

Automated Tuberculosis Detection from Chest X-Ray Images Using CNN and Transformer-Based Deep Learning Models

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Abstract. Tuberculosis (TB) is a contagious infectious disease that mainly affects the lungs and is associated with persistent cough, chest pain, fever, night sweats, and weight loss. Late diagnosis and a shortage of qualified radiologists contribute greatly to the spread of the disease and to deaths from it, especially in low- and middle-income regions. Effective and accurate diagnosis of TB is therefore necessary to improve treatment outcomes and to reduce transmission in the community. Recent advances in deep learning have substantially improved diagnostic accuracy, particularly in clinical evaluation and noninvasive methods, by introducing new techniques for the early detection of TB. This study compares convolutional neural network (CNN) and transformer models for early TB diagnosis from chest X-ray (CXR) images in the TB Chest X-ray dataset, framed as a binary classification of TB-positive and normal cases. Seven architectures were trained with a hold-out 80:20 validation split: four CNNs (VGG16, ResNet-50, EfficientNet-B0, and MobileNet-V2) and three transformers fitted with an Adaptive Patch Reduction Block (PRB), namely the Vision Transformer (ViT-PRB), the Data-efficient image Transformer (DeiT-PRB), and the Pyramid Vision Transformer (PVT-PRB). The results indicate that the transformer-based models performed better than the conventional CNNs, and PVT-PRB, which combines the PRB with global attention, achieved the highest classification accuracy of 96%.

Keywords. Tuberculosis screening; chest X-ray; deep learning; convolutional neural network; vision transformer; adaptive patch reduction

I. INTRODUCTION

Tuberculosis (TB) is a highly contagious infectious disease that predominantly affects the lungs and remains a significant public health challenge worldwide, especially in low- and middle-income nations [1]. It is caused by *Mycobacterium tuberculosis* and presents with symptoms such as persistent cough, chest pain, fever, night sweats, weight loss, and fatigue. Millions of new TB cases are reported worldwide each year, and a significant proportion of cases remain undiagnosed or are diagnosed at an advanced stage, which contributes to increased transmission and mortality [2]. Pulmonary TB causes progressive damage to lung tissue, impairing respiratory function and reducing the efficiency of oxygen exchange [3]. Structural abnormalities such as lung infiltrates, cavities, and fibrosis disrupt the normal pulmonary architecture and are key radiological indicators of TB [4]. Early-stage TB often presents with mild and non-specific symptoms that may be mistaken for common respiratory infections [5]. As the disease progresses, extensive lung damage occurs, leading to chronic respiratory complications and an increased risk of death [6].

The burden of TB continues to grow worldwide because of population growth, urbanization, and poor access to quality healthcare, which highlights the urgent need for early

and accurate diagnosis to improve treatment outcomes and reduce community transmission [7]. Conventional TB diagnostic methods include sputum smear microscopy, culture, molecular tests, and chest X-ray (CXR) imaging. CXR is commonly used in screening because it is inexpensive and widely available; however, manual interpretation depends heavily on expert radiologists and is subject to variability, fatigue, and workload. Computer-aided diagnosis (CAD) systems have been proposed to overcome these drawbacks through automated detection from medical images. Early CAD methods used handcrafted features, such as texture and shape, with classical machine learning (ML), but these were limited in learning the complex TB patterns present in chest radiographs.

In recent years, deep learning (DL) techniques have shown strong performance in medical image analysis by learning discriminative features automatically from raw images. Convolutional neural networks (CNNs) mainly detect small, localized abnormalities, whereas transformer-based systems have been proposed to capture global associations between different regions of the lung. Transformers, however, are computationally dense, which limits their feasibility in resource-constrained clinical settings. This paper presents a comparative analysis of CNN-based architectures

(VGG16, ResNet-50, EfficientNet-B0, and MobileNet-V2) and transformer-based architectures (ViT-PRB, DeiT-PRB, and PVT-PRB) enhanced with a proposed Adaptive Patch Reduction Block (PRB). The models were evaluated on the TB Chest X-ray Dataset with a hold-out 80:20 validation split to examine both diagnostic performance and computational efficiency.

