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AI-Driven Tuberculosis Detection: A Review of Machine Learning and Deep Learning Approaches

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Abstract

Tuberculosis (TB) remains one of the major infectious diseases worldwide, and early detection is essential for timely treatment and reducing disease transmission. Conventional TB diagnosis can be challenging in regions with limited access to trained healthcare professionals, advanced laboratory facilities, and specialized radiological expertise. The rapid development of Artificial Intelligence (AI), particularly Machine Learning (ML) and Deep Learning (DL), has created new opportunities for automated and computer-assisted TB detection. Among various diagnostic modalities, chest X-ray (CXR) imaging has received significant attention because of its widespread availability and important role in pulmonary TB screening. This paper presents a review and methodological framework for AI-driven tuberculosis detection using ML and DL techniques. Conventional ML algorithms, including Support Vector Machine (SVM), Random Forest (RF), and k-Nearest Neighbors (KNN), are reviewed alongside DL architectures such as Convolutional Neural Networks (CNN), VGG, Res Net, Dense Net, and transfer-learning-based models. The proposed methodology includes data acquisition, preprocessing, image augmentation, feature extraction, model training, classification, explainable AI, and performance evaluation. In addition, emerging cough-audio-based AI approaches are considered as a complementary non-invasive screening modality.

Introduction

Tuberculosis (TB) is one of the most important infectious diseases worldwide and continues to create a substantial burden on healthcare systems. Early and accurate detection is essential for initiating appropriate treatment, reducing transmission, and improving patient outcomes. Conventional TB diagnosis generally involves clinical assessment, chest radiography, microbiological testing, and other diagnostic procedures. However, limited access to trained radiologists, laboratory infrastructure, and diagnostic facilities can make timely detection difficult, particularly in resource-constrained settings [1]. Chest X-ray (CXR) is widely used for screening and assessment of pulmonary TB because it is relatively accessible and can provide rapid information about abnormalities in the lungs. Nevertheless, interpretation of CXR images requires appropriate clinical and radiological expertise, and differences between observers can affect diagnostic decisions. These challenges have encouraged the development of computer-aided detection systems based on Artificial Intelligence (AI) [1], [2].

Machine Learning (ML) techniques have been investigated for automated TB classification by extracting relevant characteristics from medical images and using them to distinguish TB-positive and TB-negative cases. Algorithms such as Support Vector Machine (SVM), Random Forest (RF), k-Nearest Neighbors (KNN), and logistic regression have been explored for this purpose [1]. Conventional ML approaches can provide useful classification performance, but they generally depend on handcrafted feature extraction, which may limit their ability to capture complex radiographic patterns. Deep Learning (DL) has significantly changed the field of medical-image analysis. In particular, Convolutional Neural Networks (CNNs) can automatically learn hierarchical features directly from chest radiographs, reducing the need for manually designed features. Lakhani and Sundaram demonstrated the potential of deep CNNs for automated pulmonary TB classification and reported an area under the curve (AUC) of approximately 0.99 for their best-performing ensemble model [2].

Subsequent research has investigated different CNN architectures and transfer-learning techniques for TB detection. Models based on architectures such as VGG, ResNet, DenseNet, and other pretrained networks have been evaluated using different CXR datasets [1], [3]. Transfer learning is particularly useful when medical datasets are relatively limited because a model pretrained on a large image dataset can be adapted to the TB classification task. The development of AI-based TB screening systems has also moved from experimental models toward clinical applications. Automated systems such as CAD4TB have been evaluated for detecting TB-related abnormalities on chest radiographs [4]. Large-scale screening studies have further demonstrated the importance of evaluating AI systems on real-world populations rather than relying exclusively on small retrospective datasets [5]. In addition to CXR-based detection, researchers have explored alternative data sources such as cough sounds. Because cough is a common symptom of pulmonary TB, acoustic analysis may provide a non-invasive and potentially low-cost screening method. Botha et al. demonstrated the feasibility of automated cough analysis for TB screening [6], while more recent research has investigated deep-learning approaches for classifying TB using cough-audio representations [7].

Literature Review

Lakhani and Sundaram (2017) developed a deep-learning-based approach for automated pulmonary TB detection from chest X-ray images. They evaluated AlexNet and GoogLeNet architectures and demonstrated that CNN-based models could effectively identify TB-related patterns in chest radiographs. Their best-performing ensemble achieved an AUC of approximately 0.99, demonstrating the potential of deep learning for automated TB classification [1]. Hansun et al. (2023) conducted a systematic literature review of machine-learning and deep-learning approaches for TB detection using chest X-rays. Their review included 47 studies and found that deep-learning approaches, particularly CNN-based architectures such as ResNet, VGG, and AlexNet, were more frequently used than conventional machine-learning methods. The authors also highlighted methodological concerns related to reference standards, dataset characteristics, and study design [2].

