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Comparative Analysis of Machine Learning Models for Tuberculosis Early Detection through Cough Analysis

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Abstract*—Tuberculosis (TB) remains a critical global health issue, requiring early and accessible detection to prevent its transmission. One of the biggest challenges in controlling TB is delayed diagnosis, which allows infected individuals to unknowingly spread the disease. This study presents a comparative analysis of machine learning (ML) models for early detection using cough audio analysis. Four models—Logistic Regression, Random Forest, Bi-LSTM + Conv2D, and Capsule Networks + FCNN—were evaluated based on accuracy, inference speed, computational complexity, and suitability for edge deployment. The comparative analysis shows that deep learning models demonstrated superior classification performance but their computational demands make them less practical for low-power devices. In contrast, Logistic Regression, with its efficiency and low resource requirements, was found to be the most suitable for real-time deployment on mobile and embedded systems. These findings will contribute to the development of scalable, AI-driven TB screening tools that balance accuracy with feasibility.

Keywords*—Tuberculosis detection, machine learning, deep learning, cough analysis, edge computing, early diagnosis.

I. INTRODUCTION

Tuberculosis (TB) remains one of the leading causes of infectious disease-related deaths worldwide with millions of new cases reported annually [1]-[3]. Early detection of TB is crucial

for effective treatment and prevention of transmission. However, traditional diagnostic methods, such as chest X-rays and culture tests, often suffer from limitations, including high costs, delayed results, and varying accuracy depending on expertise. These challenges highlight the need for more efficient and automated approaches to TB detection.

Machine learning (ML) has emerged as a promising tool for improving disease diagnosis by leveraging large datasets and advanced computational techniques. ML models can analyze diverse TB-related data, including cough sounds, chest radiographs, and clinical symptoms to enhance early detection accuracy. Various algorithms, such as Convolutional Neural Networks (CNNs), k-Nearest Neighbors (KNN), Long Short-Term Memory (LSTM), and Logistic Regression, have been explored for TB classification and prediction [4]-[6]. However, selecting the most effective model requires a thorough comparative analysis based on key performance metrics such as accuracy, precision, recall, F1-score, and inference time.

This study conducts a comparative analysis of four recent studies that employ ML models for TB detection using cough audio analysis. By evaluating these approaches based on performance, feature extraction techniques, dataset size, and computational efficiency, we aim to determine the most suitable model for real-world applications, particularly for deployment on mobile and edge devices. The findings from this research will contribute to the development of optimized ML-based TB screening systems that are both accurate and resource-efficient.

II. RELATED WORK

According to the World Health Organization (WHO), TB is one of the leading causes of death worldwide, second only to HIV/AIDS. The disease disproportionately affects economically disadvantaged and marginalized populations, where limited access to healthcare contributes to its prevalence [7].

TB is a chronic infectious disease caused by *Mycobacterium tuberculosis*, a gram-positive, acid-fast bacillus that primarily affects the lungs, leading to pulmonary tuberculosis. However, the infection can also spread to other parts of the body, including the intestines, meninges, bones, joints, lymph nodes, skin, and various tissues, resulting in extrapulmonary tuberculosis [8].

One of the biggest challenges in controlling TB is delayed diagnosis, which allows infected individuals to unknowingly spread the disease. Early and rapid detection is essential to

improving treatment efficacy and preventing further transmission within communities [9]. A newly proposed deep neural network-based method for drug-sensitive TB detection has demonstrated a recall of 83.78% and a precision of 67.55% in bacillus identification. This approach utilizes microscopy images at an optimal zoom level as input and accurately identifies suspected TB bacilli, making it a potential high-sensitivity diagnostic tool when trained on a larger scale [10].

Traditional diagnostic methods, such as smear microscopy, culture tests, and GeneXpert, are subject to limitations, including long processing times, high costs, and varying sensitivity. As a result, computer-aided diagnosis (CAD) has emerged as a promising alternative for TB detection. Various CAD approaches leveraging machine learning techniques have been applied to TB diagnostics. Additionally, hybrid systems integrating deep learning with neuro-fuzzy logic, genetic algorithms, and artificial immune systems have further enhanced diagnostic capabilities [11].

