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Chest X-Ray-Based Tuberculosis Detection Using Deep Learning: An In-Depth Review of Current Models and Future Directions

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Abstract—This Tuberculosis (TB) is still a significant global health risk, especially in middle and low-income countries. WHO Global TB Report 2023 projected that about 10.6 million new cases of TB and 1.3 million deaths were reported in 2022 alone. Detection and correct diagnosis at an early stage are paramount to prevent the spread of TB and offer better patient outcomes. Chest X-ray (CXR) imaging is a routine TB screening because it is cost-effective with quick results. CXR is usually hampered by human factors, subjectivity, and the lack of trained radiologists, particularly in resource-poor environments. Recent developments in Deep Learning (DL) and Artificial Intelligence (AI) have raised hope towards computer-aided diagnosis of TB based on CXR images. In particular, Convolutional Neural Networks (CNNs) have shown superior performance in intricate feature extraction of features and feature classification accuracy in medical image processing. This review presents a critical overview of recent DL-based approaches to detection of TB with particular focus on CNN-based models. The paper also discusses the most significant challenges including data imbalance, image quality variation, problem of generalization, model interpretability, and deployment challenges in low-resource environments. Future research directions such as developing large-scale TB-specific datasets, building explainable and lightweight models, mobile health (mHealth) solutions, federated learning, and exploiting multi-modal data are highlighted. This article attempts to enlighten researchers, medical professionals, and policymakers about the current status, challenges, and future of DL-based TB diagnosis to guide international efforts toward efficacious and accountable AI-based health care solutions.

Keywords—Tuberculosis Detection, Deep Learning, Chest X-ray (CXR) Analysis, Convolutional Neural Networks (CNN), Artificial Intelligence in Healthcare

I. Introduction

Tuberculosis (TB) is still one of the world's most fatal infectious diseases and a major global health threat. In 2022 alone, an estimated 10.6 million individuals acquired TB, and 1.3 million deaths were recorded worldwide, with most cases occurring in low and middle-income countries (WHO, 2023). The airborne transmission of TB, coupled with social determinants of poverty, malnutrition, and crowding, has facilitated its transmission, especially in resource-constrained areas.

TB is an airborne bacterial disease, spread primarily by inhalation of droplets coughed up by persons with active pulmonary TB. Its silent spread and linkage with socio-economic conditions have rendered its control and eradication particularly difficult, especially in crowded and resource-poor environments.

Some countries and areas still have very high burdens of TB, with most of the cases being reported in LMICs in Asia and Africa. The WHO has listed a number of high TB burden countries based on cases of incidence, mortality, and multidrug-resistant TB. India, Indonesia, China, the Philippines, Pakistan, Nigeria, Bangladesh, and South Africa are some of the main drivers of the global burden of TB.

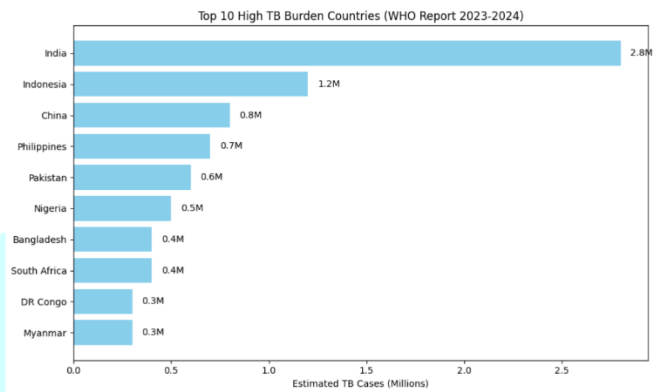


Fig. 1. Top 10 High TB Burden countries

Early detection and correct diagnosis of TB are paramount if its transmission and patient outcomes are to be enhanced. Chest X-ray (CXR) imaging is among the most widely used pulmonary TB screening methods, due to its cost-effectiveness, non-invasiveness, and rapid turnaround time [1]. However, manual interpretation of CXRs is heavily dependent on the radiologist's experience, hence likely to lead to inconsistency in diagnosis and subjective mistakes, especially in regions that face a deficit of skilled healthcare professionals [4].