Murphy et al. (2020) evaluated CAD4TB version 6, an automated computer-aided detection system designed for TB screening using chest radiographs. Their work demonstrated the potential of automated CAD systems for supporting TB screening, while also emphasizing the importance of evaluating such systems in relevant clinical populations [3]. Lee et al. (2020) investigated a deep-learning algorithm for TB detection in a large population undergoing systematic screening. Their study included nearly 20,000 asymptomatic individuals and demonstrated the importance of evaluating AI systems in screening populations rather than relying exclusively on retrospective datasets [4].

Botha et al. (2018) investigated automatic analysis of cough sounds for TB detection. Their study demonstrated that acoustic characteristics of cough could provide useful information for distinguishing TB cases, suggesting that cough-based AI could serve as a potential complementary screening approach [5]. Rajasekar et al. (2024) investigated deep-learning-based TB detection using cough audio. Their approach used capsule networks and fully connected neural networks to classify cough-related features. The study reported promising classification performance, indicating the potential of cough-audio analysis as a non-invasive AI-assisted screening modality [6].

Guo et al. (2021) proposed a deep-learning approach for TB diagnosis and localization from chest X-ray images. Their work demonstrated that AI models can potentially provide not only a TB classification but also information about the location of suspicious radiographic abnormalities, supporting the development of more interpretable computer-aided diagnosis systems [7]. Hwang et al. (2024) discussed important considerations for the implementation and evaluation of AI-based TB screening systems. Their work emphasized external validation, transparency, generalizability, and the need to evaluate AI systems beyond their performance on development datasets [8].

Methodology

The proposed methodology is designed as an AI-assisted tuberculosis detection framework using chest X-ray (CXR) images as the primary input. The framework integrates data acquisition, preprocessing, lung-region segmentation, feature learning, machine-learning/deep-learning classification, explainable AI, and performance evaluation. This structure is consistent with the direction of clinical CAD research, where AI analyzes digital CXR images and produces an abnormality score to support TB screening or triage. WHO has recommended CAD as an alternative to human interpretation of digital CXR for TB screening and triage in adults aged 15 years and older since 2021

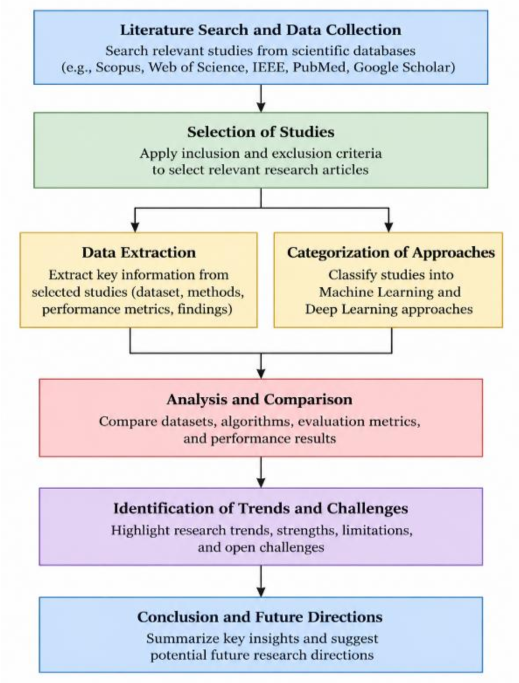

Figure 1: Methodology framework for the systematic review of machine learning and deep learning approaches for tuberculosis detection.

Figure 1. Methodology framework illustrating the systematic review process for AI-driven tuberculosis detection. The methodology includes literature search and data collection, selection of relevant studies using inclusion and exclusion criteria, data extraction, categorization of machine learning and deep learning approaches, analysis and comparison of datasets and performance metrics, identification of research trends and challenges, and formulation of conclusions and future research directions.

Algorithmic Strategy

The proposed algorithmic strategy integrates machine learning (ML), deep learning (DL), transfer learning, lung segmentation, and explainable AI (XAI) to classify chest X-ray (CXR) images as TB-positive or TB-negative. The strategy is designed to provide both a diagnostic prediction and an interpretable visualization of the image regions influencing the prediction.

Loss Function

For binary TB classification, binary cross-entropy (BCE) can be used:

$$L = -[y\log(p) + (1-y)\log(1-p)] \text{ -------}(1)$$

where:

y= actual class label,

p= predicted probability of TB.

For Ntraining samples:

$$L_{total} = -\frac{1}{N}\sum_{i=1}^{N}[\mathrm{y_i}\log(\mathrm{p_i}) + (1-\mathrm{y_i})\log(1-\mathrm{p_i})] \text{----------}(2)$$

The model parameters are updated using an optimizer such as Adam or stochastic gradient descent.

Decision Strategy

The final system can generate three outputs:

Output 1 – Classification

TB detected / TB not detected

Output 2 – Probability

Example:

$$P(TB) = 0.91 \text{-----------}(3)$$

meaning the model assigns a 91% probability to the TB class.