Furthermore, deep learning techniques have shown significant advancements in TB detection through medical imaging. A study utilizing deep convolutional neural networks (CNNs) applied transfer learning on pre-trained models, including ResNet, ChexNet, DenseNet, and MobileNet, to classify TB from chest X-ray images. The study incorporated segmentation techniques using U-Net models and found that classification using segmented lung images improved accuracy by achieving 98.6% with DenseNet201. These results highlight the potential of deep learning in automating TB diagnosis with high precision and sensitivity, further supporting its integration into clinical decision-making systems [12].

Cough audio analysis has been increasingly recognized as a promising approach for TB screening due to its non-invasive and cost-effective nature. DMRNet is a machine learning model designed to analyze cough sounds and differentiate TB patients from those with other respiratory conditions as well as healthy individuals. These findings highlight the potential of cough audio analysis as a viable TB detection method, particularly in densely populated regions where conventional diagnostic approaches may be impractical [13]. Traditional auscultation is subjective, but AI-driven models, including neural networks and wavelet transforms, enhance diagnostic accuracy. These technologies have potential for detecting conditions like asthma, COVID-19, and interstitial lung disease, paving the way for real-time respiratory monitoring in clinical practice [14]. Since coughing is a primary symptom of various respiratory illnesses, including TB, pneumonia, asthma, and COVID-19, AI algorithms can be trained to recognize patterns in cough samples and assist in early diagnosis [15]. Alqudaihi et al. identified key challenges and opportunities in utilizing AI for respiratory disease diagnosis, emphasizing the need for continued research to enhance accuracy and real-world applicability[16].

The integration of artificial intelligence into TB detection has led to significant progress, particularly in enhancing accessibility and efficiency in low-resource environments. Traditional TB detection methods that rely on chest X-ray imaging often demand high computational power, making them difficult to implement on low-cost personal computers and embedded devices. To overcome this challenge, researchers developed E-TBNet, a lightweight AI model designed for efficient TB screening on devices with limited hardware capabilities [17].

Beyond hardware-efficient AI models, machine learning combined with mobile computing presents another viable strategy for improving TB diagnosis in underserved regions [18]. In many economically disadvantaged communities, limited healthcare access leads to delayed diagnoses and increased disease transmission rates. To address this, researchers have developed comprehensive, annotated chest X-ray databases and utilized deep convolutional neural networks (CNNs) to automate TB detection. Studies indicate that CNN-based systems can classify TB symptoms from X-ray images with high precision, offering a scalable and efficient alternative to traditional diagnostic methods. Ongoing research aims to refine these models further and deploy them in TB-endemic areas, such as Carabayllo, Peru, where access to conventional screening tools is scarce.

In addition to mobile and lightweight AI models, AI-assisted diagnostic systems have been explored to support radiologists in regions with limited access to medical specialists [19]. Much of the AI-based TB research has been concentrated in urban hospitals, leaving a gap in its application in rural and low-resource areas. To bridge this divide, researchers developed an AI-driven TB screening system incorporating TB-UNet, a segmentation model that utilizes ResNeXt as an encoder for U-Net to identify infected lung regions in chest X-rays. Findings reveal that the AI model achieved 85% accuracy in TB detection, significantly outperforming local radiologists, who demonstrated only 62% accuracy without AI assistance. Additionally, AI assistance improved the sensitivity of TB diagnoses among radiologists by 11.8%, demonstrating the technology's potential to enhance diagnostic accuracy and efficiency in high-risk, low-resource populations.

Apart from imaging-based AI applications, real-time TB detection through intelligent mobile systems has emerged as a promising alternative to traditional methods. One such approach involves plasmonic ELISA-based detection of TB antigen-specific antibodies, integrated with machine learning for real-time classification [20]. This technique differs from conventional diagnostic procedures, which are often costly and time-intensive, by employing supervised learning algorithms to classify samples based on color feature extraction. A study utilizing Random Forest classification demonstrated 98.4% accuracy in detecting TB antigen-specific antibodies on a mobile device, eliminating the need for complex opto-mechanical components. This

advancement offers a portable, real-time TB screening solution, with future research focusing on clinical validation to confirm its effectiveness in real-world applications.