The rapid developments in Artificial Intelligence (AI) and Deep Learning (DL) technologies have revolutionized medical image analysis significantly. Convolutional Neural Networks (CNNs) have shown marvelous performance in feature extraction and classification tasks of intricate medical images, like CXRs [2]. Accordingly, DL model-based Computer-Aided Diagnosis (CAD) systems have been suggested to be beneficial tools to assist radiologists and make TB screening processes more effective.

Various works have considered DL-based model utilization for the identification of TB in CXR images. Though other surveys and reviews give overall insights into general disease detection using radiography or for COVID-19 diagnosis [3,5], limited focused review papers are specifically based on DL-based detection of TB in chest radiography, and more specifically focusing on post-2020 advances [1].

A. Motivation for this Review

The following review attempts to fill this gap by reviewing systematically, classifying, and comparing the existing deep learning-based TB detection methods with CXR images. As more and more research is being conducted in this area, an in-depth examination is necessary to determine the strengths and limitations of different DL approaches along with their future prospects.

B. Research Objectives

This survey paper is structured with the following aims:

- To classify and compare recent deep learning architectures employed for TB detection from chest X-ray images.
- To point out current challenges, limitations, and research gaps in this area.
- To provide recommendations for future directions for researchers, developers, and healthcare professionals working on automated TB diagnosis systems.

C. Organization of the Paper

The rest of the paper is structured as follows: Section 2 describes the research approach used for literature collection and analysis. Section 3 gives a background on TB illness and the application of CXR imaging. Section 4 gives an overview of deep learning methods used in medical imaging. Section 5 classifies and examines the recent TB detection methods using DL models. Section 6 addresses the limitations, challenges, and open research problems. Lastly, Section 7 presents the future research directions, and Section 8 concludes the study.

II. RESEARCH METHODOLOGY

This part describes the research methodology followed for systematically selecting, identifying, and surveying suitable literature regarding deep learning-based techniques for the detection of Tuberculosis (TB) using chest X-ray (CXR) images.

A. Literature Search Strategy

A systematic literature review was performed for gathering the relevant studies on detection of tuberculosis (TB) using deep learning methods applied to chest X-ray (CXR) images. The search was made on reliable scientific databases like IEEE Xplore, SpringerLink, Scopus, PubMed, MDPI, and Google Scholar. The search strategy was performed on the basis of the use of the combined keywords: ("Tuberculosis" OR "TB") AND ("Chest X-Ray" OR "CXR") AND ("Deep Learning" OR "CNN"). In addition, the reference lists of included articles were manually screened to find other relevant studies that were not captured in the initial search.

B. Inclusion and Exclusion Criteria

To maintain the quality and relevance of the selected literature, predefined inclusion and exclusion criteria were applied as follows:

TABLE I. PAPER CRITERIA

Inclusion Criteria	**Exclusion Criteria**
Publications from 2017 to 2025	Articles published in languages other than English
Studies focusing on TB detection using Deep Learning and CXR	Studies focusing on CT Scan, MRI, sputum, or other modalities
Research articles, conference papers, book chapters	Non-technical articles like editorials, commentaries, or reviews without technical depth

III. Paper Selection Flow

The selection process of literature for this survey was done systematically using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) protocol. Performing an initial search on six main scientific databases — IEEE Xplore, SpringerLink, Scopus, PubMed, MDPI, and Google Scholar — using carefully defined keywords produced 254 records. Following the exclusion of the duplicate records, 212 articles were available for further screening. Following title and abstract screening, 150 articles were deemed potentially relevant. Then, 85 full-text articles were carefully screened for eligibility according to the inclusion and exclusion criteria. Lastly, 34 high-quality and relevant studies on deep learning-based TB detection from chest X-ray images were included for detailed review and analysis in this survey.

A. Overview of Tuberculosis (TB)

Tuberculosis (TB) continues to be a major cause of infectious disease deaths globally. As reported by the World Health Organization (WHO), an estimated 10.6 million individuals got sick with TB in the world in 2022, with an estimated 1.3 million deaths among HIV-negative individuals and 167,000 deaths among HIV-positive individuals (WHO, 2023). TB is caused in most cases by the bacterium Mycobacterium tuberculosis, which mainly infects the lungs but also has the capacity to infect other organs.

