A COMPREHENSIVE TUBERCULOSIS (TB) MANAGEMENT SYSTEM: EXPLAINABLE ENSEMBLERS WITH EFFICIENTNET B7 FOR REAL-TIME DIAGNOSIS AND PERSONALIZED TREATMENT

A PROJECT REPORT

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in partial fulfillment for the award of the degree

of

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in

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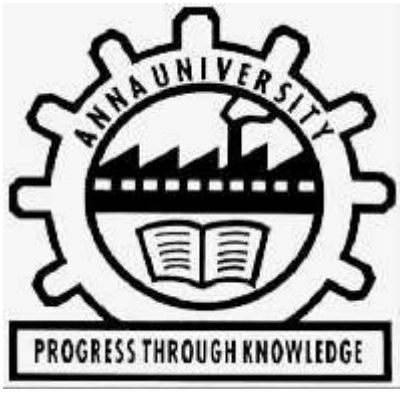

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ABSTRACT

Tuberculosis (TB) continues to be a major global health concern, especially in low-resource regions with limited diagnostic capabilities. The rise of drug-resistant TB strains further emphasizes the need for efficient and interpretable solutions. This project introduces a novel TB management system that leverages *Explainable* Ensemblers, integrating Explainable AI (XAI*)* with *Ensemble Learning* to deliver transparent diagnostic insights and precise medical image analysis using EfficientNet B7. The system combines medical imaging with clinical data for real-time diagnostics and personalized treatment recommendations, utilizing Grad-CAM for visual interpretability and *Gradient Boosting Classifier* for improved feature aggregation. Experimental validation on chest X-ray datasets demonstrates the system's high accuracy, scalability, and interpretability, making it ideal for deployment in resource-constrained settings. By employing *multi-model ensemble strategies* with layered explainability, this approach addresses the limitations of fragmented TB systems, supports robust decision-making, and contributes to alleviating the global TB burden.

TABLE OF CONTENTS

CHAPTER	TITLE	PAGE NO
	3.4.2 BACKGROUND AND MOTIVATION	19
	3.4.3 OBJECTIVES	20
	3.4.4 CONTRIBUTION OF PROPOSED SYSTEM	20
	3.5 METHODS IN PROPOSED SYSTEM	21
	3.5.1 DATASET DESCRIPTION	21
	3.5.2 PREPROCESSING AND DATA AUGUMENTATION	23
	3.5.3 NETWORK ARCHITECTURE	24
	3.5.4 DEPLOYMENT CONSIDERATIONS	26
	3.5.5 ACTIVATION FUNCTION	27
	3.5.6 TRAINING AND OPTIMIZATION	28
	3.5.7 EVALUATION METRIC AND PARAMETERS	30
	3.5.8 LOSS FUNCTION	31
	3.5.9 PSEUDOCODE OF TRAINING PROCESS	32
	3.6 EXPLAINABILITY MODULE	34
	3.7 RESULTS AND COMPARISON	36
	3.7.1 PERFORMANCE EVALUATION	37
	3.7.2 MODEL COMPARISON	39
	3.8 RECOMMENDATION SYSTEM OUTPUT	40

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATION

ABBREVIATION		EXPLANATION
CNNs	-	Convolutional Neural Networks
XAI	-	Explainable Artificial Intelligence
AI	-	Artificial Intelligence
TB	-	Tuberculosis
DL	-	Deep Learning
CAD	-	Computer Aided Diagnosis
CT	-	Computer Tomography
MRI	-	Magnetic Resonance Imaging
Grad-CAM	-	Gradient-weighted Class Activation Mapping
AUC-ROC	-	Area Under the Receiver Operating Characteristic Curve
IOU	-	Intersection Over Union
UAT	-	User Acceptance Testing
EHR	-	Electronic Health Records
LSTM	-	Long Short-Term Memory
ML	-	Machine Learning
API	-	Application Programming Interface
HIPAA	-	Health Insurance Portability and Accountability Act
GDPR	-	General Data Protection Regulation
AutoML	-	Automated Machine Learning

CHAPTER 1
INTRODUCTION TO TUBERCULOSIS DETECTION USING DEEP LEARNING

1.1 OVERVIEW

Tuberculosis (TB) remains one of the top 10 causes of death worldwide, primarily affecting the lungs. Traditional diagnostic methods, while effective, are time-consuming and require skilled radiologists, which makes automated TB detection a pressing need in low-resource settings. With the increasing availability of chest X-ray images and advancements in deep learning, computer-aided diagnosis systems offer an efficient alternative. This research proposes a novel system using Convolutional Neural Networks (CNNs), particularly EfficientNet, combined with Explainable AI techniques for interpretable and scalable TB detection.