Additionally, the emergence of Distributed Machine Learning (DML) at the edge has opened new opportunities for efficient AI-driven TB detection in decentralized healthcare settings [21]. Conventional AI models typically rely on cloud-based computing, which introduces latency issues and network dependencies that can hinder real-time diagnostics [22],[23]. To address this recent work demonstrates that decentralized machine learning at the edge, coupled with bandwidth-aware collaborative inference, offers a viable solution. Specifically, Fabila et al. [24] showed that federated learning across eight African countries enabled collaborative training of TB diagnostic models without centralizing sensitive data, proving feasibility in low-resource settings despite infrastructure challenges. Complementing this, Islam et al. [25] developed a lightweight collaborative inference framework that reduces model size by 48.6% and inference latency by 2.37% while preserving diagnostic accuracy, thereby directly mitigating the transmission overhead and connectivity constraints of cloud-only architectures. Together, these approaches enable efficient, privacy-preserving, and real-time AI-driven TB screening in decentralized healthcare environments.

These advancements underscore how AI-driven innovations—including lightweight models for low-powered devices, mobile computing for real-time screening, AI-assisted radiology, antibody-based detection on mobile platforms, and distributed AI at the edge—can collectively enhance TB detection, prevention, and control in resource-limited regions.. Future research should focus on further refining AI models, expanding datasets, and ensuring seamless deployment, particularly in areas where early TB diagnosis remains an urgent healthcare priority.

III. DATA SETS AND METHODOLOGY

This study utilizes four different datasets, each offering unique characteristics for tuberculosis (TB) cough detection. These datasets vary in size, collection methods, and recording quality, ensuring a diverse and comprehensive foundation for model training and evaluation.

1. Dataset 1 consists of 435 cough samples from 145 participants (123 males, 22 females) aged 40–70 years. Each participant provided three 6-second cough recordings, ensuring diversity across demographics [26].
2. Dataset 2, contains 1358 cough events (402 TB-related, 956 non-TB) [4].
3. Dataset 3 was collected from hospitals using smartphones, including 230 TB coughs from 70 patients and 226 non-TB coughs from 74 healthy individuals [27].
4. Dataset 4 comprises the existing CODA TB Dream Challenge Datasets, with 733,756 cough recordings from 2143 individuals [28].

Several studies have utilized different datasets for TB cough detection, each with varying sample sizes, data collection methods, and TB/non-TB distributions. Table 1 provides a comparative overview of these datasets, highlighting their key characteristics.

TABLE 1: DATA SETS COMPARISON

Data sets	Author	Total Samples	TB Samples	Non-Tb Samples	Collection Method
1	Mahmood et al. [26]	435	not stated	not stated	controlled
2	Pahar et al. [4]	1358	402	956	Non-Controlled
3	Xu et al. [27]	456	230	226	Controlled
4	CODA TB DREAM Challenge Dataset. [28]	733,756	Not stated	Not Stated	Non-Controlled

Pre-Processing Techniques

Mahmood et al. [26] applied a two-stage preprocessing approach to improve the quality of TB cough recordings:

1. Signal-to-Noise Ratio (SNR) Filtering
   - Segments cough sounds using a 2s sliding window (50% overlap).
   - Removes background noise by filtering low-SNR chunks.
   - Retains high-SNR segments (bursts) for further analysis.
2. Cough vs. Non-Cough Classification
   - Uses a deep learning model to isolate actual cough sounds from non-cough noises.
   - Manually annotated by experts for validation.
3. Feature Extraction
   - Mel-Frequency Cepstral Coefficients (MFCCs) (12 coefficients, 40 Mel filters).
   - Spectral Features (Centroid, Bandwidth, Roll-off, Contrast).
   - Energy-based Features (RMS Energy, Zero-Crossing Rate).
   - Time-Frequency Representations (Mel Spectrogram, Chroma Features).
   - Final feature set contains 206 extracted features for TB classification.

Pahar et al. [4] applied a structured feature extraction process without additional filtering or preprocessing:

1. Recording Conditions
   - Collected in a controlled booth environment to maintain consistency.
   - No correlation between recording time/date and TB status, ensuring unbiased SNR values.
2. Feature Extraction
   - Mel-Frequency Cepstral Coefficients (MFCCs) – Captures key spectral features for cough classification.
   - Log-Filterbank Energies – Extracts spectral energy patterns.
   - Zero-Crossing Rate (ZCR) – Measures waveform variability for signal classification.
   - Kurtosis – Assesses the prevalence of high-amplitude cough bursts.
   - Hyperparameter Tuning – Features were extracted from 1 to 4 cough sections, affecting dimensionality.

