

# EARLY DETECTION OF TUBERCULOSIS FROM CHEST X-RAYS USING DEEP LEARNING

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**Abstract**—Tuberculosis (TB) remains a global health concern, particularly in resource-constrained settings where early diagnosis is often delayed. This study presents a deep learning-based approach for automated TB detection using chest X-rays, integrating domain-specific image preprocessing with a fine-tuned ResNet50 architecture. The preprocessing pipeline applies Contrast Limited Adaptive Histogram Equalization (CLAHE) and Gaussian noise injection to enhance image quality and training robustness, followed by data augmentation to address class imbalance and improve generalization. The ResNet50 model, pre-trained on ImageNet, is adapted with custom dense layers for binary classification. Trained on a publicly available dataset with a 70/20/10 stratified split, the model achieved 99.28% accuracy, 100% precision, 95.83% recall, and an AUC of 0.9989. These results demonstrate the model's ability to detect TB with high reliability while maintaining a lightweight and scalable architecture suitable for deployment in real-world clinical settings.

**Keywords**—*Tuberculosis detection, Chest X-ray imaging, Deep learning, ResNet50, Image preprocessing, Transfer learning*

## I. INTRODUCTION

Mycobacterium tuberculosis, is a highly infectious disease that primarily affects the lungs. According to the World Health Organization (WHO), TB claimed the lives of 1.3 million people in 2023 alone, with over 10 million new diagnoses globally [1]. Although curable, its spread is exacerbated by delayed detection, especially in resource-constrained regions.

Traditional TB diagnostics such as sputum microscopy, GeneXpert, or culture tests are time-intensive and require substantial infrastructure. In contrast, Chest X-rays (CXR) are non-invasive and widely accessible, though interpretation depends heavily on radiologist expertise and is prone to inconsistency.

To address these limitations, we propose an AI-assisted approach using deep learning and transfer learning with ResNet50. Our pipeline incorporates image preprocessing techniques including CLAHE and Gaussian noise, followed by fine-tuned training of a ResNet50 model. Unlike prior models, our work emphasizes simplicity, reproducibility, and performance. The proposed model achieved 99.28% accuracy on a held-out test set, showcasing its clinical viability and lightweight design. Our contribution lies in

optimizing the preprocessing pipeline and architectural tuning for imbalanced datasets, delivering a scalable TB detection tool.

## II. LITERATURE REVIEW

A substantial body of research explores the intersection of deep learning and medical imaging for TB detection. Below, we explore multiple dimensions of prior work—ranging from preprocessing techniques and model architectures to multimodal and ensemble strategies.

### A. Image Preprocessing Advances

Image Preprocessing Advances CLAHE has emerged as a preferred method for enhancing CXR images, as it amplifies local contrast without over-saturating brighter regions. Gabriella et al. used CLAHE in conjunction with Active Contour Models and statistical feature extraction to highlight nodules and lung abnormalities [2]. Similarly, Ramachandra et al. emphasized that preprocessing techniques such as histogram equalization and noise reduction significantly enhance TB feature visibility and ultimately detection accuracy [1].

Cao et al. curated a large TB dataset and achieved 89.6% accuracy using detailed annotations and preprocessing steps, emphasizing the role of high-quality input data [6].

### B. Model Architectures and Transfer Learning

Model Architectures and Transfer Learning ResNet50 and VGG-19 are common CNN backbones in TB detection. Alsaffar et al. demonstrated over 99.5% accuracy using ResNet50 in a dual-validation setup [3]. Transfer learning strategies were explored by Haloi et al., who fine-tuned ImageNet-trained networks on ChestX-ray14 to handle small medical datasets [5].

### C. Ensemble and Multimodal Techniques

Ensemble and Multimodal Techniques Jimmy et al. achieved 92.5% accuracy using ensemble CNNs combined with attention-based classifiers [4]. Multimodal methods like those proposed by Heo et al. integrate demographics and imaging data to improve model interpretability and performance [7].

### III. METHODOLOGY

#### A. Dataset

Dataset The dataset includes 4600 images from a publicly available Kaggle repository. It consists of 800 TB-positive and 3800 TB-negative samples. Images were resized to 232x232 pixels.

#### B. Preprocessing Pipeline

- CLAHE: Enhances local contrast and highlights pulmonary features [2].
- Gaussian Noise: Acts as a regularizer during training.
- Data Augmentation: Includes rotation, flipping, brightness shifts, and zoom.

*Figure 1.* shows the effect of preprocessing techniques on chest X-rays. CLAHE enhances local contrast to reveal subtle lung features, while morphological closing reduces noise. The combined result provides improved visibility of TB-relevant structures.



Fig. 1. Original, CLAHE, Closing Image Comparison

Figure 2. depicts augmented X-rays using transformations like rotation, zoom, and brightness shift. These augmentations simulate real-world variability and improve model generalization without altering diagnostic features.