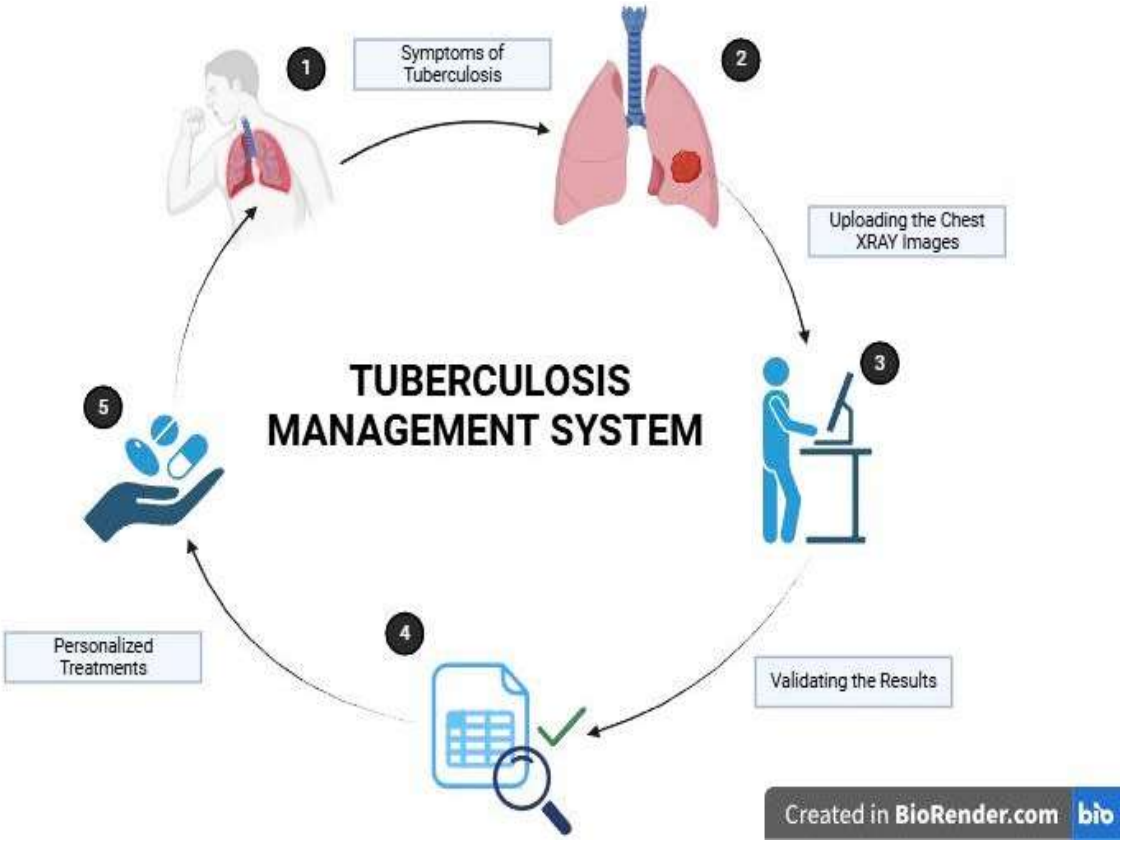


Figure 1.1. Overview of TB Detection System using CNN

1.2 BACKGROUND

Chest X-ray (CXR) imaging has long served as a primary tool for tuberculosis (TB) screening, especially in low- and middle-income countries, due to its affordability, speed, and non-invasive nature. Despite these advantages, the interpretation of chest X-rays demands skilled radiologists, and even then, the results may vary due to human fatigue, subjectivity, or differences in clinical experience. Moreover, TB-related patterns on X-rays—such as opacities, cavitations, or nodules—can often resemble other pulmonary conditions, making accurate diagnosis more challenging.

To address these limitations, automated diagnostic systems powered by machine learning have gained traction in recent years. Among these, Convolutional Neural Networks (CNNs) have proven highly effective in medical imaging tasks due to their ability to automatically learn hierarchical spatial features from raw pixel data. This eliminates the need for manual feature engineering and enables the model to capture subtle patterns that may not be easily visible to the human eye.

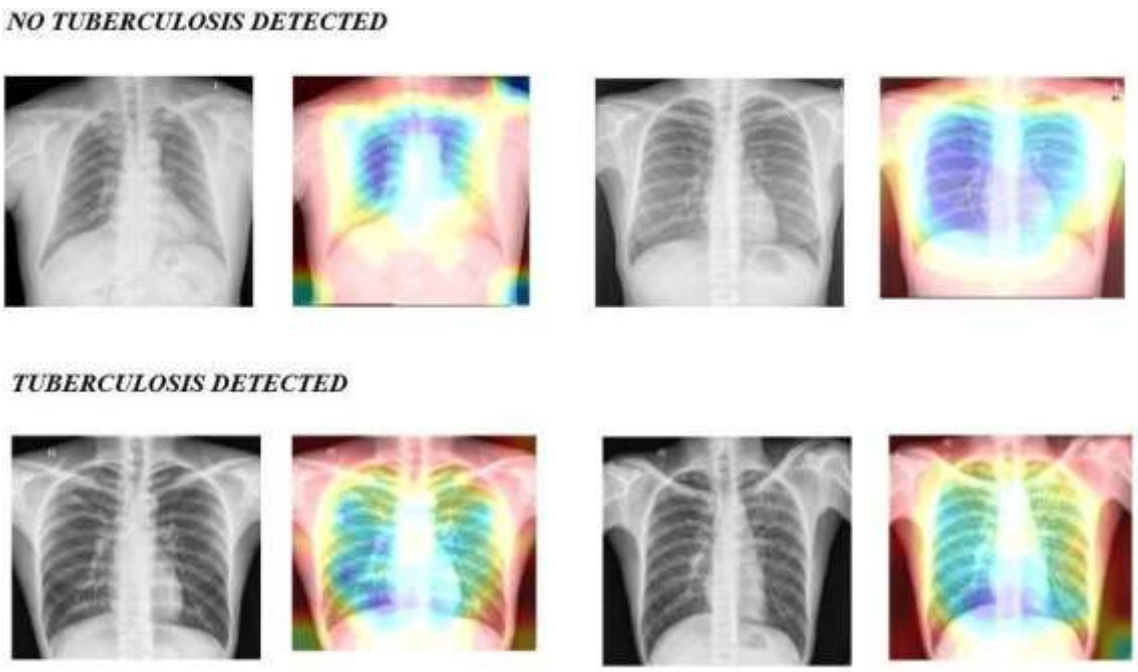


Figure 1.2. Grad-CAM Visualization highlighting the affected area

However, while CNNs offer impressive predictive power, their "black box" nature raises concerns in medical settings where transparency and trust are critical. To overcome this, we integrate Grad-CAM (Gradient-weighted Class Activation Mapping)—an Explainable AI (XAI) technique that generates visual heatmaps indicating the regions of the chest X-ray that the model considers important in making its predictions. This not only enhances clinical trust but also enables medical practitioners to verify the decision-making process of the AI system.