II. RELATED WORK

Many studies have introduced DL-based approaches for the automated detection of TB from CXR images, and the topic has attracted considerable interest in the research community [8]. A systematic review by Yayan and colleagues [9] highlighted the role of DL models in automatic TB detection from CXRs. Hansun and colleagues [10] and Ait Nasser and Akhloufi [11] similarly highlighted the effectiveness of DL over traditional ML in medical image analysis. Among CNN-based approaches, Mirugwe and colleagues [12] compared several CNN architectures and found that VGG19 with data augmentation performed best for TB detection. Sharma and colleagues [13] used DL not only to detect TB but also to visualize infected regions in CXR images. Alshmrani and colleagues [14] developed a hybrid architecture based on VGG19 for multiclass classification of TB, COVID-19, and pneumonia. Similarly, Malik and colleagues [15] presented CDC-Net, a CNN for multiclass classification that distinguishes COVID-19, pneumothorax, pneumonia, lung cancer, and TB. Kazemzadeh and colleagues [16] showed that DL-based detection of active pulmonary TB achieved performance comparable to that of radiologists, and Chatteraj and colleagues [17] confirmed the effectiveness of DL on both digital and analog chest radiographs.

Researchers have also incorporated attention and hybrid mechanisms to address the limitations of standard architectures. Huy and Lin [18] enhanced DenseNet with a convolutional block attention module (CBAM) to extract spatial and contextual features from CXR images more accurately. On the transformer side, Lu and colleagues [19] proposed CTBViT, a Vision Transformer with an efficient block and a randomized classifier that reduces computational expense and overfitting in TB classification. Ahmed and colleagues [20] combined DL features with handcrafted features and showed that hybrid feature extraction can improve TB classification performance.

III. METHODOLOGY

This section describes the dataset, the preprocessing steps, the evaluated DL architectures, the training configuration, and the proposed Adaptive Patch Reduction mechanism. The overall workflow of the proposed TB detection pipeline is shown in Fig. 1.

A. Dataset Description

The experiments were conducted on the TB Chest X-ray Dataset, which is widely used in TB diagnosis research. The composition of the dataset is summarized in Table 1.

The dataset combines 4,200 images from Tawsifur Rahman and colleagues (3,500 normal and 700 TB-positive) with 2,417 TB-positive images from Yasser Hessein. As Table 1 shows, the final dataset contains 6,617 images,

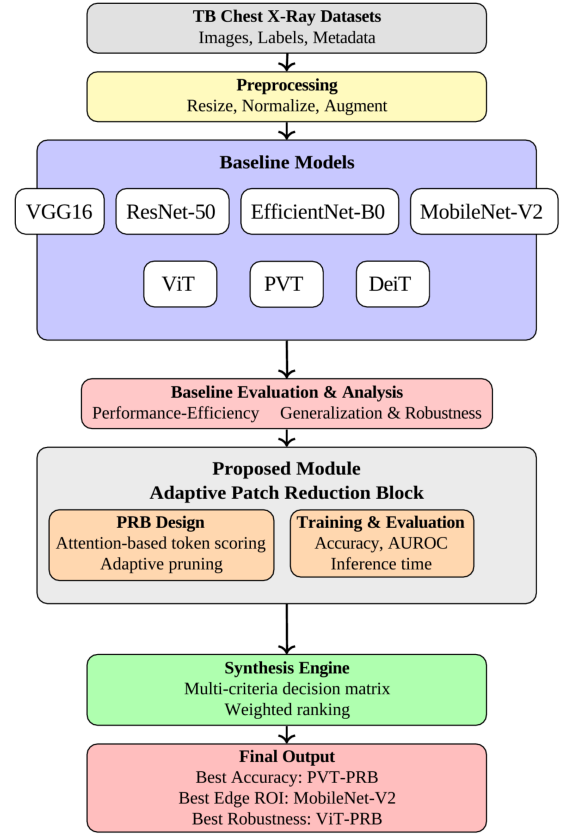


Fig. 1. Overall workflow of the proposed TB detection pipeline, including dataset preprocessing, baseline model evaluation, the Adaptive Patch Reduction Block (PRB), and final decision synthesis.

3,500 normal and 3,117 TB-positive, for binary classification. Sample CXR images of normal and TB-positive cases are shown in Fig. 2.

