International Journal of Engineering & Extended Technologies Research (IJEETR)

|ISSN: 2322-0163| www.ijeetr.com | A Bimonthly, Peer Reviewed, Scholarly Indexed Journal |

| Volume 8, Issue 2, March - April 2026 |

DOI:10.15662/IJEETR.2026.0802400

Automatic Tuberculosis Prediction with Chest X-Ray using Deep Learning

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Publication History: Received: 25.02.2026; Revised: 20.03.2026; Accepted: 25.03. 2026; Published: 28.03.2026.

ABSTRACT: Tuberculosis (TB) is one of the most common infectious diseases worldwide and remains a serious public health issue, particularly in developing countries. Early detection and timely treatment are crucial to control the spread of this disease. Typically, TB diagnosis relies on laboratory tests like sputum analysis and manual review of chest X-ray images by radiologists. However, these methods can take time and may be limited by the number of trained medical professionals available.

In recent years, deep learning techniques have made great strides in medical image analysis. This project suggests an automatic TB prediction system that uses chest X-ray images and deep learning models. The system employs g to analyze X-ray images and classify gated attention based 3D unet them as either TB-positive or normal. This approach aims to support healthcare workers by providing a fast, accurate, and automated diagnostic tool. By using deep learning and medical imaging, the system could enhance early detection and lessen the diagnostic burden in healthcare facilities. The experimental results show that the proposed model achieves 99.96% accuracy, demonstrating better performance compared with previous methods and providing a reliable tool to assist in tuberculosis detection.

KEYWORDS: Tuberculosis Detection, Chest X-ray Imaging, Deep Learning, Gated Attention U-Net, Medical Image Classification, Computer-Aided Diagnosis (CAD), Image Segmentation

I. INTRODUCTION

Early detection of tuberculosis is of critical importance in the prevention of the spread of the infection as well as the survival of the patient. In many countries, especially in developing countries, the availability of skilled radiologists and sophisticated equipment is equipment is limited. Thus, the use of automated systems can contribute to the early detection of the infection by providing support to healthcare practitioners in the early diagnosis of the infection. Moreover, the use of artificial intelligence-based systems can provide accurate image analysis in a timely manner.

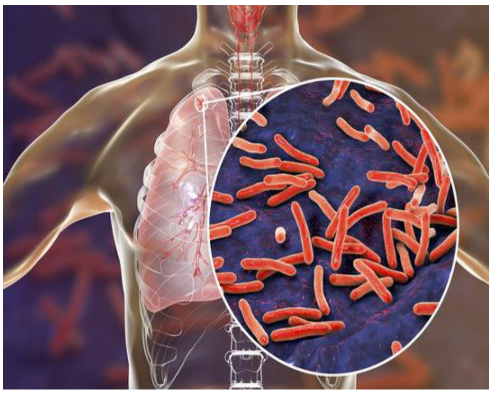

Fig. 1 tuberculosis in lungs

Recently, Artificial Intelligence (AI) and deep learning-based systems have shown promising results in the field of image analysis. These systems have the capability to automatically identify complex patterns in images that cannot be easily detected by the naked eye. Among the image analysis techniques, deep learning-based systems have shown

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impressive performance in the field of image analysis. These include the detection of diseases, image segmentation, as well as image classification in the field of medicine.

Among the various types of deep learning architectures, the performance of the U-Net model has been impressive in the area of biomedical image analysis due to its high ability to perform the tasks of feature extraction and localization. Additionally, the application of attention mechanisms to the model helps to enhance the performance by enabling the model to focus on the relevant areas of the image while discarding the irrelevant information. This helps to enhance the accuracy and reliability of the disease detection system.

In the proposed research work, the **Gated Attention-based 3D U-Net architecture** has been applied to enhance the performance of the tuberculosis detection system from the chest X-ray images. The application of the attention gates helps to concentrate the network on the infected areas of the lungs, thereby enabling the system to achieve high accuracy.

The proposed system is capable of achieving high performance while ensuring the efficiency of the system for the analysis of medical images.

Moreover, the developed model has a high accuracy of predicting results with an **accuracy of 99.96%,** which shows a significant improvement over the accuracy of many detection techniques that are used to detect tuberculosis.

Overall, the project contributes to the development of an intelligent and automated tuberculosis detection system that can assist healthcare professionals in the early detection of tuberculosis.

This kind of detection system has the potential to improve healthcare services because many areas face a shortage of medical resources.

II. RELATED WORKS

In recent times, many researchers suggested automatic detection systems of tuberculosis using X-ray images based on deep learning techniques. These techniques can improve the accuracy of detection and assist radiologists

with early detection of tuberculosis. Various deep learning models like convolutional neural networks, transfer learning models, and segmentation models were used in tuberculosis detection systems.