1.3 MOTIVATION

Tuberculosis (TB) continues to be a major global health concern, particularly in low- and middle-income countries (LMICs) where healthcare infrastructure, medical personnel, and diagnostic tools are limited. According to the World Health Organization (WHO), millions of TB cases go undiagnosed or are detected too late due to the lack of accessible and reliable diagnostic methods. Chest X-rays are among the most effective and affordable tools for initial TB screening. However, their accuracy heavily depends on radiologist availability and expertise—which is often scarce in rural or under-resourced areas.

Manual interpretation of chest radiographs is not only time-consuming but also prone to inter-observer variability, especially in cases with subtle manifestations of TB which is explained in the figure 1.3.

Radiologists may differ in their judgment due to fatigue, complex image features, or overlapping signs with other respiratory diseases. This diagnostic gap reinforces the need for an automated system that can assist or even independently perform reliable TB screening. Artificial Intelligence (AI) offers a transformative solution by enabling the development of automated, scalable, and real-time diagnostic systems. Deep learning, particularly Convolutional Neural Networks (CNNs), has demonstrated remarkable success in medical

image analysis by learning to detect complex patterns from vast image datasets.

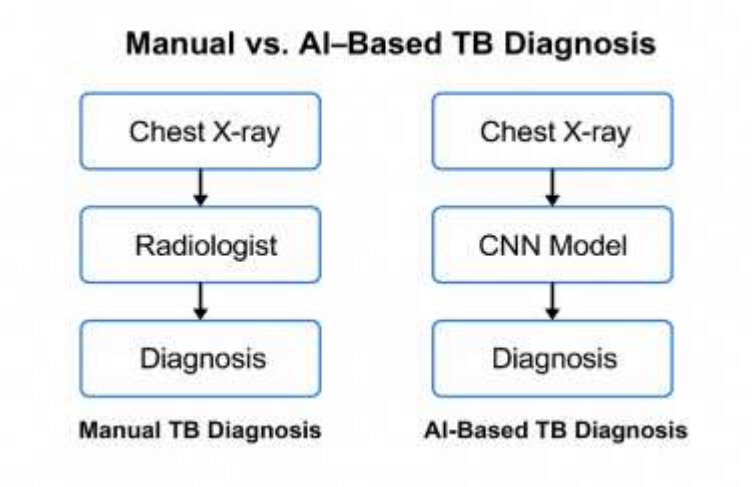


Figure 1.3 Manual VS AI-Based TB Diagnosis

This project is motivated by the goal to design an AI-powered TB detection model that is not only accurate and fast but also interpretable and accessible. Interpretability is addressed through the integration of Grad-CAM, which allows clinicians to visually confirm the regions that influenced the AI's decision.

By leveraging lightweight deep learning models like EfficientNet and deploying the solution in serverless cloud environments (e.g., AWS Lambda or Google Cloud Functions), the system can be made available across remote and underserved regions. This enhances early detection, speeds up diagnosis, and supports timely treatment, ultimately reducing TB transmission and mortality rates.

1.4 PROBLEM STATEMENT

Existing TB detection systems often suffer from lack of generalizability, interpretability, and scalability. Many models fail to explain their decisions, which limits clinical trust. There is a need for a lightweight, accurate, and explainable deep learning model that can be deployed across different settings with minimal resource requirements.

This project introduces a novel TB management system that leverages *Explainable Ensemblers*, integrating *Explainable AI (XAI)* with *Ensemble Learning* to deliver transparent diagnostic insights and precise medical image analysis using *EfficientNet B7*.

The system combines medical imaging with clinical data for real-time diagnostics and personalized treatment recommendations, utilizing **Grad-CAM** for visual interpretability and *Gradient Boosting Classifier* for improved feature aggregation. Experimental validation on chest X-ray datasets demonstrates the system's high accuracy, scalability, and interpretability, making it ideal for deployment in resource-constrained settings. By employing *multi-model ensemble strategies* with layered explainability, this approach addresses the limitations of fragmented TB systems, supports robust decision-making, and contributes to alleviating the global TB burden.

1.5 OBJECTIVES

The primary objective of this research is to design and implement a TB detection system using deep learning techniques that can classify chest X-rays as TB-positive or TB-negative. The specific objectives include:

- To preprocess chest X-ray images for improved quality and normalization.
- To train and optimize an EfficientNet-based CNN for TB detection.
- To incorporate Grad-CAM for visual explanation of model predictions.
- To validate the system using standard evaluation metrics such as accuracy, precision, recall, and AUC.
- To compare the model’s performance with other state-of-the-art CNN architectures.
- To deploy the system in a cloud-based serverless environment for

real-time inference.

