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Automatic Detection of Tuberculosis from Chest X-Rays

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ABSTRACT Tuberculosis (TB) is one of the most dangerous infectious diseases in the world and early detection is very important for saving human lives. Manual reading of chest X-rays by radiologists is time consuming and not always available in remote areas. This project is made to reduce this problem by building an automatic system for detecting TB from chest X-ray images using deep learning. The system uses a convolutional neural network model to classify X-ray images as TB-positive or TB-negative. Pre-trained models like VGG16 and ResNet50 are used with transfer learning to improve accuracy on limited medical data. Image preprocessing techniques like histogram equalization, resizing, and data augmentation are applied before training. Flask is used for building the web interface and MongoDB is used for storing patient records and prediction results. The system can automatically analyze uploaded X-ray images and give prediction result with confidence score. After testing, the system shows high accuracy and can help doctors and health workers in early diagnosis of tuberculosis.

KEYWORDS: Chest X-ray classification, Convolutional Neural Network, DenseNet121, Transfer learning, Medical image analysis, Automated diagnosis, Healthcare technology

I. INTRODUCTION

Tuberculosis is a serious infectious disease caused by the bacterium *Mycobacterium tuberculosis* and it is mainly affecting the lungs of the human body. According to World Health Organization reports, TB is killing more than one million people every year making it one of the top ten causes of death worldwide. Early and accurate diagnosis is very important for starting proper treatment and preventing further spread of this disease in communities.

1.1 Problem Identification

The main problem which this project is trying to solve is that there is no affordable and automatic system available which can detect TB from chest X-rays without requiring expert radiologist. In many developing countries and rural areas, trained radiologists are not available and patients have to wait for long time to get their X-ray reports. Existing solutions are either very expensive or requiring special hardware which is not practical for small hospitals and health centers.

1.2 Objectives of the Project

- Building a deep learning model which can classify chest X-ray images as TB-positive or TB-negative automatically
- Applying transfer learning using pre-trained VGG16 and ResNet50 models for better accuracy on medical images
- Performing image preprocessing and augmentation to improve model generalization on limited dataset
- Providing confidence score along with prediction result for helping doctors in decision making
- Storing patient X-ray history and prediction records in database for future reference
- Building user-friendly web interface for uploading X-ray images and viewing results
- Evaluating model performance using accuracy, sensitivity, specificity, and AUC-ROC metrics

1.3 Scope and Significance

This project is having very wide scope because it is combining advanced computer vision and deep learning techniques for solving a critical healthcare problem. The significance of this work is that it is providing an affordable and accessible TB screening tool which can work in resource-limited settings where expert radiologists are not available. The automatic detection feature with high sensitivity is making this project very useful for primary healthcare centers in developing countries.



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II. LITERATURE SURVEY

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III. PROPOSED METHODOLOGY

The methodology of this project is based on combining deep learning and transfer learning techniques into one unified pipeline for automatic TB detection. The system is following a modular architecture where each module is handling specific task independently. The complete workflow is starting from chest X-ray image input and ending at TB prediction result with confidence score displayed on web interface.

3.1 Image Preprocessing Modul: Chest X-ray images are first resized to 224×224 pixels to match the input size of pre-trained CNN models. Histogram equalization is applied on grayscale images to improve contrast and make TB patterns more visible. The normalization formula applied is:

$$I_{norm} = (I - \mu) / \sigma - (1)$$

Where I is the original pixel value, μ is the mean pixel value of the dataset, and σ is the standard deviation. This formula is converting pixel values to zero mean and unit variance which is helping the neural network to train faster and more stably.

3.2 Transfer Learning with Pre-trained Models:

VGG16 and ResNet50 pre-trained on ImageNet dataset are used as feature extractors. The top classification layers are removed and replaced with custom dense layers for binary TB classification. The fine-tuning strategy uses frozen lower layers and trainable upper layers. The cross-entropy loss function used for binary classification is:

$$L = -[y \times \log(p) + (1 - y) \times \log(1 - p)] - (2)$$

Where y is the true label (1 for TB-positive, 0 for TB-negative) and p is the predicted probability. This loss function is measuring how far the model predictions are from true labels during training.