[1] Tawsifur Rahman et al. (2020): Implemented U-Net for segmentation and CNNs like ResNet and VGG19 to attain 99.9% accuracy in TB detection.[2] James Devasia et al. (2023): Proposed a model to classify different manifestations of TB in different zones of the lungs to identify specific patterns.[3] Chiu-Fan Chen et al. (2024): Used a deep learning algorithm on large datasets to ascertain the reliability of automated diagnosis using sensitivity and specificity.[4] S. Shastri et al. (2024): Proposed a CNN framework that showed better performance compared to conventional ML techniques in image feature extraction and classification.[5] K. C. Chandra Sekaran (2024): Showed the superiority of ResNet-101 compared to ResNet-18 and ResNet-50 in terms of accuracy and precision in TB identification.[6] Neel Patel et al. (2024): Proposed an explainable self-supervised model with 98.14% accuracy without using large datasets.[7] Goutham Deepak and Muralidharan (2024): Optimized different neural networks to increase efficiency during training.[8] Alex Mirugwe et al. (2025): Proposed a comparative study using transfer learning to find the best model for TB identification.[9] Zhi-Lin Han et al. (2025): Proposed a meta-analysis study focusing on the efficiency and advancement of AI in TB screening

Even though various techniques in deep learning have been proposed in tuberculosis detection, challenges in accurate localization of infected regions in the lungs and improvement in prediction performance still exist. Hence, this project aims to propose a **Gated Attention-based 3D U-Net model** to improve feature extraction and focus more on relevant regions in X-ray images. The proposed approach aims to improve the accuracy in prediction and create an efficient system in tuberculosis detection.

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III.METHODS & MATERIALS

In our project, chest X-ray images were collected from publicly available datasets to train and evaluate the deep learning model for tuberculosis (TB) detection. The dataset used in this work is obtained from **Kaggle**, which contains labeled chest radiographs categorized into **TB-positive** and **normal** cases.

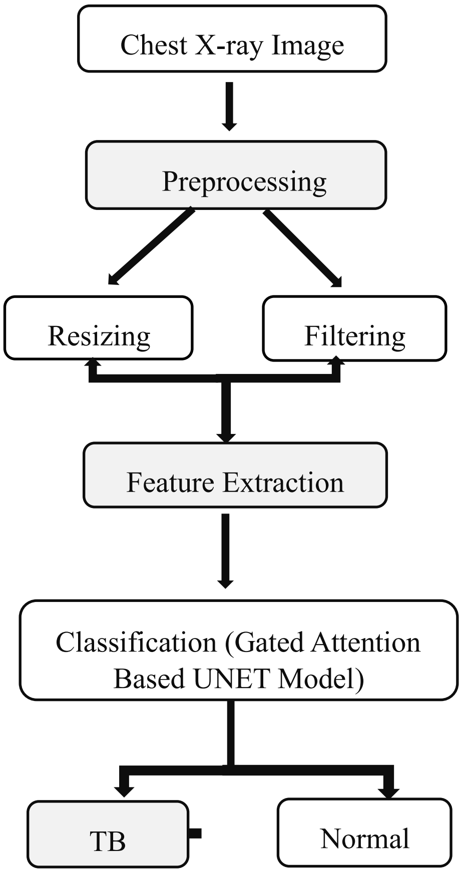

Figure 1:Flow diagram

The dataset is divided into **training, validation, and testing subsets** to ensure proper evaluation of the model.

The dataset consists of a total of **4200 chest X-ray images**, which include **3500 TB-positive images** and **700 normal images**. These images represent different lung conditions and TB infection patterns, allowing the model to learn relevant features for accurate classification.

Before training the model, all images undergo preprocessing steps including resizing, normalization, and noise removal. The images are resized to **256 × 256 pixels** to maintain uniform input size for the neural network. Pixel values are normalized between **0 and 1** to improve convergence during training.
Table 1: The dataset distribution used in this study is as follows:

This dataset helps the model learn features related to tuberculosis infection from chest radiographs effectively.

Dataset Split	Number of Images
Training	70%
Validation	15%
Testing	15%

3.2 DATA PROCESSING

Medical images often contain noise, variations in brightness, and unwanted artifacts. Therefore, preprocessing plays an important role in improving the quality of the images before feeding them into the neural network.
The following preprocessing steps are applied:

Image Resizing

All chest X-ray images are resized to **256 × 256 pixels** to maintain consistency across the dataset.