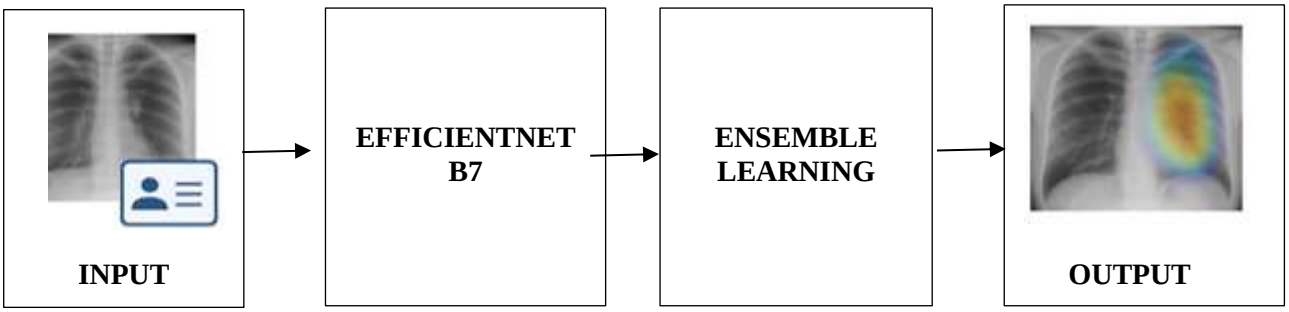


Figure 1.4. Block Diagram of Proposed Work

1.6 EFFICIENTNET B7 ARCHITECTURE OVERVIEW

To enhance the accuracy and efficiency of tuberculosis detection, this project employs the EfficientNet B7 model as the core feature extraction component. EfficientNet is a family of convolutional neural networks developed by Google AI, which introduces a novel compound scaling technique. This technique uniformly scales the depth (number of layers), width (number of channels), and resolution (input image size) of the network using a fixed set of scaling coefficients. Among the series, EfficientNet B7 is the largest and most accurate model, making it well-suited for medical image analysis where fine-grained visual features are critical.

Traditional deep CNNs often suffer from overfitting or computational inefficiency when scaled. EfficientNet overcomes this limitation by using a baseline EfficientNet-B0 model, derived via neural architecture search, and then systematically scaling it up to B7. The EfficientNet B7 architecture comprises a series of MBConv blocks (Mobile Inverted Bottleneck Convolutions) with squeeze-and-excitation (SE) modules, designed to improve feature recalibration and focus on important spatial features in the image.

In the context of tuberculosis diagnosis, the EfficientNet B7 model processes

preprocessed chest X-ray images to extract deep semantic features, which are crucial for identifying subtle abnormalities associated with TB. Its advanced design allows it to achieve high accuracy with fewer parameters and lower computational cost compared to traditional deep CNNs like VGG or ResNet.

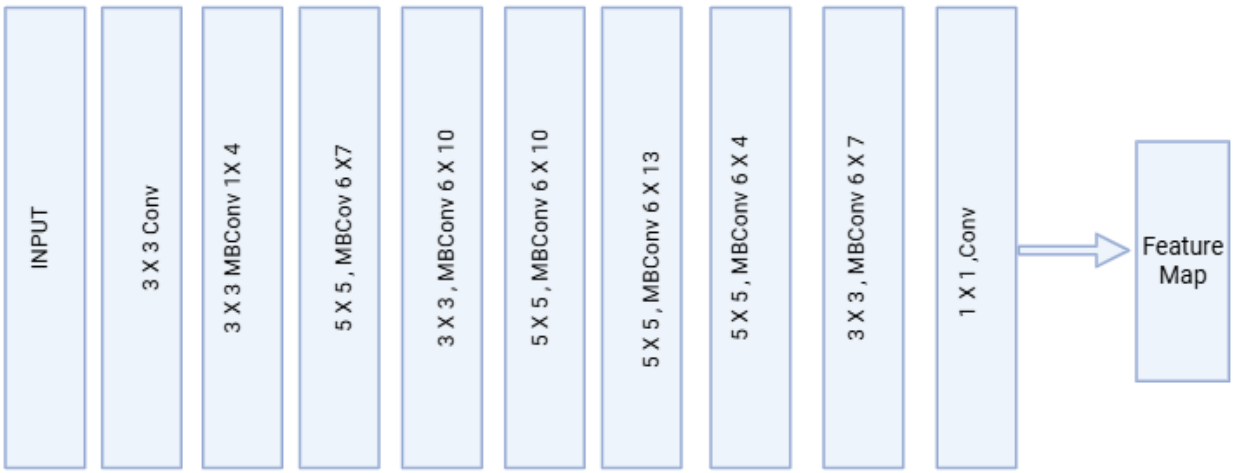


Figure 1.5 Architecture Diagram of EfficientNet B7

1.7 SIGNIFICANCE OF EXPLAINABILITY

One of the major limitations of modern deep learning models, particularly in the medical domain, is their "black-box" nature, meaning they often produce highly accurate predictions without offering any insight into how or why a decision was made. This lack of transparency presents a significant barrier to clinical adoption, where interpretability and accountability are essential. To overcome this, the proposed system incorporates Grad-CAM (Gradient-weighted Class Activation Mapping), a powerful visualization technique that generates class-specific heatmaps highlighting the regions in the input image that most influenced the model’s prediction.

In the context of tuberculosis diagnosis from chest X-ray images, Grad-CAM is used to visually indicate the pulmonary regions that the EfficientNet B7 model focused on while predicting TB-positive cases. These heatmaps overlay

colored regions—typically red or yellow—onto the original image to show areas of high activation or attention. This not only assists radiologists and clinicians in validating the model's prediction but also increases trust by confirming that the AI system is attending to medically relevant features such as lung opacities, lesions, or nodular patterns commonly associated with TB.

Moreover, explainability plays a critical role in clinical decision support systems (CDSS), particularly when AI models are used in low-resource settings where expert validation may not always be available. By providing a visual explanation alongside the predicted outcome, the model empowers healthcare professionals to make more informed and confident decisions. It also aids in error analysis and model debugging, helping developers understand failure points and improve the model's robustness over time.