TABLE 1. OVERVIEW OF THE TB DATASET

Dataset	Total	TB-positive	Normal	Notes
TB Chest X-ray Dataset	6,617	3,117	3,500	Chest X-ray images

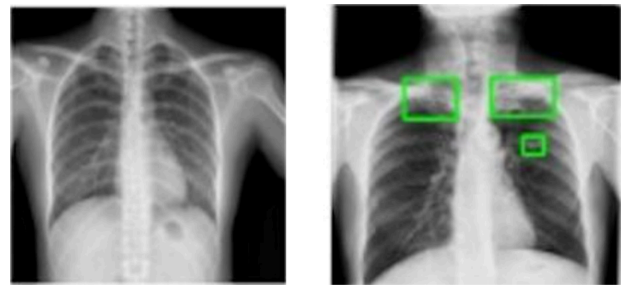


Fig. 2. Sample chest X-ray images: normal (left) and TB-positive (right).

B. Preprocessing

The CXR images were rescaled to 224×224 pixels and normalized to the $[0, 1]$ range to meet the input requirements of the CNN and transformer models. Data augmentation, including horizontal flipping, rotation of $\pm 10^\circ$, zooming, and brightness adjustment, was used to improve model generalization. The dataset was split into 80% for training and 20% for validation so that all models were assessed fairly and consistently.

C. Evaluated Models

The evaluated models provide a comparison of CNN-based and transformer-based systems for TB detection, and their key characteristics are summarized in Table 2. Lightweight CNN backbones remain important for real-time imaging applications under the computational constraints of medical deployments [21]. MobileNet and similar variants use depthwise separable convolutions, which offer an acceptable trade-off between accuracy and efficiency for mass TB screening. ViT architectures instead represent images as a sequence of visual tokens processed through self-attention layers, which models global context efficiently and has proved effective across a variety of computer vision tasks.

TABLE 2. OVERVIEW OF THE EVALUATED MODELS

Model	Type	Key feature
VGG16	CNN	Deep baseline
ResNet-50	CNN	Residual connections
EfficientNet-B0	CNN	Compound scaling
MobileNet-V2	CNN	Depthwise separable convolution
ViT-PRB	Transformer	Global self-attention with PRB
PVT-PRB	Transformer	Hierarchical attention with PRB
DeiT-PRB	Transformer	Data-efficient transformer with PRB

VGG16, pretrained on ImageNet, was fine-tuned for binary TB classification by replacing its final fully connected layer. Images were downsampled to 224×224 pixels, and the stacked convolutional layers were trained with the Adam optimizer and a binary classification loss, so that VGG16 served as a deep baseline. ResNet-50 was used to improve training stability through residual skip connections; the final classification layer was fine-tuned from pretrained weights, which allowed efficient gradient flow and richer feature learning under Adam optimization with data augmentation. EfficientNet-B0 was selected for its parameter-efficient scaling of depth, width, and resolution; its diagnostic performance was moderate despite its compact size, which illustrates the trade-off between efficiency and representational capacity. MobileNet-V2 was implemented as a lightweight CNN optimized for fast inference and low memory use. Despite its compact design, it generalized well, which makes it suitable for resource-constrained and edge-based TB screening.

The Pyramid Vision Transformer with PRB (PVT-PRB) captures hierarchical spatial representations with transformer blocks that include adaptive patch reduction. Images are converted into patch embeddings that are merged across pyramid stages, and the PRB module removes redundant tokens to improve efficiency while preserving contextual features. The Data-efficient image Transformer with PRB (DeiT-PRB) was fine-tuned from pretrained transformer weights with adaptive token pruning, combining data-efficient learning with reduced attention complexity for effective training on limited datasets. The Vision Transformer with PRB (ViT-PRB) processes CXR images as fixed-size patches and uses global self-attention to capture long-range dependencies, with the PRB removing less informative tokens. The pretrained ViT model was fine-tuned with a modified classification head and achieved good performance

with efficient computation. Together, these models cover both local-feature CNNs and global-attention transformers.

D. Training Configuration

The configuration and hyperparameters used to train the models are listed in Table 3.

