Ensemble and DL models	CXR and clinical features from EHR	Pediatric TB treatment and prediction	enhances risk evaluation capabilities by achieving precision levels between 85 and 90%.	PbTB detection across all cohorts
Saini *et al.*[14]	CNN	CXR	AI, CXR-based diagnosis	Highest accuracy value for PbTB and pneumonia detection	CXR and incorporated in PbTB
Haque *et al.*[15■■]	CNN and Transfer learning	TB CXRs	Classification based on AI-CXR	Optimizes the classification of TB	Specific for high PbTB burden settings
Gómez-Valverde *et al.*[16]	BITScreen PTB	CXR and telemedicine	Pediatric TB and telemedicine	Effective in triage	PbTB in rural settings
Aurangzeb *et al.* [17■]	EVAL-PAEDTBAID	CXR	AI-CXR-based diagnosis	Highest accuracy value (>90%) for PbTB AI protocols	PbTB in multiple centers
Fossati *et al.*[18■■]	ML models	Biomakers	Proteomics (Biomarkers)	Biosignature distinguishing active and latent TB	PbTB-HIV high-burden countries
Basu and Chakraborty [19■]	New AI-powered detection	Multiple diagnostics	Pediatric TB diagnosis	Enhanced accuracy in AI-molecular diagnosis	LMICs PbTB diagnosis
Picoli *et al.*[20]	Prototyping and AI	TB Kids prototype kit	Mobile application	Mobile app supports TST, triage diagnosis	Pediatric pulmonary Tuberculosis
Chen *et al.*[21■]	ML models	TB DNA targeted NGS	Diagnosis using NGS and ML models	Ultrasensitive in detecting paucibacillary PbTB	Paucibacillary PbTB and Meningitis
Bijker *et al.*[22]	ML model (SVM)	VOCs	Breath Triage Analysis	Used in triage, and results meet WHO sensitivity and specificity values	Mostly used in outpatient PbTB screening
Zeng *et al.*[23■■]	ANN	Medical smears	ML Models, Treatment, and Prediction	Accurate in predicting liver injury based on the AUC value	PbTB cohort
AI tool regulatory [24■■]	CNN Qure.ai	qXR-pTB Clearance	High burden pediatric area	Highly accurate in early PbTB detection	High-burden PbTB areas
Kim *et al.*[25■]	AI and	CXRs, Xpert, radiographic scoring	PbTB cohorts	Accuracy value is >89.6%	PbTb multiple center
Asori *et al.*[26]	ML models (RF and SVM)	Survey	Diagnostic/Biochemical analysis	Highly precise in PbTB prediction	National PbTB survey
Hong *et al.*[27]	Swin Transformer	CXR	Multimodal generative AI and CXRs	Highly sensitive and specific for PbTB	Screening PbTB in a prevalent setting
Kazemzadeh *et al.* [28■■]	CXR AI systems	CXR	Multiple site validation and CXR	Compares radiologist accuracy values	PbTB-HIV high-burden areas

AI, artificial intelligence; ANN, artificial neural network; AUC, area under the curve; BITScreen PTB, BITScreen Pediatric Tuberculosis (AI-based screening tool); CNN, convolutional neural network; CXR, chest X-ray; DL, deep learning; EHR, electronic health records; EVAL-PAEDTBAID, Evaluation of Pediatric Tuberculosis AI Diagnosis (tool/protocol); LMICs, low and middle-income countries; ML, machine learning; NGS, next-generation sequencing; PbTB, pediatric tuberculosis; qXR-pTB, qXR Pediatric Tuberculosis (Qure.ai's AI tool for CXR interpretation); RF, random forest; SVM, support vector machine; TB, tuberculosis; TST, Tuberculin Skin Test; VOCs, volatile organic compounds.

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the pediatricians of low-risk children who do not require antibiotics or the use of interferon-gamma release assay (IGRA)/tuberculin skin test (TST), compared to high-risk children who require gene expert confirmation.