Xu et al. [27] applied multiple feature extraction techniques and a feature fusion method to improve TB cough classification:

3. Feature Fusion & Classification
   - Extracted deep features using CNN and Bi-LSTM models for cough classification.
   - Applied feature fusion techniques by combining MFCCs, spectral, and energy-based features for improved TB detection accuracy.

Rajasekar et al. [28] applied a multi-stage preprocessing pipeline to enhance TB cough detection accuracy:

1.Noise Reduction & Normalization
   - Resampled audio to 16 kHz for consistency.
   - Weiner filter denoising to remove background noise and enhance clarity.
   - Silence Removal by thresholding non-silent intervals, ensuring only relevant cough segments remain.

1. Spectrogram & Time-Frequency Analysis
   - Short-Time Fourier Transform (STFT) used to analyze frequency changes over time.
   - Spectrogram amplitudes were converted to decibels (dB) for better visualization.

2. Feature Extraction
   - Histogram of Oriented Gradients (HOG) – Captures texture and patterns in spectrogram images.
   - Principal Component Analysis (PCA) – Applied to reduce feature dimensions and computational

1. Feature Extraction Techniques
   - Mel-Frequency Cepstral Coefficients (MFCCs) – Extracted 44 coefficients per cough frame using pre-emphasis, FFT, and DCT.
   - Zero-Crossing Rate (ZCR) – Measured how frequently the audio signal crosses zero amplitude, used for detecting abrupt signal changes.
   - Short-Time Energy (TSE) & RMS Energy – Captured the intensity variations in cough signals.
   - Chroma CENS (Chroma Energy Normalized Statistics) – Divided the frequency spectrum into 12 equal-width bands and applied a logarithmic transformation to obtain tonal features.

2. Spectrogram Conversion
   - Applied Hanning windowing (width = 256 samples) to segment the cough sound.
   - Performed Fast Fourier Transform (FFT) on each window to obtain spectrogram representations.
   - Used logarithmic transformation of frequency-domain signals to enhance feature clarity

complexity.Preprocessing plays a crucial role in improving the quality of cough audio recordings for tuberculosis (TB) detection. Different studies have employed various noise reduction, segmentation, and feature extraction techniques to enhance model accuracy.

Table 2 provides a comparative overview of the preprocessing methods used in different studies.

TABLE 2: PRE- PROCESSING COMPARISON

Study	Pre-processing approach	Feature Extraction
Mahmood et al. [26]	SNR filtering, Cough vs. Non-Cough Model	MFCC, Spectral & Energy Features
Pahar et al. [4]	No filtering, recorded in controlled booth	MFCC, Log-Filterbank Energies, ZCR, Kurtosis
Xu et al. [27]	Smartphone-based noise filtering	MFCC, ZCR,TSE and RMS Energy, Chroma CENS
Rajasekar et al. [28]	Noise reduction (Weiner filter), STFT, Silence Removal	Spectrogram (HOG, PCA)

IV. RESULT AND DISCUSSION

This section presents the results of the comparative analysis of machine learning models for tuberculosis (TB) detection using cough audio recordings. The performance of different datasets and preprocessing techniques is analyzed,

highlighting their effectiveness in feature extraction and classification accuracy. Additionally, comparisons are made with existing studies to assess improvements in detection efficiency, computational requirements, and suitability for real-world deployment.

Table 3 summarizes the accuracy, precision, recall, F1-score, AUC, and sensitivity of the evaluated models table 3. Performance Comparison of Machine Learning Models for TB Detection.