TABLE 3. CONFIGURATION AND HYPERPARAMETERS USED FOR MODEL TRAINING

Feature	Configuration
Input image size	$224 \times 224 \times 1$ (grayscale)
Task type	Binary classification (TB vs. normal)
Dataset split	80% training, 20% validation
Batch size	16
Number of epochs	10 to 15
Optimizer	Adam
Learning rate	1×10^{-4} (CNN), 5×10^{-5} (transformer)
Loss function	Cross-entropy loss

E. Proposed Adaptive Patch Reduction Block (PRB)

To reduce the computational cost of dense patch processing in transformers, the PRB is introduced as an efficiency-oriented module that selectively removes uninformative patches before the attention computation. The procedure is given in Algorithm 1, and the internal workflow (patch embedding, importance scoring, thresholding, and token pruning) is shown in Fig. 3.

ALGORITHM 1. ADAPTIVE PATCH REDUCTION BLOCK (PRB)

Require: patch set $P = \{p_1, p_2, \dots, p_n\}$	
Ensure: filtered patch set P_{filtered}	
1:	for each patch $p_i \in P$ do
2:	Extract embedding vector e_i
3:	Compute importance score a_i with a lightweight scoring head
4:	end for
5:	Compute mean μ_a and standard deviation σ_a of the scores
6:	Compute dynamic threshold $T = \mu_a - \lambda\sigma_a$
7:	Identify low-importance patches $R = \{p_i \mid a_i < T\}$
8:	Prune redundant patches: $P_{\text{filtered}} = P \setminus R$
9:	Forward P_{filtered} to the transformer encoder
10:	return P_{filtered}

IV. RESULTS AND DISCUSSION

Table 4 compares the performance of the models used for TB detection; its F1 scores are computed from the listed precision and recall as $F_1 = 2PR/(P + R)$. PVT-PRB achieved the highest accuracy of all the models, 96%, with an area under the curve (AUC) of 0.991, which demonstrates the effectiveness of hierarchical attention combined with the proposed PRB. ViT-PRB and DeiT-PRB also achieved strong results, with accuracies of 94% and 93%, respectively. Among the CNN-based models, MobileNet-V2 performed best, with an accuracy of 93% and an AUC of 0.983, while EfficientNet-B0 had the lowest accuracy, 76%.

The results indicate that the transformer-based models consistently outperformed the CNN-based models for TB classification. Unlike CNNs, which focus mainly on local image features, transformer-based models use self-attention to capture relationships between different regions of a CXR.

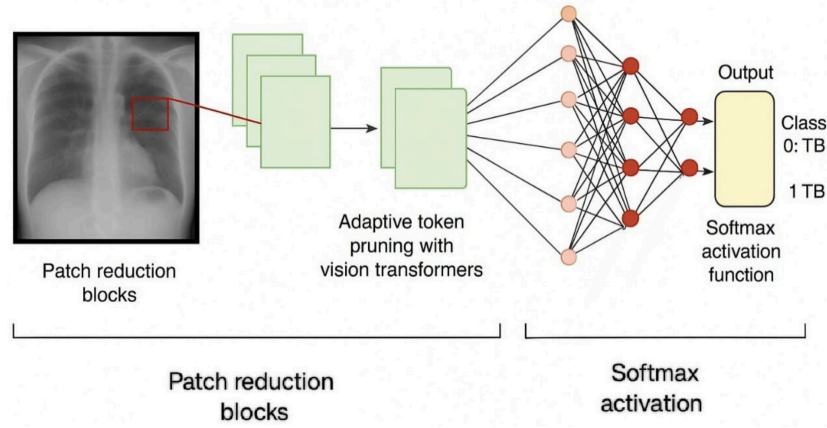


Fig. 3. The Adaptive Patch Reduction Block (PRB), showing patch embeddings, importance scoring, thresholding, and token pruning.

TABLE 4. PERFORMANCE COMPARISON OF THE EVALUATED MODELS

Model	Precision	Recall	F1	Acc. (%)	AUC	Spec. (%)
VGG16	0.88	0.82	0.85	88	0.955	94.00
ResNet-50	0.92	0.69	0.79	82	0.931	95.08
EfficientNet-B0	0.89	0.59	0.71	76	0.854	93.67
MobileNet-V2	0.93	0.85	0.89	93	0.983	99.86
ViT-PRB	0.95	0.95	0.95	94	0.984	93.70
DeiT-PRB	0.96	0.90	0.93	93	0.988	96.80
PVT-PRB	0.98	0.93	0.95	96	0.991	98.10

This helps the model understand the overall image context and identify TB-related abnormalities more reliably, which results in better performance. The proposed PRB improves transformer efficiency by eliminating less informative image patches before the attention computation, which reduces redundant token processing while preserving diagnostically relevant information. The superior performance of PVT-PRB suggests that adaptive patch reduction contributes to both effective feature representation and improved classification accuracy.