Additionally, another emerging trend in deep learning multiview to curb the pediatric data scarcity was the use of generative artificial intelligence, which synthesizes 800 pediatric CXRs to about 20 000, thereby improving the detection of PdTB [27]. It recorded 91.3% accuracy in identifying PbTB, which is lower compared to the result obtained from two (2) radiologists. The generative artificial intelligence has the capacity to achieve 94.1 and 93.5% accuracy for the two (2) radiologists, respectively [27]. Again, the regulatory developments have witnessed a great milestone in clinical screening, for example, the European AIDS Treatment Group (EATG), anchored by Qure.ai, recorded ground groundbreaking artificial intelligence-powered PbTB screening tool (Qure.ai's qXR-pTB tool) [24▪▪], which is in accordance with the WHO treatment decision guidelines [Treatment Decision Algorithm A (TDA) especially in low and medium-income countries (LMICs)]. Clinically, for a busy pediatrician, these tools: two (2) cloud-based artificial intelligence CXRs will enhance PdTB triage efficiency [28▪▪]. They were used in a study for detecting TB and for prospective multiple-site validation. Despite the ten (10) radiographers employed to review the TB Images, the artificial intelligence powered CXR had 97% sensitivity and 79% specificity compared to the human evaluations [28▪▪]. Furthermore, telemedicine technologies such as BITScreen PbTB (launched July 2024) [16] incorporate artificial intelligence within reputable online platforms, enabling remote PdTB diagnosis across rural regions. BITScreen PbTB helps clinicians upload chest X-rays through mobile applications and receive artificial intelligence identified risk assessments within seconds, with validation facilitated by integration with GeneXpert. Nevertheless, Ethiopia had another recent implementation of artificial intelligence powered software for the identification of PbTB [29▪]. The software was able to identify above 30% of PdTB, notwithstanding the senior radiographers flagging 94.4% as PbTB positive, whereas actually, only 9% of this value agreed with the artificial intelligence powered CXR.

ARTIFICIAL INTELLIGENCE AND BIOMARKERS USING PLASMA PROTEOMICS AND EXHALED BREATH ANALYSIS

The PdTB biomarker diagnosis is a noninvasive alternative to the sputum production by the children. As a result, the newest trend utilizes the application of artificial intelligence in plasma proteomics and exhaled breath analysis [18▪▪] by using machine learning models to identify each child's specific biological signatures, targeting WHO sensitivity or specificity goals of 90% for triage [30]. The Plasma Proteomics methodology uses mass spectrometry (MS) techniques in a 4-D proteomics concurrently with artificial intelligence models such as Random forests or neural networks to discern TB-discriminatory panels [18▪▪], especially HIV-TB co-infection, a prevalent condition in children. This method recorded an average result of 0.88 for AUC, which is within the WHO minimum accuracy diagnostic threshold. The aforementioned method was modified by incorporating B-lymphocyte activation markers, utilizing a layered ensemble ML for the prediction of TB in children below 5 years [31]. The incorporation of artificial intelligence facilitates or addresses proteome complexity, eliminating noise, thus facilitating point-of-care (POCT) testing using multiplex ELISA kits [31]. In the clinic, Plasma Proteomics and Exhaled Breath Analysis facilitate diagnosis without sputum in pediatric. The pediatricians conduct standard blood tests, utilize artificial intelligence powered panels, and assess risks, such as children with elevated interferon patterns that necessitate fast GeneXpert testing, thus preventing unnecessary hospital admissions [18▪▪].

The presence of volatile organic chemicals (VOCs), including naphthalene and hexane, in breath is an indication of the presence of *Mycobacterium TB*. Artificial intelligence categorizes spectrum patterns by using deep learning models with a focus on pediatric characteristics, where the presence of VOCs differs from that in adults due to underdeveloped lungs [22]. Meanwhile, to the clinicians, the exhaled breath analysis is a transformative influence (game-changer), because it is noninvasive, pediatric-friendly about ten seconds of exhalation, and applicable even in day care settings. It has been validated by clinicians in Kenya, demonstrating efficacy as a triage test for children aged 0–5 years [22]. They recorded 86% sensitivity in identifying PbTB. Then, for the outpatient, Artificial intelligence apps are developed on portable devices that identify positive cases for chest X-ray. This app reduces the time spent in triage, facilitating home screening and preventing spread through contacts [32].