TABLE 3: PERFORMANCE COMPARISON OF MACHINE LEARNING MODELS FOR TB DETECTION

Reference	Model	Accuracy	Precision	Recall	F1-score	AUC	Sensitivity
[26]	Support Vector Classifier (SVC)	95	92% (TB Not), 99% (TB Likely)	95	95	NA	NA
	Logistic Regression (LR)	92	92% (TB Not), 92% (TB Likely)	92	92	NA	NA
	Multi-Layer Perceptron (MLP)	94	96% (TB Not), 92% (TB Likely)	92/97	94	NA	NA
	K-Nearest Neighbors (KNN)	92	99% (TB Not), 86% (TB Likely)	84/99	91/92	NA	NA
	Random Forest (RF)	97	99% (TB Not), 94% (TB Likely)	93/100	96/97	NA	NA
[4]	LR + Sequential Forward Selection (SFS)	84.54	93	NA	NA	94	93
[27]	Bi-LSTM + Speech Spectrogram	96.33	NA	NA	NA	92	98.13
[28]	Capsule Networks + FCNN	97	97	NA	97	97	98

This study presents a comparative analysis of machine learning models for TB detection using cough audio analysis.

The performance of different models was evaluated based on classification accuracy, precision, recall, F1-score, AUC, and sensitivity. The results indicate that deep learning models outperform traditional machine learning approaches in TB classification. Among the traditional models, Logistic Regression (LR) achieved 92% accuracy, but its performance improved with Sequential Forward Selection (SFS), achieving an AUC of 0.94 and a sensitivity of 93%. Support Vector Classifier (SVC) performed well, reaching 95% accuracy, demonstrating its ability to effectively distinguish TB from non-TB cases. K-Nearest Neighbors (KNN) also showed competitive performance with 92% accuracy, though its sensitivity was slightly lower than other models.

Deep learning models exhibited higher classification accuracy and sensitivity. The Bi-LSTM model, when combined with speech spectrogram features, reached 96.33% accuracy, significantly outperforming traditional models in sensitivity at 98.13%. Capsule Networks combined with a Fully Connected Neural Network (FCNN) achieved 97% accuracy and a high F1-score of 97%, demonstrating its effectiveness in capturing complex cough audio patterns. Feature selection and hybrid models played a crucial role in improving classification performance. The feature fusion approach in Bi-LSTM + Speech Spectrogram enhanced performance compared to traditional methods, while Capsule Networks + FCNN proved effective in learning complex cough patterns. Models incorporating sequential feature selection (SFS) showed improvements in AUC and sensitivity, highlighting the impact of feature optimization.

The findings also indicate that several models exceed the World Health Organization's (WHO) recommended threshold of 90% sensitivity and 70% specificity for community-based TB triage tests. Notably, Bi-LSTM + Speech Spectrogram achieved 98.13% sensitivity, while Capsule Networks + FCNN reached 98%, making them strong candidates for real-world TB detection applications. However, despite their promising performance, several challenges remain. Variability in recording conditions and noise levels across datasets may affect model generalization. Deep learning models, while highly accurate, require significant computational resources, limiting their feasibility on low-power edge devices. Additionally, dataset imbalance, particularly in TB-positive cases, may introduce bias in model predictions

V. CONCLUSION

This study highlights the potential of machine learning models in improving early TB detection through cough analysis, offering a non-invasive and scalable approach to screening. The analysis revealed that deep learning models such as Bi-LSTM and Capsule Networks + FCNN achieve high accuracy and sensitivity, making them promising for automated TB diagnosis. However, their computational complexity poses challenges for deployment on low-power edge devices. Traditional models like Logistic Regression, while slightly less accurate, offer a balance of efficiency and feasibility for mobile implementation. The study also emphasizes the importance of feature selection, dataset quality, and preprocessing techniques in enhancing model performance. Future research should prioritize optimizing deep learning architectures for resource-limited environments, integrating hybrid models to improve efficiency, and expanding real-world testing to ensure robustness across diverse populations. By refining these AI-driven methods, TB screening can become more accessible,

particularly in low-income and high-burden regions where early diagnosis is critical for disease control.

REFERENCES

[1] World Health Organization, “Tuberculosis,” WHO Fact Sheets, Nov. 2025. [Online]. Available: https://www.who.int/news-room/fact-sheets/detail/tuberculosis.