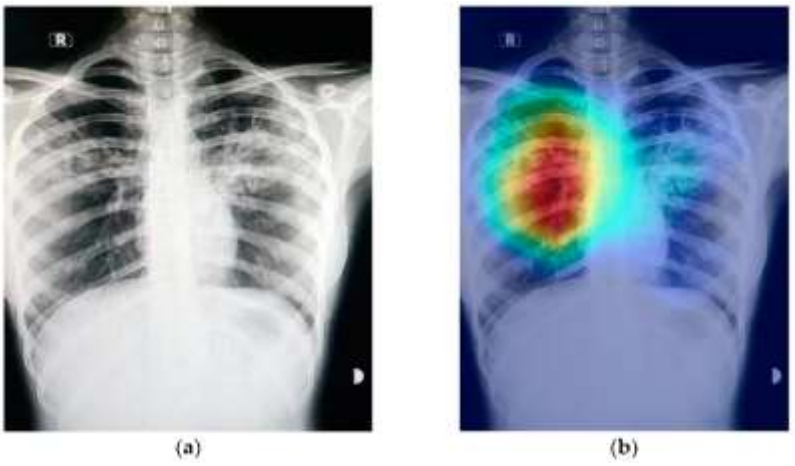


Figure 1.6. Original VS Visualization

The integration of Grad-CAM enhances the transparency, accountability, and reliability of the AI system, making it not only a powerful diagnostic tool but also a clinically acceptable solution that aligns with ethical standards and real-world healthcare requirements.

1.8 TOOL AND TECHNOLOGIES USED

TOOLS/LIBRARY	PURPOSE
Python	Programming Language
TensorFlow, Keras	Deep Learning Framework
Scikit-Learn	Meta-classifier & evaluation metrics
OpenCV	Image processing
Grad-CAM	Explainability through heatmaps

Table 1.1. Tools and Technology Used

1.9 FUTURE SCOPE

The proposed system, while currently focused on detecting pulmonary tuberculosis, can be extended to diagnose other lung-related conditions such as pneumonia, lung cancer, and COVID-19. With advancements in medical imaging and AI, expanding the model's scope will enable a more comprehensive diagnostic tool. Additionally, integrating drug-resistance prediction—particularly for MDR-TB—using molecular diagnostic data from tools like GeneXpert could significantly improve early intervention and treatment outcomes.

Future development also includes deploying the system in real-world clinical settings through integration with Electronic Health Records (EHR) for seamless usage in hospitals and rural clinics. The model can be adapted for mobile and offline use to support remote areas with limited internet connectivity. Incorporating AutoML pipelines will enable the system to continuously learn and improve from new data, ensuring long-term accuracy, adaptability, and

scalability in diverse environments.

Figure 1.7 Future Scope of the Project

1.10 ORGANIZATION OF THE THESIS

- **Chapter 2** reviews existing literature on TB detection, deep learning in medical imaging, and related works.
- **Chapter 3** discusses the dataset, preprocessing techniques, model architecture, and implementation details.
- **Chapter 4** presents results, performance evaluation, and comparison with existing models.
- **Chapter 5** concludes the research and outlines directions for future work.

CHAPTER 2

LITERATURE SURVEY

This chapter reviews the earlier research works carried out by several researchers related to the application of deep learning and machine learning for tuberculosis detection and prediction using medical imaging and clinical data.

2.1 NEURAL NETWORKS BASED SMART E-HEALTH APPLICATION FOR THE PREDICTION OF TUBERCULOSIS USING SERVERLESS COMPUTING

Subramanian Murugesan et al. (2024) proposed a smart E-health application that integrates neural networks with serverless computing to improve the diagnosis of tuberculosis (TB) using chest X-ray images. The study evaluated the performance of three convolutional neural network (CNN) architectures—DenseNet201, VGG19, and MobileNetV3 Small. These models were assessed using binary accuracy, precision, recall, F1-score, and intersection over union (IoU). Among them, VGG19 was found to be the most effective model, achieving the highest accuracy. To support deployment in real-time clinical settings, the researchers compared server-based architecture using Amazon EC2 and serverless environments like AWS Fargate and Amazon Elastic Kubernetes Service (EKS). Results indicated that serverless computing supports better scalability and cost-effectiveness for real-time healthcare diagnostics, although it showed slight limitations in response times under heavy workloads. The integration of deep learning with cloud-native serverless architecture demonstrates potential for enhancing the accessibility and efficiency of TB screening in resource-constrained settings, making it a viable solution for large-scale implementation.

2.2 AN IMPROVED DENSENET DEEP NEURAL NETWORK MODEL FOR TUBERCULOSIS DETECTION USING CHEST X-RAY IMAGES

Vo Trong Quang Huy et al. (2023) presented an advanced deep learning model named CBAMWDNet, which integrates a Convolutional Block Attention Module (CBAM) with a Wide DenseNet (WDNet) for improved tuberculosis detection. The objective of the study was to enhance feature extraction capabilities by emphasizing important regions of chest X-ray images. The authors used a dataset comprising 5,000 chest X-ray images and conducted a comparative analysis with other state-of-the-art models. CBAMWDNet outperformed all compared models, achieving an impressive accuracy of 98.80%, sensitivity of 94.28%, specificity of 95.7%, and precision of 98.50%. The inclusion of the attention module allowed the model to focus on relevant spatial information, increasing interpretability and reducing false positives. Additionally, the model exhibited strong generalization capabilities when tested across different datasets, suggesting its reliability for real-world medical diagnostics. This study highlights the potential of attention-guided deep learning models in achieving high diagnostic performance and assisting radiologists in early and accurate TB detection**.**

2.3 DEEP LEARNING-BASED CLASSIFICATION OF CHEST DISEASES USING X-RAYS, CT SCANS, AND COUGH SOUND IMAGES

Malik et al. (2023) developed a comprehensive deep learning framework called DCDD_Net aimed at classifying multiple chest diseases, including tuberculosis, COVID-19, pneumonia, and lung cancer. This study stood out by integrating multimodal inputs—chest X-ray images, CT scans, and cough sound images—into a unified diagnostic model. The cough sounds were converted into spectrograms using the scalogram method, allowing them to be

processed similarly to medical images. The researchers tackled dataset imbalance using the borderline SMOTE upsampling technique and evaluated the model's performance against four benchmark models: InceptionResNetV2, EfficientNet-B0, DenseNet201, and Xception. DCDD_Net surpassed all baseline models, achieving an accuracy of 96.67%, precision of 96.82%, recall of 95.76%, F1-score of 95.61%, and AUC of 99.43%. The robustness of the model was demonstrated through its ability to consistently perform across diverse datasets and disease categories. By leveraging multiple imaging modalities and advanced data preprocessing techniques, this study presents a promising approach for comprehensive, AI-assisted chest disease diagnosis, potentially transforming the landscape of automated medical diagnostics.