B. Symptoms and Diagnosis of TB

TB signs are normally chronic cough, fever, weight loss, sweats at night, and chest pain. Early and correct diagnosis is critical for preventing the spread of TB, particularly in a high disease burden setting [1]. The conventional diagnostic methods for TB include sputum smear microscopy, culture, molecular tests (such as GeneXpert), and radiological examination. Among them, chest X-ray (CXR) is still one of the most popular screening methods because it is easily accessible and quick.

C. Use of Chest X-Rays in TB Identification

Chest X-ray imaging is of vital significance during primary screening and diagnosis of pulmonary TB. It facilitates visualization of the abnormalities such as cavitations, nodules, infiltrates, and fibrosis in lung tissues [2]. CXR performs particularly well within population-based screening for TB as well as a helpful diagnostic in detecting active and latent infections of TB.

D. Limitations in Manual Chest X-ray Diagnosis

Despite the use of CXR in TB diagnosis, manual radiological interpretation is threatened by a variety of problems, primarily in low-income nations:

- Radiologist shortage: Low- and middle-income countries lack a sufficient number of radiology professionals to provide solutions to the large volume of CXR tests [1].
- Inter-reader Variability: Human reading of CXRs tends to be subjective and susceptible to inter-reader variability, thus resulting in unreliable diagnoses [4].
- Latent TB Detection: Subtle radiographic manifestations might be observed in early-stage or latent cases of TB, hence difficult detection with precise instruments without sophisticated tools [5].

IV. Deep Learning in Medical Image Analysis

A. Introduction to Deep Learning

Deep Learning (DL), a branch of Artificial Intelligence (AI), has come to be a revolutionary technology in the field of medical image analysis. DL models, especially multi-layer neural networks, have proved to outperform others in the identification of intricate patterns out of very large data sets. DL models can learn hierarchical features from raw data automatically without much manual intervention, which makes them very appropriate for medical imaging applications [3].

B. The Function of Convolutional Neural Networks (CNNs)

Among different DL structures, Convolutional Neural Networks (CNNs) have also attracted tremendous attention because of their strong ability to handle and examine visual data like medical images. CNNs are particularly applied in the identification of spatial hierarchies of images due to their layer-based architecture made up of convolutional, pooling, and fully connected layers [1]. CNNs have extensively been applied in TB detection from Chest X-Rays (CXR) due to their precision in identifying faint patterns of the disease, which human eyes are not easily able to detect.

C. Shared Workflow in Deep Learning-Based Medical Imaging

The shared workflow in DL-based detection of TB from CXR includes a few major phases, which are illustrated below [1, 5]:

a) Image Preprocessing: Preprocessing enhances the quality of input images and normalizes them. Preprocessing techniques like resizing, removal of noise, contrast stretching, and normalization of pixel intensities are common.

b) Feature Extraction: CNNs are trained to automatically extract image features at various levels like edges, textures, and high-level patterns. CNNs are discriminative and descriptive in contrast to human-crafted features employed in typical Machine Learning (ML) techniques.

c) Classification: Extracted features are passed on to dense layers or classifiers like Softmax in order to classify the input image as TB-positive or TB-negative. Advanced models may also utilize segmentation masks in order to identify specific lung regions for improved accuracy [3].

D. Advantages of Deep Learning over Traditional Machine Learning

DL methods have various benefits over traditional ML methods in medical imaging applications [2, 6]:

- Automatic Feature Learning: Contrary to conventional ML, which uses hand-engineered features, DL models learn the features relevant to the problem from the input data automatically.
- High Accuracy: DL models are capable of learning complex and nonlinear patterns within the data, thus resulting in better diagnostic accuracy.
- Scalability: DL models can be scaled and retrained on updated data to enhance their generalization power.
- Reduction in Human Bias: Automatic feature learning decreases reliance on domain-specific knowledge and human intrusion.

E. Significance of Explainability in Clinical Diagnosis

Though DL models are highly accurate, their "black-box" characteristic is a matter of concern from the point of trust and transparency in clinical usage. Explainable AI (XAI) methods, including Gradient-weighted Class Activation Mapping (Grad-CAM), Local Interpretable Model-Agnostic Explanations (LIME), and SHapley Additive exPlanations (SHAP), have been progressively used to interpret model decisions and identify areas of interest on CXR images [5, 7]. The use of XAI guarantees that DL models do not just execute well but also give understandable and reliable outputs for clinicians.