Relatedly, research on biological markers and protein domains has demonstrated potential in this new global economy. According to Fossati *et al.* [18▪▪], biological markers and proteins have become a central issue for the identification of proteomics from Plasma, showing novelty in PdTB, thus providing an environmentally friendly alternative to CXR. The biomarkers were identified using ultra-high-performance liquid chromatography in combination with

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high-resolution mass spectrometry (UHPLC-HRMS), possibly attaining an exceptional sensitivity value (>95%). Menon and Koura [33] PbTB EHR artificial intelligence apps customize therapy, identify hepatotoxicity promptly, and minimize relapses. Bijker *et al.*' s [22] study focused on exhaled breath analysis as a triage test, yielding encouraging findings in pediatric patients; however, specificity requires enhancement. These biomarker methodologies address the constraints of chest X-rays, such as the shortage of radiologists; nonetheless, issues persist in achieving consistency across diverse populations and validating these methods in low-resource environments, where the burden of TB is most significant.

ARTIFICIAL INTELLIGENCE AND PREDICTIVE MODELS FOR PEDIATRIC TUBERCULOSIS TREATMENT OUTCOMES

Predicting PdTB treatment outcomes, success rate, complications, or detrimental effects influences the personalized nature of treatment regimens; however, limited pediatric data constrain the applicability of conventional scoring systems. To mitigate this, integration of multimodal ML ensembles, which combine clinical, radiographic, and biochemical data were simulated and then interpreted using SHapley Additive exPlanations (SHAP) explainable artificial intelligence (XAI), promoting clinician confidence [33]. The SHAP XAI explains the rationale behind each model's predictive ability. For example, Menon *et al.* used machine learning models, such as ANN, to predict early treatment outcome and resistance to rifampicin in the treatment of PbTb [34]. The model predicted a 6-month success rate with a 92% area under the receiver operating characteristic curve (AUROC). In Korea, a multiple-center artificial intelligence research used PdTB mediastinal lymphadenopathy, therapy adherence, as well as smears, as essential variables to predict early treatment response, recording an accuracy value of 89% [25▪]. The artificial intelligence and predictive model technique was applied in multiple-center field work by the use of cough/speech sound analysis, which recorded above 92% as an AUROC value. In all, XAI was employed, which explained that social determinants play a major role in the spread of PbTB. There is also a recent app for PbTB Electronic Health Record (EHR artificial intelligence apps) embedded in hospital beds, which flags high-risk children for intensive monitoring [33]. This bedside PbTB EHR artificial intelligence apps result in cost reduction as well as has biochemical algorithms that predict hepatotoxicity in about 82% of those diagnosed with PbTB for the first time.

SENSITIVITIES AND SPECIFICITIES OF ARTIFICIAL INTELLIGENCE ASSISTED DIAGNOSIS, TREATMENT, AND PREDICTIVE MODELS

This review is intriguing, especially the evaluation metrics, showcasing sensitivity, specificity, area under the receiver operating characteristic curve (AUCROC), and accuracy values. Sensitivity, often referred to as recall, quantifies the ratio of accurately diagnosed or modelled positive TB cases in children. It measures the diagnostic test's efficacy in identifying the PdTB that has been identified, hence reducing the number of false negatives. PdTB sensitivities are difficult to ascertain and to accurately report because of the unique clinical complexities: children exhibit paucibacillary disease, a variety of symptoms, including but not limited to recurring coughs, and above all, difficulties associated with sputum collection. As a result, 78.9% of the studies reported sensitivities instead of 100%. Higher values of sensitivity guarantee prompt PdTB identification, because more than 20% (mortality rate) of the untreated cases could lead to miliary TB or meningitis [35]. Artificial Intelligence-based techniques, such as using CNN algorithms for CXR, exhibit excellent sensitivity results. It is also very important in resource-constrained environments that are characterized by a scarcity of radiologists, hence allowing for timely referrals to confirmatory testing, including GeneXpert. Additionally, according to Barac *et al.*[36], the sensitivity value for TB diagnostics, especially in places with higher-burden contexts, is more than 90% [36,37].