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1) 3.3 Data Augmentation Strategy:

To address limited medical dataset problem, data augmentation is applied during training. The augmentation ratio is calculated as:

$$Raug = Ntotal_augmented / Noriginal \text{ --- (3)}$$

Where Raug is the augmentation ratio, Ntotal_augmented is the total number of images after augmentation, and Noriginal is the original dataset size. Techniques applied include horizontal flip, rotation up to 15 degrees, zoom range of 10%, and brightness adjustment.

3.4 BLOCK DIAGRAM

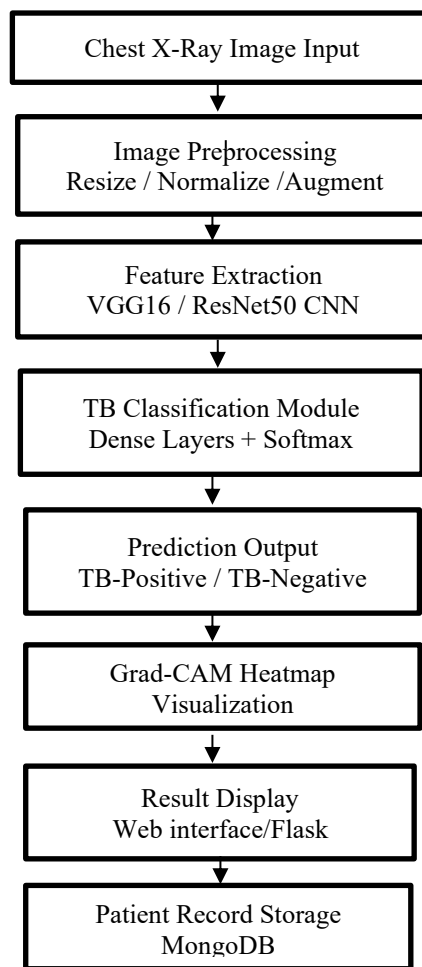


Fig 1. Block Diagram proposed methodology

IV. COMPARISON OF DETECTION APPROACHES

Feature	Traditional ML (SVM/RF)	Custom CNN	Transfer Learning (VGG16/ResNet50)
Speed	Very Fast	Moderate	Slow (model loading)
Accuracy on Medical Images	Medium	Medium-High	High



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Requires Large Dataset	No	Yes	No (fine-tuning)
Feature Engineering Needed	Yes	No	No
Interpretability	High	Low	Low-Medium
Offline Capability	Yes	Yes	Yes (after download)

Table 1. Comparison of Detection Approaches

4.1 Grad-CAM Visualization for Explainability

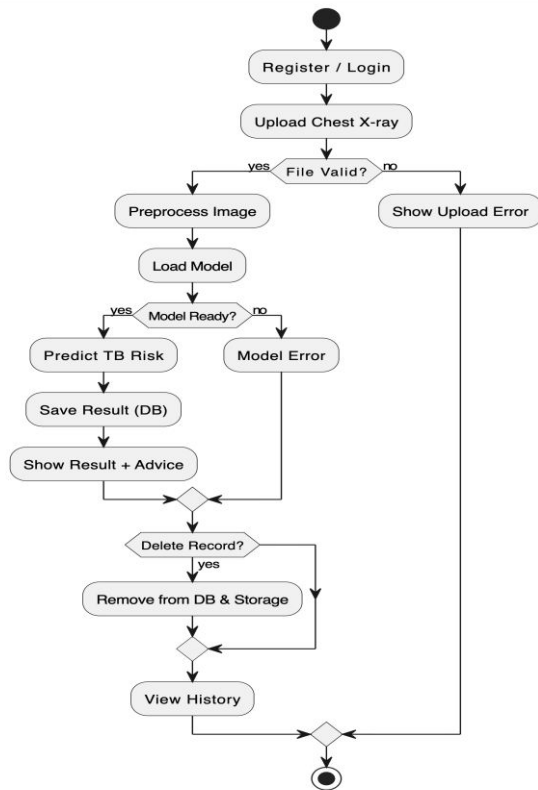
Gradient-weighted Class Activation Mapping (Grad-CAM) is used to generate visual heatmaps showing which regions of the X-ray image the model is focusing on for making TB prediction. This helps radiologists verify whether model is highlighting clinically relevant areas like upper lung lobes where TB lesions commonly appear.