Recent work introduces numerous deep learning methods for computerized Tuberculosis (TB) detection from Chest X-Ray (CXR) images. These methods can be widely classified according to the model architecture, learning method, or methodological advancement utilized. The succeeding sub-sections elaborate on these categories.

V. Categorization of TB Detection Approaches

CNN-Based Architectures: CNN-based models have been the most used method for TB detection because of their strong feature extraction ability from medical images. Primary CNN models include convolutional layers, pooling layers, and fully connected layers that aid in extracting textural and spatial features from CXR images. Experiments such as Sidume et al. (2024) used CNN models coupled with methods like Dropout to prevent overfitting and Batch Normalization to improve training speed. Techniques such as rotation, flipping, and adjustment of contrast are generally used for dataset limitation bypassing. These models serve as a basic guideline for TB classification, especially for early DL research. Several recent studies have explored the application of Deep Learning (DL) techniques, namely Convolutional Neural Networks (CNN), for early and precise Tuberculosis (TB) detection through Chest X-ray (CXR) images. Researchers have achieved significant improvements in diagnostic accuracy, sensitivity, and specificity, with some models achieving accuracy levels higher than 96% and outstanding AUC values higher than 0.97. These advances provide promising aid tools for medical clinicians to enable faster and more accurate TB screening, especially for resource-limited settings [6].

Transfer Learning Methods: Transfer Learning (TL) has been considerably successful in detecting TB, particularly in cases with limited labeled medical data. Through this method, pre-trained models like VGG, ResNet, DenseNet, and InceptionV3, initially trained on extensive datasets like ImageNet, are utilized again for feature extraction or fine-tuned for TB-related tasks. [2, 6] showed that TL-based models were more efficient and precise than regular CNNs. Feature extraction is from learned features without modifying pre-trained weights, and fine-tuning modifies model layers based on CXR images for more personalized learning. CNNs have been found to hold much promise in detection of Tuberculosis (TB) from Chest X-ray (CXR) images. Transfer learning, and also automatic feature extraction, CNNs minimize human interaction and maximize precision. Research has shown TB detection accuracy rates between 80% and 97%, which reflects that CNNs are an effective and valuable medical image classification, and early detection of TB, tool [27].

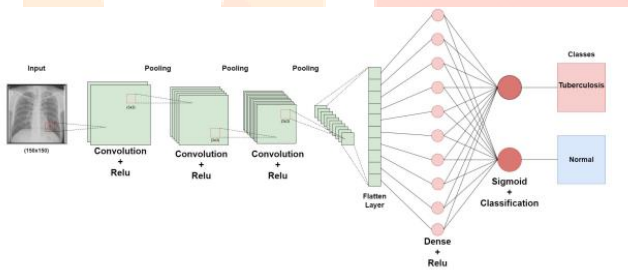


Fig. 2. Yolov8 [33]

Hybrid & Attention-Enhanced Models: Hybrid frameworks integrate CNN frameworks with other smart methods such as fuzzy logic or attention mechanisms to improve detection precision. [5] fuzzy-enhanced CNN framework that works well in dealing with uncertainty and noise during CXR images.Hybrid frameworks have also integrated attention mechanisms such as Attention Gates and Spatial Attention into CNN models to allow the model to selectively pay attention to lung areas possibly infected with TB. [9] emphasized that attention modules help in more accurate feature localization, which leads to more interpretable and accurate predictions. Pulmonary Tuberculosis (TB) is a major health issue in developing countries. Early detection through Chest X-ray (CXR) imaging is crucial to its containment. A CBAM-ResNet model with a two-stage warmup-to-finetuning (W2F) method for improving the accuracy of TB detection is proposed by this study. The model, using data augmentation and SGD with gradient centralization, had an accuracy of 91.1% on the Shenzhen dataset and 86.4% on the Montgomery dataset. The technique provides an important tool to assist early diagnosis of TB and support healthcare personnel [28].