Concerning specificity, it quantifies the ratio of accurately recognized negative instances, that is, children who have no TB as evident from the diagnostic test or the modeling result. Specificity evaluates the diagnostic capacity to exclude the disease when it is not present, hence reducing false positive (FP). In a significant study, Haque *et al.*[15▪▪], using CNN and CXR images, integrating transfer learning, recorded the highest specificity value of 98.2%. This was achieved by employing various methodologies for diagnosing PdTB, highlighting a collaborative approach to enhance detection precision, particularly in children, where conventional diagnostics, such as sputum samples for tests, are problematic due to low bacterial load and challenges in sample acquisition. Principal domains encompass artificial intelligence enhanced CXR evaluation, plasma proteomics, exhaled breath examination, and machine learning-driven predictive models. In pediatric cases, when TB mimics prevalent illnesses such as pneumonia and HIV co-infection, higher values of specificity guarantee the precise exclusion of the real TB from the infectious diseases. This alleviates the healthcare burden, especially in resource-limited environments. Furthermore, AI-CXR

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techniques enhance sensitivity in triage; nevertheless, low values of specificity result in expensive confirmatory tests, whereas high specificity values, like 98.2% in Haque *et al.*[15■■], facilitate efficient PdTB screening, especially in endemic regions.

Furthermore, AUCROC, as used in this study, measures the total diagnostic efficacy of an algorithm graphing sensitivity versus 1-specificity across several thresholds. AUC can differentiate between positive and negative cases of PdTB. In PdTB and artificial intelligence, the AUC threshold-independent efficiency facilitates the comparison of models, such as CNN, across various datasets. Additionally, the AUC is a reliable metric that factors out decisions by pediatricians for low-risk children not needing antibiotics or IGRA/TST, unlike high-risk children who require gene expert validation. What stands out based on AUC is that Capellán-Martín *et al.*[11■■], Yilmaz [13■], Haque *et al.*[15■■], and Basu and Chakraborty [19■] recorded the highest values of AUC, while Bijker *et al.*[22] and Aurangzeb *et al.*[17■] recorded the lowest values for AUC. Likewise, focus area distribution showcases the robustness of the model, especially where PdTB presentation requires balanced values from sensitivity and specificity.

CONCLUSION

Overall, we found that artificial intelligence based methodologies, especially in CXR analysis, enhance the diagnosis and treatment of PdTB. The review shows that artificial intelligence methods like CNNs, transfer learning, and stacked ensemble machine learning can make very accurate diagnoses. Studies reviewed showed sensitivity values ranging from 76.0 to 98.2%, specificity values ranging from 70.0 to 98.0%, and an AUC of 0.98, approximately. These numbers show that artificial intelligence can improve the accuracy of detection, particularly among places where resources are limited and standard diagnostics have trouble with paucibacillary illness and getting sputum samples from children. Also, artificial intelligence powered predictive algorithms show potential in predicting treatment results and finding hazards like liver damage, with AUC values above 0.85 in several circumstances. New methods like plasma proteomics and exhaled breath analysis provide other ways to diagnose, although their accuracy and generalizability need more testing. The combination of artificial intelligence with current diagnostic technologies like GeneXpert and its use in telemedicine platforms makes PdTB screening faster and more accurate, which is important for improving pediatric medical care. Even with these improvements, the fact that there are not enough datasets for children and the necessity for multicenter validation are still big problems. In the future, we hope to concentrate on augmenting pediatric data, integrating multimodal methodologies, and verifying artificial intelligence models in varied, resource-limited environments to optimize their influence on PdTB therapy.

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Conflicts of interest

There are no conflicts of interest.

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Papers of particular interest, published within the annual period of review, have been highlighted as:

■ of special interest
■■ of outstanding interest

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It has an outstanding performance by using an approved clinical artificial intelligence technology for the detection of PbTB. It showcases a real-world application.

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