[2] Centers for Disease Control and Prevention, “Global tuberculosis,” CDC, 2025. [Online]. Available: https://www.cdc.gov/global-hiv-tb/media/pdfs/2025/03/2025_DGHT-TB-Overview-Factsheet.pdf

[3] World Health Organization, *Global Tuberculosis Report 2025*. Geneva, Switzerland: World Health Organization, 2025. [Online]. Available: https://iris.who.int/server/api/core/bitstreams/e97dd6f4-b567-4396-8680-717bac6869a9/content

[4] M. Pahar, M. Klopper, B. Reeve, R. Warren, G. Theron, and T. Niesler, "Automatic cough classification for tuberculosis screening in a real-world environment," *Physiol. Meas.*, vol. 42, no. 10, p. 105012, Oct. 2021, https://arxiv.org/pdf/2103.13300v1

[5] M. Pahar, M. Klopper, B. Reeve, R. Warren, G. Theron, and T. Niesler, "Automatic Tuberculosis and COVID-19 cough classification using deep learning," *Computers in Biology and Medicine*, vol. 147, p. 105759, Aug. 2022 [Online]. Available: https://arxiv.org/pdf/2205.05480

[6] B. Nansamba, J. Nakatumba-Nabende, A. Katumba, and D. P. Kateete, "A systematic review on application of multimodal learning and explainable AI in tuberculosis detection," *IEEE Access*, vol. 13, pp. 1–18, 2025, https://ieeexplore.ieee.org/document/10955390

[7] A. Natarajan, P. M. Beena, A. V. Devnikar, and S. Mali, “A systematic review on tuberculosis,” Indian J. Tuberc., vol. 67, no. 3, pp. 295–311, 2020.

[8] M. K. Khan, M. N. Islam, J. Ferdous, and M. M. Alam, “An overview on epidemiology of tuberculosis,” Mymensingh Med. J., vol. 28, no. 1, pp. 259–266, Jan. 2019.

[9] B. Dong, Z. He, Y. Li, X. Xu, C. Wang, and J. Zeng, “Improved conventional and new approaches in the diagnosis of tuberculosis,” Front. Microbiol., vol. 13, p. 924410, 2022.

[10] S. Kant and M. M. Srivastava, “Towards automated tuberculosis detection using deep learning,” in Proc. IEEE Symp. Ser. Comput. Intell. (SSCI), Nov. 2018, pp. 1250–1253.

[11] M. Singh, G. V. Pujar, S. A. Kumar, M. Bhagyalalitha, H. S. Akshatha, B. Abuhaija, A. R. Alsoud, L. Abualigah, N. M. Beeraka, and A. H. Gandomi, “Evolution of machine learning in tuberculosis diagnosis: A review of deep learning-based medical applications,” Electronics, vol. 11, p. 2634, Aug. 2022. doi: 10.3390/electronics11172634.

[12] T. Rahman, A. Khandakar, M. A. Kadir, K. R. Islam, K. F. Islam, R. Mazhar, T. Hamid, et al., “Reliable tuberculosis detection using chest X-ray with deep learning, segmentation and visualization,” IEEE Access, vol. 8, pp. 191586–191601, 2020.

[13] S. J. S. Rajasekar, A. R. Balaraman, D. V. Balaraman, S. M. Ali, K. Narasimhan, N. Krishnasamy, and V. Perumal, “Detection of tuberculosis using cough audio analysis: A deep learning approach with capsule networks,” Discover Artificial Intelligence, vol. 4, no. 1, p. 77, 2024.

[14] A. K. Sethi, P. Muddaloor, P. Anvekar, J. Agarwal, A. Mohan, M. Singh, K. Gopalakrishnan, A. Yadav, A. Adhikari, D. Damani, et al., “Digital pulmonology practice with phonopulmography leveraging artificial intelligence: Future perspectives using dual microwave acoustic sensing and imaging,” Sensors, vol. 23, p. 5514, 2023. doi: 10.3390/s23125514.

[15] A. Ijaz, M. Nabeel, U. Masood, T. Mahmood, M. S. Hashmi, I. Posokhova, and A. Imran, “Towards using cough for respiratory disease diagnosis by leveraging artificial intelligence: A survey,” Informatics in Medicine Unlocked, vol. 29, p. 100832, 2022.

[16] K. S. Alqudaihi, N. Aslam, I. U. Khan, A. M. Almuhaideb, S. J. Alsunaidi, N. M. A. R. Ibrahim, and M. S. Alshahrani, “Cough sound detection and diagnosis using artificial intelligence techniques: Challenges and opportunities,” IEEE Access, vol. 9, pp. 102327–102344, 2021.