Segmentation-Assisted Classification: Segmentation approaches have been incorporated into TB detection systems to separate lung areas from the background, making classification more accurate. Mask R-CNN and U-Net are widely used segmentation models that aid in drawing attention to important areas in CXR images. [11, 14, 15, 17] segmentation-assisted classification approach where segmented lung areas were fed into a classifier, filtering out noise and unnecessary features. The Proposal Networks (RPN) are used in order to make efficient localization of unusual regions before final classification [13, 16].

Lightweight & Mobile Models: For remote or low-resource environments, light models such as EfficientNet and MobileNet are increasingly popular as they use less computation and provide quicker inference times. [8, 10, 12] highlighted the use of these models for real-time screening through portable devices or mobile-based healthcare. These models guarantee deployment viability in underdeveloped regions with limited medical facilities. Deep learning has proved to be an effective discriminator in the detection of TB, breaking the limits of conventional manual processes. Lite-YOLOv8, an optimized light-weight model, obtained a mean average precision (mAP) of 86.3% in detecting Tubercle Bacilli from sputum samples with considerably less parameters and computational cost. Similarly, CNN models implemented on chest X-ray (CXR) images have proved to be extremely accurate for diagnosing TB with reduced human errors and increased speed of detection. While some models provide better accuracy, their computation costs render them resource-intensive in resource-constrained settings where real-time use could be hindered [24, 31, 32].

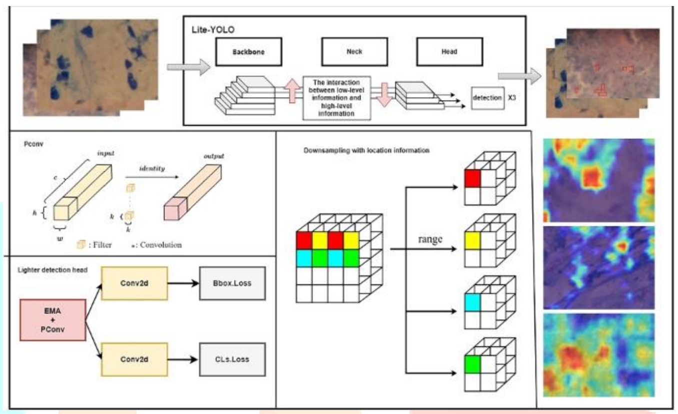


Fig. 2. Yolov8 [32]

Explainable AI (XAI) in TB Detection: XAI techniques have been vital in medical imaging to assure transparency in decision-making. Visualization methods like Grad-CAM, SHAP, and LIME have been used to create heatmaps or plots of feature importance, assisting radiologists in understanding the model's attention regions during TB detection.

Grad-CAM visualization to demarcate lung abnormalities in CXR images, improving clinical trust and AI system acceptance. This paper is concerned with the detection and diagnosis of various airway diseases such as pneumoconiosis, pulmonary embolism, Covid-19, tuberculosis, and lung cancer through deep learning techniques [3]. Different CNN models such as InceptionResNetV2, MobileNet, Xception, ResNet152, EfficientNetV2M, and DenseNet169 were utilized on chest X-ray images and CT scan images. Sharpening techniques such as sharpening techniques were utilized for sharpening images to enhance image quality for appropriate feature extraction. Among all models, InceptionResNetV2 achieved a highest accuracy of 99.15% along with high precision, recall, and F1-score [29, 30, 34].

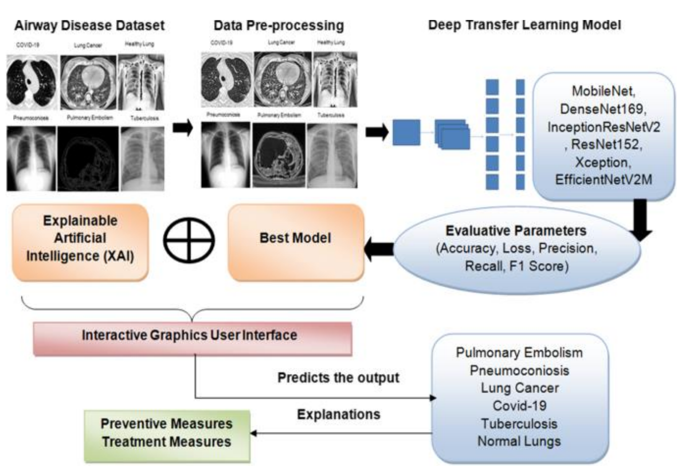
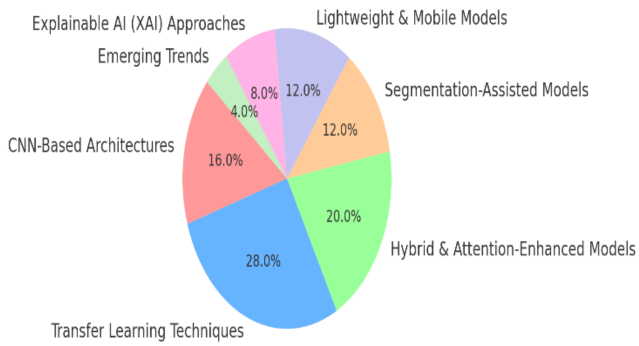