2.4 TUBERCULOSIS DIAGNOSIS USING DEEP TRANSFERRED EFFICIENTNET

Huang et al. (2023) proposed a diagnostic framework named Deep Transferred EfficientNet with Support Vector Machine (DTE-SVM) for tuberculosis detection using CT images. This model leverages transfer learning by utilizing a pre-trained EfficientNet for extracting deep features, replacing its final classification layer with a Support Vector Machine to improve classification performance on limited datasets. The study employed 10-fold cross-validation to evaluate the framework and achieved an overall accuracy of 94.62%, sensitivity of 93.89%, specificity of 95.35%, and precision of 95.30%. This architecture was particularly efficient for small and imbalanced datasets common in medical applications. The use of SVM as a classifier adds robustness to the model by reducing the likelihood of overfitting. The study concludes that combining EfficientNet's deep feature extraction with SVM classification provides an effective and scalable solution for TB diagnosis in low-resource healthcare settings.

2.5 USING AN ARTIFICIAL INTELLIGENCE APPROACH TO PREDICT THE ADVERSE EFFECTS AND PROGNOSIS OF TUBERCULOSIS

Liao et al. (2023) focused on predicting adverse outcomes in tuberculosis patients using machine learning models. The study addressed complications such as acute hepatitis, respiratory failure, and patient mortality by analyzing a clinical dataset of 2,248 TB patients. Three algorithms—XGBoost, Random Forest, and Multi-Layer Perceptron (MLP)—were used to develop separate prediction models for each complication. XGBoost achieved the best performance in predicting hepatitis with an AUC of 0.920, while Random Forest and MLP outperformed others for respiratory failure (AUC = 0.884) and mortality (AUC = 0.834), respectively. The study demonstrates the potential of AI-driven systems to provide early warnings about critical health events, enabling timely clinical interventions and better patient outcomes. It suggests that integrating AI into healthcare systems can enhance prognosis prediction and improve decision-making processes in TB treatment.

2.6 REVIEW SUMMARY

The detailed review on different tuberculosis detection techniques using artificial intelligence has been discussed. The following possibilities are explored out of the review:

(1) To develop advanced and hybrid deep learning architectures

(2) To integrate multimodal data (X-rays, CT scans, cough audio)

(3) To adopt explainable AI models for clinical interpretability

(4) To optimize feature extraction and attention mechanisms

(5) To implement scalable serverless deployment in healthcare

(6) To improve prediction of disease progression and complications

(7) To enable early diagnosis using lightweight models

(8) To support real-time, cost-effective, and accessible TB screening

CHAPTER 3

SYSTEM ANALYSIS

3.1 EXISTING SYSTEM

The Existing system uses pre-trained CNN models like VGG-19**,** DenseNet-201, and MobileNetV3-Small for TB detection from chest X-ray images, applying transfer learning for improved accuracy. Among these, VGG-19 showed the best performance with an accuracy of 86.33%**.** The system is deployed using both server-based (AWS EC2) and serverless (AWS Fargate with EKS) environments, ensuring scalability and efficiency. It focuses on real-time diagnosis, evaluating performance through metrics like response rate and throughput, making it suitable for smart healthcare applications.