Table 5 compares the proposed model with recently published TB detection approaches. The proposed PVT-PRB achieved a classification accuracy of 96%, higher than the existing methods, which reported accuracies between 92% and 94.89%. The AUC of 0.991 further demonstrates strong discriminative capability and highlights the effectiveness of combining hierarchical transformer attention with the proposed PRB mechanism.

Although the PRB-enhanced transformer models achieved superior performance, no ablation study isolating the contribution of the individual PRB components was conducted in this work. Future research will evaluate transformer architectures with and without the PRB to better quantify the effect of adaptive token reduction on classification performance and computational efficiency.

V. CONCLUSION

This study compared CNN-based and transformer-based models for TB detection from CXR images using the TB Chest X-ray Dataset. The transformer-based models outperformed the CNN-based models: PVT-PRB performed best, with 96% accuracy, and ViT-PRB and DeiT-PRB also showed strong results.

TABLE 5. PERFORMANCE COMPARISON OF PREVIOUS TUBERCULOSIS DETECTION STUDIES AND THE PROPOSED MODEL (P, PRECISION; R, RECALL)

Ref.	Study	P (%)	R (%)	F1 (%)	Acc. (%)	AUC	Spec. (%)
[22]	Goswami 2023	94.10	94.10	94.10	94.00	0.934	91.49
[10]	Hansun 2023	94.70	93.66	94.70	93.71	0.934	96.69
[23]	Chen 2024	86.00	86.00	86.00	92.00	0.930	65.00
[12]	Mirugwe 2025	97.90	98.60	98.30	94.89	0.983	97.00
[13]	Sharma 2024	94.00	95.00	94.50	94.50	0.950	93.00
[24]	Hansun 2025	94.00	93.00	94.00	93.00	0.950	92.00
	PVT-PRB (ours)	98.00	93.00	95.00	96.00	0.991	98.10

PVT-PRB performed well because the PRB improves feature representation without significantly increasing inference complexity. The results show the benefit of PRB-assisted transformer designs for the early diagnosis of TB from CXR images.

AUTHOR CONTRIBUTIONS

All authors contributed to the conception and preparation of this work and approved the final version of the manuscript.

FUNDING

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

DECLARATION OF GENERATIVE AI USE

The authors declare that no generative artificial intelligence tools were used in the preparation of this manuscript. The authors take full responsibility for the content of the publication.

DATA AVAILABILITY

This study used the publicly available TB Chest X-ray Dataset, compiled from the Tawsifur Rahman and Yasser Hessein tuberculosis chest X-ray collections (Kaggle).

ETHICS STATEMENT

This study used publicly available, de-identified data and did not involve direct interaction with human participants or animals; ethical approval was therefore not required.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