Fig. 3. Explainable AI [34]

TABLE II. SUMMARY OF TB DETECTION APPROACHES



Approach	**Models/Techniques Used**	**Key Advantages**
CNN-Based Architectures (Sidume et al., 2024)	Basic CNN, Dropout, Batch Normalization	Strong baseline, Robust feature extraction
Transfer Learning Techniques (Singh et al., 2024; Godbin et al., 2025)	VGG, ResNet, DenseNet, InceptionV3	Efficient training, Better accuracy with limited data
Hybrid & Attention-Enhanced (Ieracitano et al., 2022; Sanida et al., 2024)	Fuzzy CNN, Attention Gates, Spatial Attention	Focused learning, Handles uncertainty
Segmentation-Assisted Models (Sharma et al., 2022)	U-Net, Mask R-CNN, RPN	Better localization, Noise reduction
Lightweight & Mobile Models (Sidume et al., 2024)	EfficientNet, MobileNet	Real-time detection, Low computational load
Explainable AI (XAI) (Sharma et al., 2022)	Grad-CAM, SHAP, LIME	Interpretability, Clinician trust

Fig. 4. Deep Learning Techniques for TB detection

TABLE III. SUMMARY TB DETECTION APPROACHES

Method	**Model/Technique Used**	**Advantages**	**Accuracy/AUC Achieved**
CNN-Based Architectures	Basic CNN with Convolutional, Pooling, Fully Connected Layers + Dropout & Batch Normalization	Strong feature extraction, handles textural & spatial features, prevents overfitting	Accuracy= 96%, AUC = 0.97
Transfer Learning (TL)	Pre-trained Models like VGG, ResNet, DenseNet, InceptionV3	Effective with small datasets, automatic feature extraction, faster convergence, higher precision	Accuracy 80% - 97%, High AUC
Lightweight	Rotation, Flipping, Contrast Adjustment	Reduces overfitting, expands dataset variability	mAP= 86.3%
Attention-Enhanced	SGD, warmup-to-finetuning	prevents overfitting	Accuracy= 91.1%
Explainable AI	Sharpening techniques, feature extractor	higher precision	ACC= 99.17%

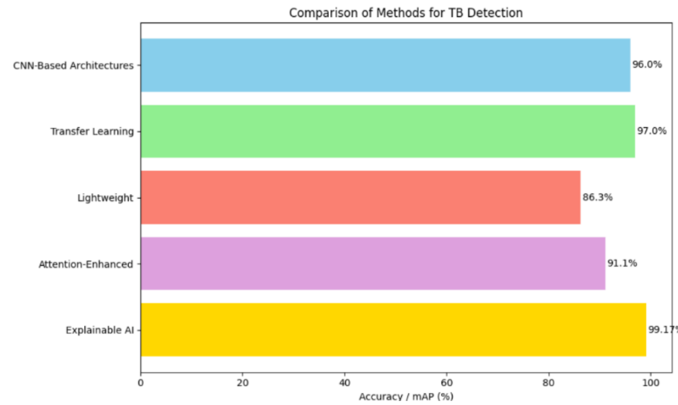


Fig. 5. Comparison of TB detection methods

A. Emerging Trends in TB Detection

Current studies reveal some emerging directions of DL-based TB detection:

TABLE IV. EMERGING TRENDS

Trend	Descrpition
Self-Supervised Learning	Utilizes unlabelled data to pre-train models before fine-tuning on limited TB datasets
Multi-modal Fusion	Combines CXR images with clinical data (e.g., patient history, symptoms) for improved predictions.
Federated Learning	Distributed model training across multiple locations ensuring patient data privacy without data sharing.