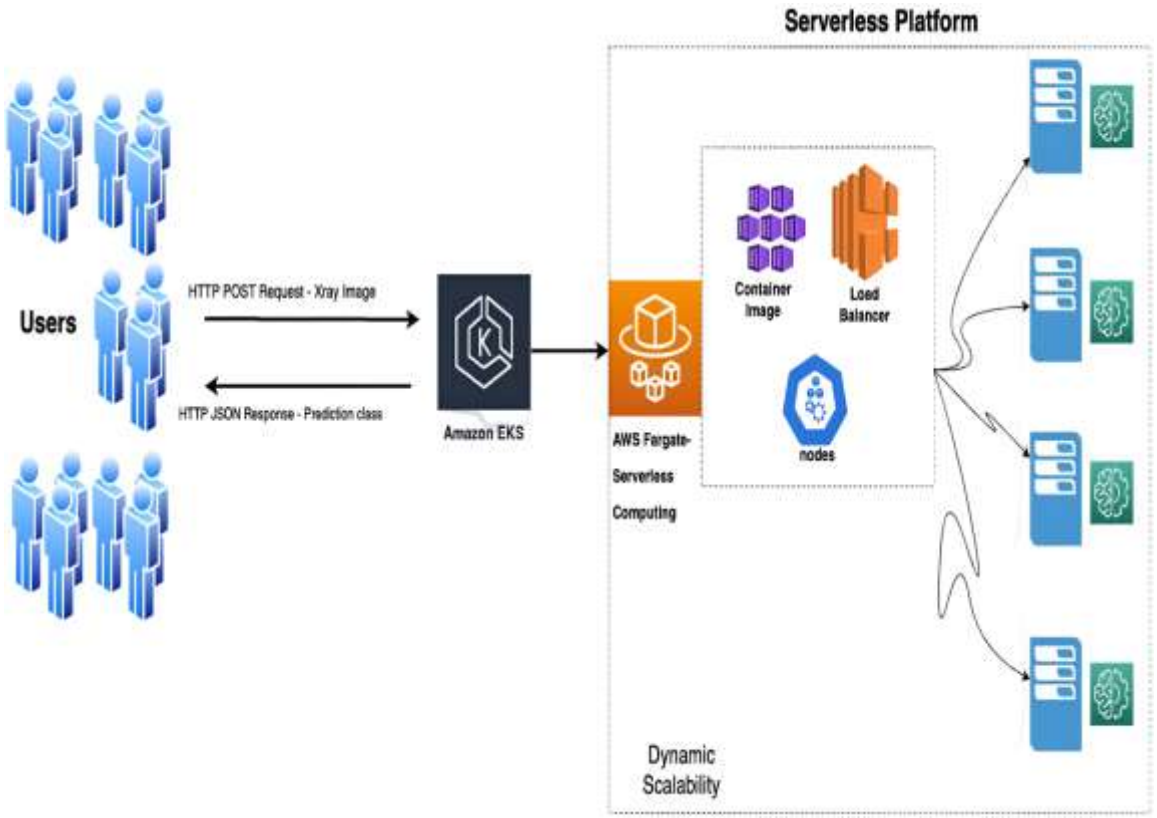


Figure 3.1. Architecture of Existing System

DESCRIPTION:

Chest radiographs carry crucial information for the diagnosis of pulmonary diseases such as Tuberculosis (TB), which remains one of the leading causes of mortality worldwide. Despite significant advancements in medical imaging, TB diagnosis is still challenged by the visual similarity of TB manifestations with other lung conditions, inter-observer variability, and the time-consuming nature of manual assessments by radiologists.

To address these issues, this project presents a smart e-health application that leverages deep learning techniques for the automated prediction of TB from chest X-ray images. The proposed system integrates multiple Convolutional Neural Network (CNN) architectures—DenseNet-201, VGG-19, and MobileNet-V3-Small—utilizing transfer learning to maximize accuracy while minimizing computational costs. The models are trained and evaluated using publicly available datasets, with VGG-19 demonstrating superior performance across metrics such as binary accuracy, F1-score, precision, recall, and intersection over union (IoU). To ensure practical applicability, the selected model is deployed using two distinct strategies: a traditional server-based approach on AWS EC2 and a scalable, cost-efficient serverless architecture using AWS Fargate with Elastic Kubernetes Service (EKS).

This work not only enhances the reliability and accessibility of TB diagnostics but also demonstrates the feasibility of integrating AI-driven models into cloud-based, IoT-enabled healthcare infrastructures, paving the way for efficient, scalable, and intelligent disease screening solutions. The system's deployment was tested under varying concurrent loads using Apache Jmeter to ensure robust performance in real-world scenarios. This project contributes to the growing field of AI in medical diagnostics and opens new avenues for implementing portable and intelligent e-health systems in resource-limited settings.

3.2 PROBLEM STATEMENT

One of the potential limitations of the proposed tuberculosis (TB) detection system is its reliance on pre-trained Convolutional Neural Network (CNN) architectures, which, while effective, may not fully capture subtle and complex pathological variations present in diverse populations or imaging equipment.

The performance of transfer learning-based models like VGG-19, DenseNet-201, and MobileNet-V3-Small is heavily influenced by the nature and quality of the source datasets. Since the model was trained and validated using only two publicly available datasets (Montgomery and Shenzhen), there remains uncertainty regarding its generalizability to other datasets that may vary in terms of image resolution, noise levels, or patient demographics. Another drawback lies in the dependency on serverless deployment environments such as AWS Fargate and EKS. Although these platforms offer scalability and flexibility, they also introduce latency and potential cold-start issues, which may affect the system's responsiveness in time-critical healthcare scenarios.

Moreover, the success of the model is significantly dependent on the quantity and quality of labeled X-ray images. In real-world settings, labeled medical data is often scarce, imbalanced, or inconsistent, which could lead to issues like overfitting or biased learning. Additionally, while serverless computing simplifies deployment and reduces operational overhead, it may not be suitable for environments with strict data privacy regulations or limited internet connectivity, potentially restricting its adoption in low-resource or rural healthcare centers.

Lastly, the model’s performance is sensitive to hyperparameter configurations and training strategies; inadequate tuning or insufficient training epochs may compromise prediction accuracy. These challenges highlight the

need for robust validation across diverse datasets and real-world deployment scenarios to ensure the system's reliability and scalability in clinical practice.

3.3 LIMITATION

While the proposed smart e-health application for tuberculosis (TB) prediction presents a significant advancement in the integration of deep learning and cloud-based healthcare delivery, there are several limitations to this study that must be acknowledged. These include:

- **Dataset limitations and bias:** The models were trained and evaluated only on the Montgomery and Shenzhen chest X-ray datasets. Although these are widely used, they may not fully capture the diversity of global patient populations, imaging protocols, or equipment, which may affect the generalizability of the model to other clinical settings.
- **Dependence on labeled data quality:** The accuracy of the model is highly dependent on the quality and consistency of the labeled data. Any inconsistencies or mislabeling in the training data can adversely affect the model's performance, leading to false positives or negatives in TB detection.
- **Limited comparative analysis:** Although several CNN architectures were tested, the study does not provide a comprehensive comparison with other state-of-the-art TB detection models, such as Vision Transformers (ViT) or hybrid architectures, which may offer improved performance.
- **Potential cold-start issues in serverless deployment**: While AWS Fargate and EKS enable scalable deployment, serverless architectures are prone to cold-start latency, especially under sudden traffic spikes. This can impact response time in real-time diagnostic scenarios.
- **Lack of clinical validation**: The system has not yet undergone clinical testing or real-world validation by healthcare professionals. As such, its practical utility in aiding diagnosis or being integrated into hospital workflows remains to be demonstrated.