REFERENCES

- [1] Karthikeyan Sundaram and Venkataraman Prabhu, "Contagious illness of tuberculosis and correlation with various types of cancer," *Med. Microecol.*, vol. 24, Art. no. 100123, 2025, doi: 10.1016/j.medmic.2025.100123.
- [2] Hyewon Lee, Jinsun Kim, Jieun Kim, and Young-Joon Park, "Review of the global burden of tuberculosis in 2023: Insights from the WHO Global Tuberculosis Report 2024," *Public Health Wkly. Rep.*, vol. 18, no. 11 suppl., pp. S55-S69, 2025, doi: 10.56786/PHWR.2025.18.11suppl.5.
- [3] Alex Kayongo, Brian Nyiro, Trishul Siddharthan, Bruce Kirenga, William Checkley, Moses Lutaakome Joloba, Jerrold Ellner, and Padmini Salgame, "Mechanisms of lung damage in tuberculosis: Implications for chronic obstructive pulmonary disease," *Front. Cell. Infect. Microbiol.*, vol. 13, Art. no. 1146571, 2023, doi: 10.3389/fcimb.2023.1146571.
- [4] Nickolas Yedgarian, Jacqueline Agopian, Brandon Flaig, Fouad Hajjar, Arshavir Karapetyan, Kannan Murthy, Ani Patrikian, Kirakos Tomas, Kevin Tumanyan, Mohammad J. Nasiri, Selvakumar Subbian, and Vishwanath Venketaraman, "The intricate process of calcification in granuloma formation and the complications following *M. tuberculosis* infection," *Biomolecules*, vol. 15, no. 7, Art. no. 1036, 2025, doi: 10.3390/biom15071036.
- [5] Imane Djerfi and Imane Belfethi, "Study of tuberculosis treatment," M.S. thesis, Inst. Natural and Life Sci., Abdelhafid Boussouf Univ. Center, Mila, Algeria, 2025. [Online]. Available: <https://dspace.univ-mila.dz/jspui/bitstream/123456789/4327/1/study%20of%20tuberculosis%20treatment.pdf>
- [6] Vetriselvan Subramaniyan, Shivkanya Fuloria, Mahendran Sekar, Shalini Shanmugavelu, Kamini Vijeeppallam, Usha Kumari, Kamal Narain, Dhanalekshmi Unnikrishnan Meenakshi, Mohammad Nazmul Hasan Maziz, and Neeraj Kumar Fuloria, "Introduction to lung disease," in *Targeting Epigenetics in Inflammatory Lung Diseases*. Singapore: Springer, 2023, pp. 1-16, doi: 10.1007/978-981-99-4780-5_1.
- [7] Vartika Srivastava, Ravinder Kumar, Mohmmad Younus Wani, Keven Robinson, and Aijaz Ahmad, "Role of artificial intelligence in early diagnosis and treatment of infectious diseases," *Infect. Dis.*, vol. 57, no. 1, pp. 1-26, 2025, doi: 10.1080/23744235.2024.2425712.
- [8] Evans Kotei and Ramkumar Thirunavukarasu, "A comprehensive review on advancement in deep learning techniques for automatic detection of tuberculosis from chest X-ray images," *Arch. Comput. Methods Eng.*, vol. 31, no. 1, pp. 455-474, 2024, doi: 10.1007/s11831-023-09987-w.
- [9] Josef Yayan, Karl-Josef Franke, Melanie Berger, Wolfram Windisch, and Kurt Rasche, "Early detection of tuberculosis: A systematic review," *Pneumonia*, vol. 16, Art. no. 11, 2024, doi: 10.1186/s41479-024-00133-z.
- [10] Seng Hansun, Ahmadreza Argha, Siaw-Teng Liaw, Branko G. Celler, and Guy B. Marks, "Machine and deep learning for tuberculosis detection on chest X-rays: Systematic literature review," *J. Med. Internet Res.*, vol. 25, Art. no. e43154, 2023, doi: 10.2196/43154.
- [11] Adnane Ait Nasser and Moulay A. Akhloufi, "A review of recent advances in deep learning models for chest disease detection using radiography," *Diagnostics*, vol. 13, no. 1, Art. no. 159, 2023, doi: 10.3390/diagnostics13010159.
- [12] Alex Mirugwe, Lillian Tamale, and Juwa Nyirenda, "Improving tuberculosis detection in chest X-ray images through transfer learning and deep learning: Comparative study of convolutional neural network architectures," *JMIRx Med*, vol. 6, Art. no. e66029, 2025, doi: 10.2196/66029.