These advancements show promising potential for developing more accurate, efficient, and privacy-preserving TB diagnostic tools.

VI. CHALLENGES AND LIMITATIONS IN APPLYING DEEP LEARNING TECHNIQUES TO TB DETECTION

Although there has been continuous success with Deep Learning (DL) methods in medical image analysis, there are some limitations and challenges in successfully applying them to detect TB from Chest X-ray (CXR) images [20]. The constraints stretch across data-level, model-level, and deployment-level.

A.Data Imbalance & Annotation Scarcity:

One of the primary challenges in TB detection with DL is the data imbalance problem. The majority of the publicly available TB CXR datasets have a significantly larger number of non-TB (normal) images than TB-positive images. This imbalance usually results in biased learning, where the model starts learning better for normal images while not learning rare TB cases as efficiently [25, 26].

Moreover, there is a serious shortage of annotations. Highly expert radiologists or pulmonologists are needed for accurate TB lesion annotation in CXR images, and manual labelling is not only time-intensive but also costly. This constrains the prevalence of well-labelled datasets essential in training supervised DL models.

B. CXR Dataset Variability & Quality:

CXR images employed to detect TB vastly differ in image quality based on variations in:

- Radiography machinery
- Imaging protocols
- Posture of the patient
- Noise and artifacts
- Illumination and contrast problems

This kind of variability tends to lead to deterioration in the performance of DL models when they are tested on unexpected data from new clinical environments or locations [11, 12]. Besides, poor quality or out-of-focus images, commonly found under low-resource setups, also make it challenging to achieve precise feature extraction and categorization.

C. Issues of Generalizability Across Population & Device Types

Deep learning models that are trained on individual datasets (frequently from a single hospital or region) do not necessarily generalize to heterogeneous populations because:

- Anatomical variation between ethnic groups
- Varying rates of TB sub-types in different regions
- Variation in imaging conditions across devices and hospitals

This is a domain shift problem that restricts the robustness of TB detection systems in actual multi-center settings [18, 19].

E. Interpretability of Deep Learning Models

DL models, particularly CNN-based models, have been popularly criticized as black boxes. Clinicians require models not just to be precise but also explainable in order to facilitate clinical decision-making. The lack of explanations by models for their predictions lowers the confidence of clinicians in adopting models, which affects acceptance [21, 22, 24].

Visualization methods such as Grad-CAM, LIME, and SHAP provide certain levels of interpretability but should become more improved and streamlined for use in medicine.

F. Deployment in Low-resource Settings

TB is predominantly found in low- and middle-income countries (LMICs), where access is limited to:

- Sophisticated computing infrastructure
- Internet connectivity
- Cloud storage
- Expert IT professionals

It is often the case that most cutting-edge DL models demand excessive computational resources for both training and prediction, thus rendering their deployment difficult in distant or rural settings [23]. The requirement for GPU-based systems restricts it to widespread use in low-resource environments.

G. Ethical & Privacy Concerns

Utilizing patient imaging data raises significant privacy and ethical concerns:

- Ensuring patient data privacy
- Proper handling of sensitive health data
- Compliance with data protection law like GDPR or HIPAA
- Challenges of misuse or data loss

Moreover, using publicly available CXR datasets seldom offers insight into patient consent or data-sharing principles, which is an ethical issue [21, 25].

VII. Future Directions

To tackle the current challenges and fill the gaps in TB detection with Deep Learning (DL), many prospective future directions are being energetically explored. These directions are meant to improve model robustness, fairness, explainability, and real-world usability, especially in diverse and resource-scarce settings.

A. Creating Large Multi-center TB-specific Datasets

One of the greatest future needs is the creation of large-scale, multi-center, and TB-specific Chest X-ray (CXR) datasets. The majority of current datasets are small in size, low in diversity, and lacking in representativeness. Hospitals, government health departments, and international research centers must work together to produce datasets that cover:

- Multiple geographic locations
- Diverse patient populations (age, gender, ethnicity)
- Variations in TB strains and disease stages
- Different imaging equipment and acquisition settings

Such datasets will make sure that DL models are not biased against a particular population and can generalize well across different clinical settings. These datasets also need to prioritize standardized annotation protocols with TB specialists and radiologists to ensure high-quality labels.