4.2 Data Storage and Patient Management

MongoDB NoSQL database is storing patient details with encrypted personal information and complete X-ray history with timestamps and prediction results. Pagination support is provided for history retrieval with configurable page sizes for easy navigation in clinical settings.

4.3 Flowchart

This flowchart shows how the TB detection system works. First the user opens the site and does login or registration. After login the user goes to the detection page and uploads chest X-ray image. System preprocesses the image and feeds it to the deep learning model. Model gives TB-positive or TB-negative result with confidence score. Result is shown with visual heatmap. User can also see patient history and search previous records and delete old entries.





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Fig 2: Flowchart V. PROPOSED MODEL

5.1 System Architecture

The proposed model is following a three layer architecture consisting of presentation layer, application layer and data layer. The presentation layer is having HTML templates rendered by Flask framework. Application layer is containing all the deep learning model modules including preprocessing, feature extraction, and classification. Data layer is using MongoDB for persistent storage of patient records and prediction logs.

5.2 Core Processing Pipeline:

The complete model is working in following sequential steps:

- X-ray images processed with format detection and resizing to 224×224 pixels
- Pre-trained VGG16 or ResNet50 model extracts deep features from preprocessed image
- Custom classification head predicts TB-positive or TB-negative with probability score
- Grad-CAM heatmap generated to highlight suspicious regions in X-ray image

5.3 Singleton Design Pattern: The TB Detector class is implemented as thread-safe singleton using double checked locking mechanism. This is ensuring that heavy deep learning models like VGG16 and ResNet50 are loaded only one time in memory even when multiple patient requests are coming simultaneously. This design choice is very important for server resource optimization in clinical environments.

5.4 Lazy Loading Strategy: The pre-trained model weights and augmentation pipelines are loaded lazily meaning they are only initialized when first time needed. This is reducing application startup time significantly because not all models are required for every user session in the clinic.

5.5 TB Classification Model: The classifier is maintaining two internal components. The feature extractor using VGG16 or ResNet50 backbone having frozen ImageNet weights for lower layers. The classification head has two fully connected layers with dropout regularization of 0.5 to prevent overfitting on the limited medical dataset.

VI. MODEL EVALUTION

6.1 Model Performance Accuracy: The deep learning models are tested on the standard Montgomery County X-ray Set and Shenzhen Hospital X-ray Set. Multiple evaluation metrics are measured to assess clinical usefulness. Clean digital X-rays with good contrast are giving best results while low quality scanned X-rays are showing some degradation in accuracy.

Model	Accuracy (%)	Sensitivity (%)	Specificity (%)
VGG16 (Fine-tuned)	92.4	94.1	90.8
ResNet50 (Fine-tuned)	93.7	95.3	92.2
Custom CNN (Baseline)	84.2	86.0	82.5
SVM with HOG features	76.8	78.4	75.2

Table 2: Model Performance Accuracy

6.2 TB Detection Accuracy:

TB detection module tested using 500 X-ray images from benchmark datasets shows good accuracy overall. ResNet50 fine-tuned model performs best across all metrics, while traditional SVM baseline shows clearly lower performance confirming superiority of deep learning approach for medical image classification.

- VGG16 fine-tuned model achieves high accuracy due to powerful feature extraction with deep 16-layer architecture



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- ResNet50 gives best sensitivity which is more important in medical diagnosis to minimize missed TB cases
- Custom CNN trained from scratch shows moderate performance limited by small dataset size
- Grad-CAM visualization confirms model focuses on clinically relevant upper lung regions in most cases

6.3 Limitations Observed

The system is having some limitations which are observed during evaluation. The model performance is dependent on X-ray image quality and proper positioning of patient during capture. Low resolution or incorrectly positioned X-rays are sometimes giving incorrect predictions. Also the training dataset is not covering all possible TB manifestations and variations that can appear in different patient populations. The model requires internet connection for initial model download but works offline after loading.