[17] L. An, K. Peng, X. Yang, P. Huang, Y. Luo, P. Feng, and B. Wei, “E-TBNet: Light deep neural network for automatic detection of tuberculosis with X-ray DR imaging,” Sensors, vol. 22, p. 821, 2022. doi: 10.3390/s22030821.

[18] Y. Cao, C. Liu, B. Liu, M. J. Brunette, N. Zhang, T. Sun, et al., “Improving tuberculosis diagnostics using deep learning and mobile health technologies among resource-poor and marginalized communities,” in Proc. 2016 IEEE First Int. Conf. Connected Health: Appl., Syst. Eng. Technol. (CHASE), Washington, DC, USA, 2016, pp. 274–281, doi: 10.1109/CHASE.2016.18.

[19] M. Nijiati, Z. Zhang, A. Abulizi, H. Miao, A. Tuluhong, S. Quan, et al., “Deep learning assistance for tuberculosis diagnosis with chest radiography in low-resource settings,” J. X-ray Sci. Technol., vol. 29, no. 5, pp. 785–796, 2021. doi: 10.3233/XST-210944.

[20] A. M. Shabut, M. Hoque Tania, K. T. Lwin, B. A. Evans, N. A. Yusof, K. J. Abu-Hassan, and M. A. Hossain, “An intelligent mobile-enabled expert system for tuberculosis disease diagnosis in real time,” Expert Syst. Appl., vol. 114, pp. 65–77, Dec. 2018. doi: 10.1016/j.eswa.2018.07.014.

[21] S. Warnat-Herresthal et al., “Swarm learning for decentralized and confidential clinical machine learning,” *Nature*, vol. 594, no. 7862, pp. 265–270, May 2021, doi: 10.1038/s41586-021-03583-3

[22] I. Dal and H. B. K., “Multidisciplinary evaluation of an AI-based pneumothorax detection model: Clinical comparison with physicians in edge and cloud environments,” *J. Multidiscip. Healthc.*, vol. 18, pp. 1–15, 2025, doi: 10.2147/JMDH.S535405

[23] P. Karpagam, M. Karthikeyan, G. Kalpana, and A. Suresh, "Edge-AI enabled secure IoT framework for real-time patient monitoring and anomaly detection in smart healthcare systems," *Scientific Reports*, vol. 16, Art. no. 29225, 2026, doi: 10.1038/s41598-026-59602-8

[24] J. Fabila, L. Garrucho, V. M. Campello, C. Martín-Isla, and K. Lekadir, "Federated learning in low-resource settings: A chest imaging study in Africa — Challenges and lessons learned," May 2025 https://www.catalyzex.com/paper/federated-learning-in-low-resource-settings-a

[25] M. S. Islam, M. R. A. Khan, A. K. Saeed, and K. M. Rabie, “A lightweight, bandwidth-aware framework for collaborative inference in medical diagnostics,” in *Proc. 2025 IEEE Int. Conf. E-health Netw., Appl. Services (Healthcom)*, Abu Dhabi, UAE, Oct. 2025, pp. 1–6,DOI:10.1109/HealthCom60686.2025.11343621

[26] H. Mahmood, M. Iftikhar, A. Wali, A. Ali, and M. Gulzar, “A novel cascaded approach for classification of tuberculosis using cough audio in real-time environment,” IEEE Access, vol. 12, pp. 191980–191993, 2024. doi: 10.1109/ACCESS.2024.3519296.

[27] W. Xu, X. Bao, X. Lou, X. Liu, Y. Chen, X. Zhao, et al., “Feature fusion method for pulmonary tuberculosis patient detection based on cough sound,” PLoS ONE, vol. 19, no. 5, p. e0302651, 2024. doi: 10.1371/journal.pone.0302651.

[28] S. J. S. Rajasekar, A. R. Balaraman, D. V. Balaraman, et al., “Detection of tuberculosis using cough audio analysis: A deep learning approach with capsule networks,” Discover Artif. Intell., vol. 4, p. 77, 2024. doi: 10.1007/s44163-024-00179-4.