B. Lightweight & Explainable Model Development

The future of TB detection models must strike a balance between interpretability and accuracy and computational efficiency. Lightweight models can be obtained using techniques like:

- Model Compression
- Removal of redundant layers or neurons
- Quantization for smaller memory usage

Explainability is similarly crucial for medical applications. Adding Explainable AI (XAI) tools such as Grad-CAM, LIME, and SHAP will allow clinicians to identify why a model produces certain predictions. This is essential to generate trust and transparency in computer-aided TB diagnosis systems, particularly upon deployment in clinical practice or rural health delivery.

C. Integration with Mobile Health (mHealth) Applications

The increasing smartphone and mobile technology penetration in the healthcare sector presents a special opportunity to incorporate DL-based TB detection into mobile health (mHealth) applications. The apps can:

- Enable point-of-care TB screening
- Offer rapid analysis independent of internet connectivity
- Empower non-specialist staff and community health workers
- Support early-stage TB detection in remote and underserved regions

Subsequent studies need to concentrate on creating easy-to-use, light-weight mobile apps to process CXR images through on-device DL models with high accuracy and reliability.

E. Cross-region Adaptation using Federated Learning & Transfer Learning

Data privacy issues tend to restrict sharing of sensitive healthcare images between institutions. Federated Learning (FL) solves the problem by enabling collaborative model training without sharing raw data. Model updates are shared instead to ensure data protection [23].

Further, Transfer Learning would be utilized for tailoring pre-trained models for detecting TB into the unique locations or populations of patients where minimal local data exist. Mixing FL with Transfer Learning would assist in building even more generalizable and privacy-enabled TB diagnosis models around the world by various locations.

F. Model Standardization & Benchmarking Frameworks

A significant research lacuna exists in the lack of uniform protocols for testing and benchmarking DL models for TB detection. Urgently, there is a need to develop:

- Uniform benchmarking datasets
- Standardized performance metrics such as Accuracy, Sensitivity, Specificity, AUC, and F1-Score
- Clear reporting guidelines
- Open-source platforms for unbiased model comparisons

Standardization will assist the research community in comparing various TB detection models under uniform and comparable

settings, promoting scientific progress.

G. Emphasis on Latent TB Detection

Existing studies mainly focus on the detection of active TB from CXR images. Yet, latent TB infection (LTBI), which is symptom-free, is a major challenge. Future studies must focus on creating DL models that can estimate the probability of latent TB or reactivation based on:

- Subtle imaging patterns
- Biomarkers
- Clinical and laboratory data

Early detection of latent TB would revolutionize the face of TB control and prevention globally.

H. Multi-modal Data Use (CXR + Symptoms + Patient History)

Using more than one source of data holds a very promising future direction. Relying only on CXR images, there can be no full representation of a patient's status in all situations. Future TB detection systems must explore the following combinations:

- Radiological Data (CXR Images)
- Clinical Signs (Cough, Fever, Weight Loss)
- Patient Background (History of past TB exposure, Immunity level)
- Lab Results (Sputum analysis, GeneXpert reports)

These multi-modal DL models will lead to improved, more accurate, and patient-centric TB identification, mimicking the holistic approach employed by doctors when diagnosing patients.

VIII. Conclusion

Deep learning is now a cutting-edge technology for medical image analysis, particularly in detecting tuberculosis (TB) via chest X-rays (CXR). The literature reviewed here introduces a diverse array of CNN models, transfer learning techniques, combination models, and explainable AI methods that have significantly improved the accuracy of TB detection.

Nevertheless, some of the challenges remain, such as data imbalance, low image quality, low generalizability, and black-box nature of DL models. Solving these challenges needs joint efforts in constructing large-scale datasets, enhancing model explainability and guaranteeing privacy-preserving AI solutions.

In the future, responsible development of AI is critical so that TB detection systems are deployable, interpretable, and ethical in practical environments, particularly low-resource settings. Researchers and professionals need to aim for lightweight, privacy-conscious, and standardized solutions that bridge the gap between clinical practice and research.

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