Results

Table 1. Performance of Deep Learning Models for CXR-Based TB Detection

Author(s)	Year	Model/Approach	Modality	Reported Performance
Lakhani & Sundaram [1]	2017	AlexNet + GoogLeNet	CXR	AUC ≈ 0.99
Qin et al. [4]	2019	Deep-learning systems	CXR	Promising multi-site performance
Nafisah & Muhammad [11]	2022	EfficientNetB3 + XAI	CXR	Accuracy 99.1%; AUC ≈ 99.9%
Iqbal et al. [12]	2022	TBXNet	CXR	Accuracy 98.98–99.17%
Sharma et al. [15]	2024	U-Net + Xception + Grad-CAM	CXR	Accuracy 99.29%; AUC 0.999

Analysis: The results Table 1, indicate that deep-learning models provide strong performance for automated TB detection from chest X-rays. Early CNN architectures such as AlexNet and GoogLeNet demonstrated high discriminative ability [1], while later transfer-learning and hybrid architectures achieved similarly high performance [11], [12], [15]. The combination of lung segmentation and classification, as demonstrated by Sharma et al. [15], provides an additional strategy for concentrating model analysis on pulmonary regions. However, these results are dataset-dependent and should not be interpreted as direct evidence of clinical performance.

Table 2. Clinical and External Validation of AI-Based TB Detection

Author(s)	Year	AI System/Approach	Evaluation Setting	Key Result
Harris et al. [5]	2019	AI-based CAD	Systematic review	Promising accuracy; methodological limitations identified
Murphy et al. [6]	2020	CAD4TB v6	Clinical evaluation	Demonstrated potential for TB screening
Pande et al. [7]	2020	qXR + CAD4TB	Prospective study	Evaluated against culture-confirmed disease
Tavaziva et al. [8]	2022	DL-based CAD	Individual-patient meta-analysis	Supported potential for TB triage
Kazemzadeh et al. [14]	2023	Deep learning	Four-country evaluation	AUC 0.89; sensitivity 88%; specificity 79%

Analysis: Table 2 shows, Clinical and external-validation studies provide a more realistic assessment of AI performance than studies conducted only on development datasets. Kazemzadeh et al. reported an AUC of 0.89 with 88% sensitivity and 79% specificity on a multinational test set, illustrating that performance can decrease when models are evaluated across diverse populations. Therefore, external validation and prospective evaluation are essential before AI systems are considered for widespread TB screening.

Table 3. Comparison of AI Approaches and Explainability

Approach	Representative Studies	Main Strength	Main Limitation
Conventional ML	[5], [10]	Works with engineered features	Requires manual feature extraction
CNN	[1], [4]	Automatically learns image features	Requires adequate training data
Transfer Learning	[11], [12]	Effective with limited datasets	Possible domain-shift problems
Segmentation + CNN	[15]	Focuses on lung regions	Adds computational complexity
CNN + Transformer	[13]	Captures local and global features	Higher computational requirements
CNN + XAI	[11], [15]	Improves interpretability	Heatmaps require careful interpretation

Analysis: The Table 3 shows a clear progression from conventional ML toward deep-learning and hybrid approaches. CNNs have become dominant because they can automatically learn complex image representations. Transfer learning further improves the practicality of DL when TB datasets are limited. More recent approaches combine segmentation, CNNs, transformers, and XAI. Among these, segmentation + classification + Grad-CAM is particularly relevant to the proposed framework because it combines detection with interpretability.

Conclusion and Discussion

The present review demonstrates that Artificial Intelligence (AI), particularly machine learning (ML) and deep learning (DL), has considerable potential for automated tuberculosis (TB) detection, especially through chest X-ray (CXR) analysis. The reviewed studies show a clear progression from conventional ML techniques toward CNN-based architectures, transfer learning, hybrid models, and explainable AI [1], [4], [10]–[15]. Several studies reported very high performance on their respective datasets, with approaches such as EfficientNetB3, TBXNet, and U-Net combined with Xception achieving accuracy values close to or above 99% [11], [12], [15]. These findings indicate that deep-learning models can effectively learn complex radiographic patterns associated with TB. However, reported performance varies considerably depending on dataset characteristics, patient population, image quality, reference standards, and evaluation methodology. Multisite and multinational studies [4], [8], [14] demonstrate that models achieving excellent results on controlled datasets may show reduced performance when evaluated on independent populations. Therefore, external validation is essential for determining the real-world generalizability of AI-based TB detection systems. The incorporation of lung segmentation can help focus the model on relevant pulmonary regions, while explainable AI techniques such as Grad-CAM can provide visual information regarding the areas influencing model predictions [11], [15]. In addition, emerging cough-audio approaches [2], [16] indicate the possibility of developing complementary non-invasive screening methods and, in the future, multimodal systems combining CXR, cough sounds, and clinical information. Despite these advances, AI should currently be considered a screening and decision-support tool rather than a replacement for established clinical and microbiological diagnosis. Overall, the findings support the proposed framework combining image preprocessing, lung segmentation, transfer-learning-based deep learning, explainable AI, and independent external validation. Future research should focus on larger and more diverse datasets, standardized evaluation protocols, prospective clinical validation, model calibration, interpretability, and robust performance across different healthcare environments. This integrated approach can contribute toward developing reliable, interpretable, and clinically useful AI-assisted TB screening systems.

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