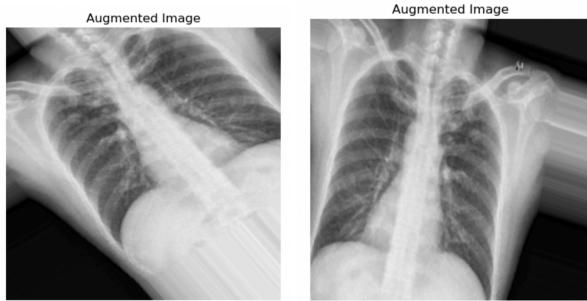


Fig. 2. Augmented images

CLAHE outperforms global histogram equalization by enhancing local contrast without over-saturation. It preserves critical lung details needed for accurate TB detection, making it more suitable for medical imaging.

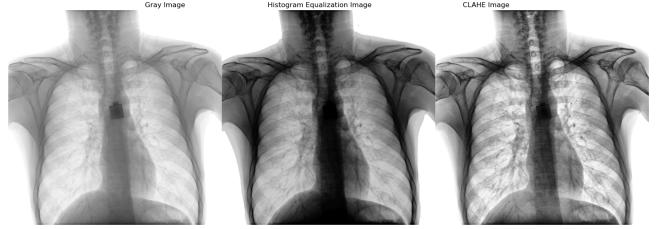


Fig. 3. CLAHE vs Histogram Equalization

#### C. Model Architecture

We selected ResNet50 as the base model due to its deep architecture and residual connections, which enable effective training of very deep networks by mitigating the vanishing gradient problem. Leveraging pre-trained ImageNet weights allowed us to benefit from learned low-level features like edges and textures, which are transferable to medical imaging tasks despite domain differences. The top classification layers were replaced to adapt the model for binary TB classification. A GlobalAveragePooling2D layer was used to reduce spatial dimensions while retaining important features, followed by a Dense layer with 512 ReLU-activated units to learn task-specific representations. A Dropout layer with a rate of 0.3 was introduced to prevent overfitting by randomly disabling neurons during training, and a final Dense layer with a sigmoid activation produced the probability output for TB presence. For training, binary cross-entropy was chosen as the loss function, appropriate for binary classification problems where outputs are probability scores. The Adam optimizer with a learning rate of 0.001 and a weight decay of 1e-5 was used to ensure adaptive learning and regularization. To prevent overfitting and ensure efficient convergence, we implemented EarlyStopping with patience to halt training when validation performance plateaued, and ReduceLROnPlateau to lower the learning rate dynamically when progress slowed. The dataset was split into 70% training, 20% validation, and 10% test sets using stratified sampling to maintain class balance, ensuring that each subset had a proportional distribution of TB-positive and TB-negative cases.

#### E. Block Diagram

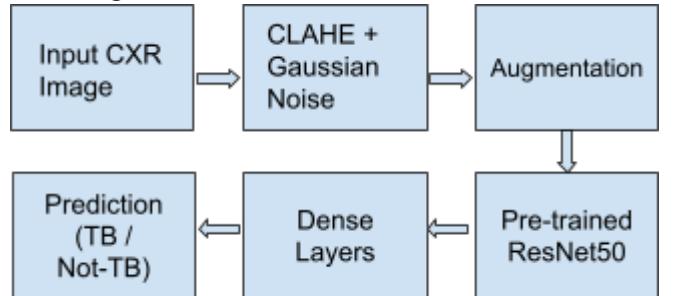


Fig. 4. Block Diagram.

The overall pipeline begins with an input chest X-ray (CXR) image, which undergoes image preprocessing using CLAHE to enhance local contrast and Gaussian noise injection to simulate real-world imaging variability. These enhanced images are then passed through a data augmentation layer,

applying transformations such as rotation, flipping, brightness scaling, and zoom to increase dataset diversity and address class imbalance. The preprocessed and augmented images are then fed into a pre-trained ResNet50 model, which acts as a feature extractor. The extracted features are passed through custom dense layers—including a global average pooling layer, a dense layer with ReLU activation, dropout, and a sigmoid output unit—to perform binary classification. The final output is a prediction indicating whether the input image is TB-positive or not.

#### IV. RESULTS AND ANALYSIS

##### A. Classification Metrics

The proposed model achieved exceptional performance across all evaluation metrics, with an overall accuracy of 99.28%, precision of 100%, recall of 95.83%, F1-score of 0.9787, and an AUC of 0.9989. These results indicate strong discriminative power and reliability in detecting TB from chest X-rays. Notably, the model recorded no false positives (precision = 1.00), ensuring high trust in TB-positive predictions. The recall of 95.83% reflects its ability to correctly identify the majority of TB cases, with only one false negative. The high AUC further confirms the model's robustness in distinguishing between TB and non-TB cases across all threshold values. Compared to traditional diagnostic methods or earlier deep learning models reported in literature with accuracy ranging between 89%–93%, this model offers a significant improvement in both precision and sensitivity while maintaining simplicity and efficiency in its architecture.