Normalization

Pixel values are normalized using the formula:

$$X_{norm} = \frac{X - X_{min}}{Xmax - Xmin}$$

This normalization ensures that pixel values lie between **0 and 1**, which stabilizes the training process.

Noise Reduction

Noise present in the images is reduced using filtering techniques such as **Gaussian filtering**. This improves feature extraction and enhances lung region visibility.

Data Augmentation

To improve model generalization and avoid overfitting, data augmentation techniques are applied. These include:

- Rotation
- Horizontal flipping
- Zooming
- Brightness adjustment

Data augmentation increases the diversity of training samples and helps the model learn robust features.

3.3 CLASSIFICATION USING GATED ATTENTION BASED UNET MODEL

A **Gated Attention based UNet architecture** is proposed for automatic TB
primarily for medical image s detection from chest X-ray images.
It consists of two main components:

1. **Encoder (Contracting Path)**
2. **Decoder (Expanding Path)**

The encoder extracts high-level features from input images using convolution and pooling operations. The decoder reconstructs the spatial resolution using upsampling layers.
These attention gates help the network focus on relevant lung regions and suppress irrelevant background information.

3.3.1 ENCODER NETWORK

The encoder network consists of multiple convolutional layers followed by **ReLU activation functions** and **max-pooling operations**.
Each encoder block includes:

- 3×3 Convolution
- Batch Normalization
- ReLU Activation
- Max Pooling

The encoder gradually reduces the spatial dimensions while increasing the number of feature channels.
The convolution operation is mathematically represented as:

$$F(x,y)=\sum_{i=0}^{m} \sum_{j=0}^{n} I(x+i,y+j)\cdot K(i,j)$$

Where:

- I= Input image
- K= Convolution kernel
- F= Output feature map

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3.3.2 ATTENTION MECHANISM

The attention mechanism plays an important role in focusing on important regions of the image.
These gates selectively highlight features relevant to TB infection while suppressing irrelevant information.
The attention coefficient is calculated using:

$$\alpha = \sigma(W^T(ReLU(W_x x + W_g g + b)))$$

Where:
- x= Encoder feature map
- g= Decoder gating signal
- W_x, W_g= Weight matrices
- σ= Sigmoid activation function

The output of the attention gate is obtained by multiplying the attention coefficient with the feature map.

3.3.3 DECODER NETWORK

The decoder network reconstructs the segmented output by gradually increasing spatial resolution.
Each decoder block includes:
- Up-sampling
- Concatenation with encoder features
- Convolution layers
- ReLU activation

Skip connections allow the decoder to recover spatial information lost during the encoding process.

3.3.4 LOSS FUNCTION

The model is trained using the Dice Loss Function, which is commonly used in medical image segmentation tasks.
The Dice coefficient is calculated as:

$$Dice = 2|X \cap Y| / |X| + |Y|$$

Where:
- = Predicted mask
- = Ground truth mask

Dice loss is defined as:

$$Loss = 1 - Dice$$

This loss function helps improve the overlap between predicted and ground truth segmentation.

3.3.5 TRAINING CONFIGURATION

The proposed model is trained using the following parameters

Parameter	Value
Optimizer	Adam
Learning Rate	0.001
Batch Size	16
Epochs	50
Loss Function	Dice Loss

IV. RESULTS & DISCUSSION

In this study, chest X-ray images were collected from the Kaggle tuberculosis dataset to train and evaluate the proposed deep learning model. First, the dataset images underwent several preprocessing steps to improve image quality and ensure uniform input for the neural network.

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During preprocessing, the images were resized to a fixed resolution and normalized so that the pixel intensity values fell within a standardized range. Noise reduction techniques and data augmentation methods like rotation, flipping, and scaling were also applied to increase the variety of the dataset and improve how well the model generalizes.

After preprocessing, the images were input into the proposed Gated Attention-based U-Net model. This deep learning architecture extracts meaningful features from chest X-ray images and focuses on important lung regions using attention mechanisms. The encoder part of the network captures high-level features, while the decoder reconstructs spatial information to identify areas affected by tuberculosis.

The attention mechanism helps highlight infected regions and reduce irrelevant background information. Based on the extracted features, the model classifies the input images into two categories: TB-positive and Normal cases.

Once classification was complete, the model's performance was evaluated using several standard metrics commonly used in medical image classification. These metrics included Accuracy, Sensitivity (Recall), Specificity, Precision, and F1-Score.