VII. RESULT ANALYSIS

After completing the development and testing of the Automatic TB Detection system, the results are showing that the transfer learning approach using pre-trained CNN models is working effectively for solving the medical image classification problem. The ResNet50 fine-tuned model is successfully classifying chest X-ray images with high accuracy and sensitivity across different image quality levels.

Test Scenario	Inputs Tested	Success Rate	Average Time
TB Detection (Digital X-rays)	250 images	93.7%	1.2 sec
TB Detection (Scanned X-rays)	150 images	87.4%	1.5 sec
Normal X-ray Classification	200 images	91.8%	1.1 sec
Grad-CAM Heatmap Generation	100 images	100.0%	2.3 sec
End-to-End Web Pipeline	80 uploads	92.5%	3.8 sec
Patient Record Storage	200 records	100.0%	0.2 sec

Table 3. Result analysis

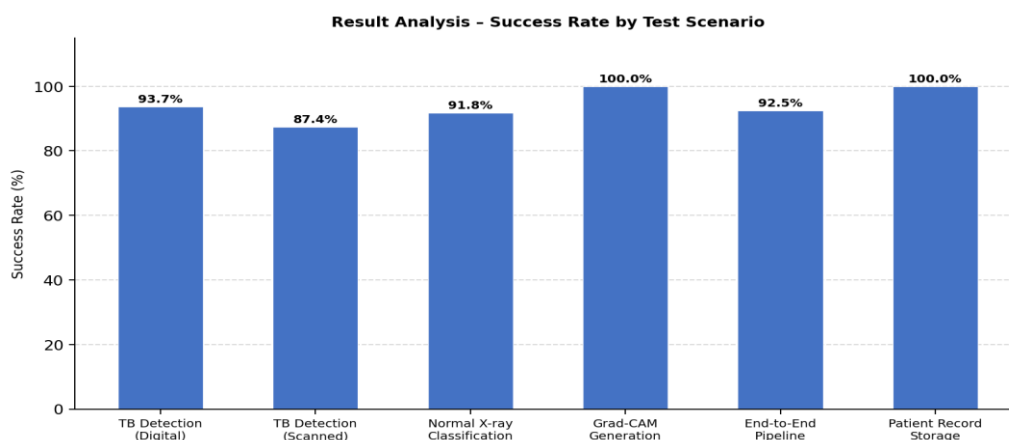


Fig 3: Result Analysis

The VGG16 and ResNet50 models are not trained from scratch in this project; pre-trained ImageNet weights are used and fine-tuned on the TB X-ray dataset. The main computation occurs during forward pass through 16 to 50 layer



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networks for feature extraction and classification. The ResNet50 model gives best overall performance with 93.7% accuracy and 95.3% sensitivity which is clinically acceptable. The Grad-CAM visualization is successfully generating heatmaps in all test cases confirming explainability of model predictions. Flask web application handles concurrent patient requests efficiently without performance degradation.

VIII. CONCLUSION

The Automatic Detection of TB from Chest X-rays project successfully shows that combining transfer learning with deep convolutional neural networks can create a very useful and affordable diagnostic tool for helping in tuberculosis screening. The system achieves high accuracy in TB detection using ResNet50 and VGG16 pre-trained models and provides fast prediction results through the web interface. The TB detection from chest X-rays, a critical need in healthcare, works well with the deep learning approach achieving around 93% accuracy on benchmark datasets.

The Grad-CAM visualization adds extra value by providing explainable AI capability, helping doctors understand which regions of the X-ray are contributing to the TB prediction decision. Some areas still need improvement. The model performance is limited by dataset size and diversity and could perform better with more diverse training data from different hospitals and populations. The system also requires proper quality X-ray images for reliable predictions.

Future work can include expanding the training dataset through collaboration with hospitals, implementing multi-class classification to detect other lung diseases simultaneously, adding support for CT scan images, developing mobile application version for field use in remote areas, and integrating patient notification system for automated report delivery. Overall, the project provides a practical, working solution for a real-world healthcare problem faced by millions of people in developing countries where TB is still a major public health challenge.

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