- [13] Vinayak Sharma, Nillmani, Sachin Kumar Gupta, and Kaushal Kumar Shukla, "Deep learning models for tuberculosis detection and infected region visualization in chest X-ray images," *Intell. Med.*, vol. 4, no. 2, pp. 104-113, 2024, doi: 10.1016/j.imed.2023.06.001.
- [14] Goram Mufarah M. Alshmrani, Qiang Ni, Richard Jiang, Haris Pervaiz, and Nada M. Elshennawy, "A deep learning architecture for multi-class lung diseases classification using chest X-ray (CXR) images," *Alex. Eng. J.*, vol. 64, pp. 923-935, 2023, doi: 10.1016/j.aej.2022.10.053.
- [15] Hassaan Malik, Tayyaba Anees, Muizzud Din, and Ahmad Naeem, "CDC_Net: Multi-classification convolutional neural network model for detection of COVID-19, pneumothorax, pneumonia, lung cancer, and tuberculosis using chest X-rays," *Multimed. Tools Appl.*, vol. 82, no. 9, pp. 13855-13880, 2023, doi: 10.1007/s11042-022-13843-7.
- [16] Sahar Kazemzadeh, Jin Yu, Shahar Jamshy, Rory Pilgrim, Zaid Nabulsi, Christina Chen, Neeral Beladia, Charles Lau, Scott Mayer McKinney, Thad Hughes, Atilla P. Kiraly, Sreenivasa Raju Kalidindi, Monde Muyoyeta, Jameson Malemela, Ting Shih, Greg S. Corrado, Lily Peng, Katherine Chou, Po-Hsuan Cameron Chen, Yun Liu, Krish Eswaran, Daniel Tse, Shravya Shetty, and Shruthi Prabhakara, "Deep learning detection of active pulmonary tuberculosis at chest radiography matched the clinical performance of radiologists," *Radiology*, vol. 306, no. 1, pp. 124-137, 2023, doi: 10.1148/radiol.212213.
- [17] Subhankar Chatteraj, Bhargava Reddy, Manoj Tadeipalli, and Preetham Putha, "Comparing deep learning models for tuberculosis detection: A retrospective study of digital vs. analog chest radiographs," *Indian J. Tuberc.*, vol. 72, suppl. 2, pp. S43-S46, 2025, doi: 10.1016/j.ijtb.2024.05.008.
- [18] Vo Trong Quang Huy and Chih-Min Lin, "An improved DenseNet deep neural network model for tuberculosis detection using chest X-ray images," *IEEE Access*, vol. 11, pp. 42839-42849, 2023, doi: 10.1109/ACCESS.2023.3270774.
- [19] Si-Yuan Lu, Ziquan Zhu, Yao Tang, Xin Zhang, and Xingxiang Liu, "CTBViT: A novel ViT for tuberculosis classification with efficient block and randomized classifier," *Biomed. Signal Process. Control*, vol. 100, Art. no. 106981, 2025, doi: 10.1016/j.bspc.2024.106981.
- [20] Ibrahim Abdulrab Ahmed, Ebrahim Mohammed Senan, Hamzeh Salameh Ahmad Shatnawi, Ziad Mohammad Alkhraisha, and Mamoun Mohammad Ali Al-Azzam, "Multi-techniques for analyzing X-ray images for early detection and differentiation of pneumonia and tuberculosis based on hybrid features," *Diagnostics*, vol. 13, no. 4, Art. no. 814, 2023, doi: 10.3390/diagnostics13040814.
- [21] Ibomoiye Domor Mienye, Theo G. Swart, George Obaido, Matt Jordan, and Philip Ilono, "Deep convolutional neural networks in medical image analysis: A review," *Information*, vol. 16, no. 3, Art. no. 195, 2025, doi: 10.3390/info16030195.
- [22] Sanjeev K. Goswami, "Deep learning classification of tuberculosis chest X-rays," *Cureus*, vol. 15, no. 7, Art. no. e41583, 2023, doi: 10.7759/cureus.41583.
- [23] Chiu-Fan Chen, Chun-Hsiang Hsu, You-Cheng Jiang, Wen-Ren Lin, Wei-Cheng Hong, I-Yuan Chen, Min-Hsi Lin, Kuo-An Chu, Chao-Hsien Lee, David Lin Lee, and Po-Fan Chen, "A deep learning-based algorithm for pulmonary tuberculosis detection in chest radiography," *Sci. Rep.*, vol. 14, Art. no. 14917, 2024, doi: 10.1038/s41598-024-65703-z.
- [24] Seng Hansun, Ahmadreza Argha, Ivan Bakhshayeshi, Arya Wicaksana, Hamid Alinejad-Rokny, Greg J. Fox, Siaw-Teng Liaw, Branko G. Celler, and Guy B. Marks, "Diagnostic performance of artificial intelligence-based methods for tuberculosis detection: Systematic review," *J. Med. Internet Res.*, vol. 27, Art. no. e69068, 2025, doi: 10.2196/69068.