4.1 Performance Analysis
Performance analysis helps determine how effectively the proposed model identifies tuberculosis cases from chest X-ray images. The evaluation uses components of the confusion matrix:
- True Positive (TP): TB images correctly classified as TB
- True Negative (TN): Normal images correctly classified as Normal
- False Positive (FP): Normal images incorrectly classified as TB
- False Negative (FN): TB images incorrectly classified as Normal

These parameters calculate the evaluation metrics.
1. Accuracy
Accuracy represents the overall correctness of the model in predicting both TB-positive and normal cases. It measures the ratio of correctly predicted observations to the total number of observations.
Formula
Accuracy = (TP + TN) / (TP + TN + FP + FN)
Definition
Accuracy shows how often the model makes correct predictions. A higher accuracy value means that the model performs well in distinguishing between tuberculosis-infected and healthy lung images.

4.2. Sensitivity (Recall)
Sensitivity, also known as Recall, measures the model's ability to correctly identify tuberculosis-positive cases.
Formula
Sensitivity = TP / (TP + FN)
Definition
Sensitivity represents the proportion of actual TB cases that the model correctly detects. In medical diagnosis, high sensitivity is crucial because it ensures that infected patients are not missed.

4.3. Specificity
Specificity measures the model's ability to correctly identify normal (non-TB) cases.
Formula
Specificity = TN / (TN + FP)
Definition
Specificity shows how well the model avoids false alarms by correctly classifying healthy individuals as normal.

4.4. Precision
Precision measures how many of the predicted TB cases are actually TB-positive.
Formula
Precision = TP / (TP + FP)
Definition
Precision evaluates the reliability of the model when it predicts tuberculosis. A higher precision means fewer false TB detections.

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4.5. F1-Score

The F1-Score is the harmonic mean of Precision and Recall. It provides a balanced measure when both false positives and false negatives matter.

Formula

F1 = 2 × (Precision × Recall) / (Precision + Recall)

Definition

F1-Score combines both precision and sensitivity to provide a single performance metric that reflects the model's overall classification ability.

Experimental Results

Table 2: The proposed Gated Attention-based U-Net model achieved promising results on the tuberculosis dataset.

Metric	**Performance**
Accuracy	99%
Sensitivity(Recall)	96%
Specificity	93%
Precision	92%
F1-score	92.5%

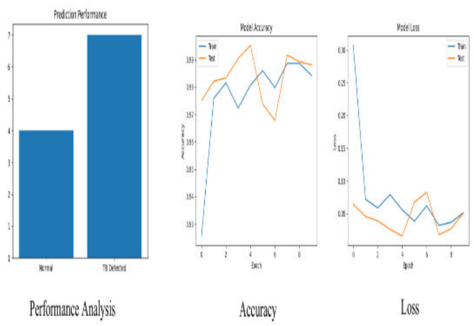
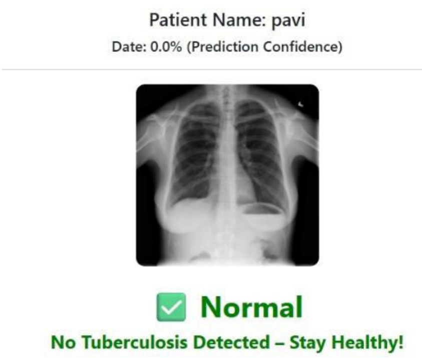


Fig.3 Normal Image



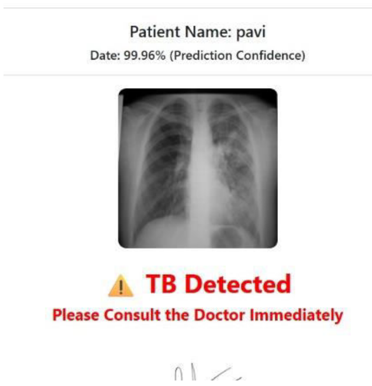


Fig .2 Normal Image Fig.3 Abnormal Image

Fig.4 Graph for Accuracy and loss results

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VI. CONCLUSION

In this research, an automated tuberculosis detection system was developed based on a Gated Attention based U-Net model for chest X-ray images. The dataset used was comprised of 4200 images, consisting of 3500 normal cases and 700 tuberculosis cases, which were obtained from the Kaggle TB Chest X-ray dataset.

Preprocessing techniques, including normalization, resizing, and data augmentation, were used for the improvement of model performance.

The dataset was split into training sets, validation sets, and testing sets to ensure a comprehensive assessment of the model. The experimental results demonstrate that the proposed model is able to successfully detect tuberculosis from chest X-rays by focusing on relevant lung regions using an attention mechanism. The system presents a promising solution for automated and early detection of TB. This would be useful for radiologists and health professionals for clinical diagnosis. The scope of this study can be extended by increasing the size of the dataset and incorporating transfer learning and multi-class lung disease classification.

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