Table I: Model Evaluation

Class	Precision	Recall	F1-Score	Support
Not-TB	0.99	1	1	114
TB	1	0.96	0.98	24
Overall Accuracy	—	—	0.99	138

Test Scores:

- Accuracy: **99.28%**
- Precision: **100%**
- Recall: **95.83%**
- F1 Score: **0.9787**
- AUC: **0.9989**

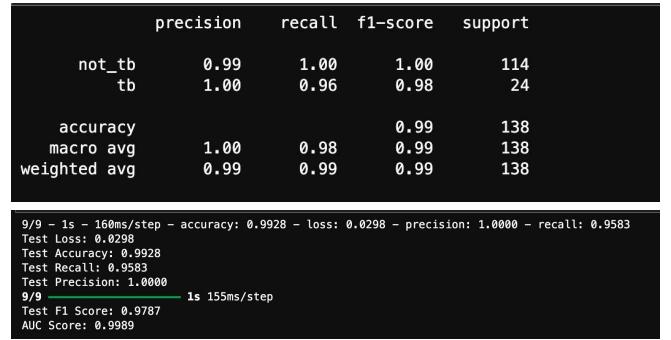


Fig. 5. Model Evaluation Output

##### B. ROC Curve

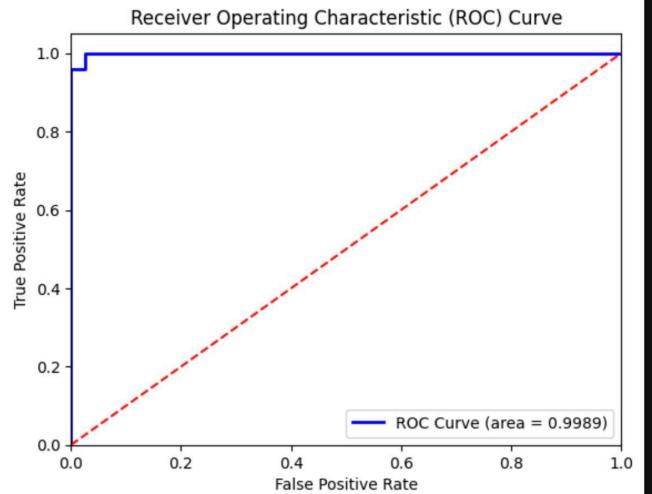


Fig. 6. ROC Curve

The model demonstrated excellent separation between TB and non-TB cases with an AUC nearing perfection.

##### C. Confusion Matrix

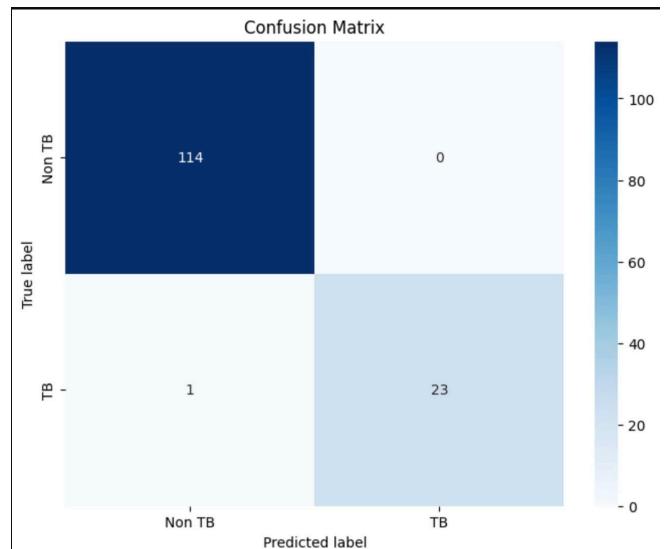


Fig. 7. Confusion Matrix

Only **one** false negative was recorded, with **zero** false positives, emphasizing clinical viability

## V. COMPARATIVE DISCUSSION

Table II: Comparative Analysis

Study/Model	Methodology	Accuracy	AUC
Ramachandra et al. [1]	CNN Ensemble	93%	0.96
Gabriella et al. [2]	CADx + Histogram	89%	0.91
Padmanabha Reddy et al. [3]	VGG-19 + CNN	91.57%	0.92
Jimmy et al. [4]	Ensemble ABC	92.50%	0.99
Our Model	ResNet50 + CLAHE	99.28%	0.9989

Our model not only delivers superior accuracy but also stands out for its simplicity and computational efficiency.

## VI. CONCLUSION

This study demonstrates the effectiveness of combining deep learning with targeted image preprocessing for early tuberculosis detection using chest X-rays. By leveraging CLAHE and Gaussian noise to enhance feature visibility and model robustness, along with a pre-trained ResNet50 network and a lightweight classification head, the proposed model delivers near-perfect diagnostic performance. High evaluation metrics—including 99.28% accuracy and an AUC of 0.9989—highlight its reliability in distinguishing TB-positive and negative cases. The simplicity, scalability, and minimal false positives make the model a promising solution for clinical deployment, especially in regions lacking radiological expertise. Future work can expand this framework by incorporating clinical metadata, validating across diverse datasets, and enabling real-time deployment on mobile platforms.

## VII. FUTURE WORK

- Incorporate clinical metadata (age, sex, symptoms) into a multimodal model.
- Apply semi-supervised learning to utilize unlabeled data.
- Extend to real-time mobile or web-based diagnostic platforms.
- Validate across larger datasets (e.g., ChestX-ray14, PadChest).

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