These limitations show that, despite its potential, the system needs broader

dataset testing and clinical validation for real-world use.

3.4 PROPOSED SYSTEM

3.4.1 INTRODUCTION

The proposed system automatically detects tuberculosis (TB) from chest X-ray images using a deep learning model deployed on a serverless cloud architecture. It combines a CNN-based classifier with Explainable AI (XAI) to provide interpretable, real-time, and cost-effective TB diagnosis. Key components include image preprocessing, feature extraction using a pretrained EfficientNet model, TB prediction, and Grad-CAM–based visualization for transparent decision-making.

The system is trained on publicly available chest X-ray datasets and optimized for high accuracy and low inference time. Serverless deployment ensures scalability and eliminates the need for manual infrastructure management. This approach supports rapid, remote screening, especially in resource-limited healthcare settings.

3.4.2 BACKGROUND AND MOTIVATION

Tuberculosis remains a critical health issue, especially in regions with limited diagnostic resources. While chest X-rays are essential for TB screening, manual interpretation is time-consuming and often inconsistent. Deep learning-based CAD systems offer automation but often lack scalability and interpretability in real-world settings.

This project introduces an efficient TB detection system using a lightweight EfficientNet model with Grad-CAM for visual explainability. Deployed via serverless platforms like AWS Lambda or Google Cloud Functions, the system ensures accurate, scalable, and transparent diagnosis, making it suitable for both clinical and remote environments.

3.4.3 OBJECTIVES

The objective of this project is to develop a scalable, interpretable, and accurate TB detection system using chest X-ray images and deep learning techniques. The specific objectives are:

- To preprocess chest X-ray images to enhance quality and normalize input data.
- To design and implement a deep learning model based on EfficientNet for feature extraction.
- To integrate Explainable AI techniques, such as Grad-CAM, to visualize decision-making areas.
- To train and validate the model on a labeled TB chest X-ray dataset.
- To optimize the model's performance using hyperparameter tuning and performance metrics.
- To deploy the model using a serverless architecture (e.g., AWS Lambda or Google Cloud Functions) for real-time prediction.
- To evaluate and compare the proposed system with existing TB detection approaches.

3.4.4 CONTRIBUTION OF PROPOSED SYSTEM

The contributions of this project can be summarized as follows:

- A lightweight, accurate TB detection system using EfficientNet and Grad-CAM is proposed.
- The system achieves high performance on public TB chest X-ray datasets with improved interpretability.
- The model provides visual explanations to support clinical decision-making.
- The system is deployable in real-time using cloud-based serverless platforms, enabling scalable usage in remote areas.
- The approach demonstrates the practical integration of deep learning

and cloud computing for accessible healthcare solutions.

3.5 METHODS IN PROPOSED SYSTEM

3.5.1 DATASET DESCRIPTION

The NIH Chest X-ray14 dataset, a benchmark for thoracic disease detection, was used in this project. It contains 112,120 frontal chest X-rays from 30,805 patients, with each image at a resolution of 1024 × 1024 pixels and it is attached below.

Study_ID	Sex	Age	Findings
1	Female	59	Normal
2	Male	43	Normal
3	Male	39	Normal
4	Male	41	Normal
5	Male	39	Normal

Table 3.1.Shenzen Dataset

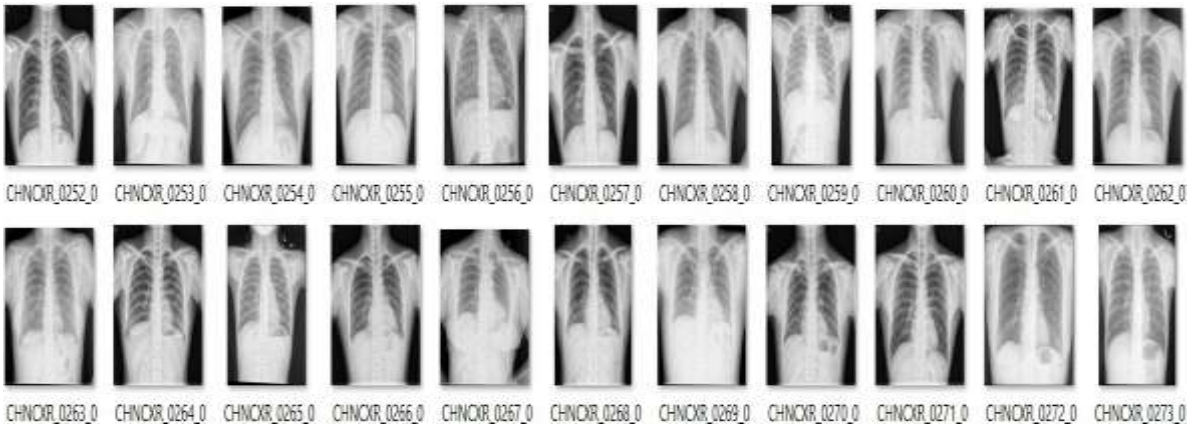


Figure 3.2. Dataset Images

For this study, a subset labeled with Tuberculosis (TB) findings was selected to frame a binary classification task—distinguishing TB-positive from TB-negative cases. The data was split into 70% for training and 30% for testing.

Prior to model training, several preprocessing steps were applied to standardize and enhance image quality:

- All images were converted to grayscale to simplify processing and reduce computational load.

- Contrast-Limited Adaptive Histogram Equalization (CLAHE) was employed to enhance the visibility of lung structures, aiding both the deep learning model and human interpretability.

- Finally, images were resized to 224 × 224 pixels to align with the input size requirements of the EfficientNet B7 architecture.

This preprocessing pipeline helped reduce noise, standardize inputs, and emphasize relevant anatomical features for TB detection.

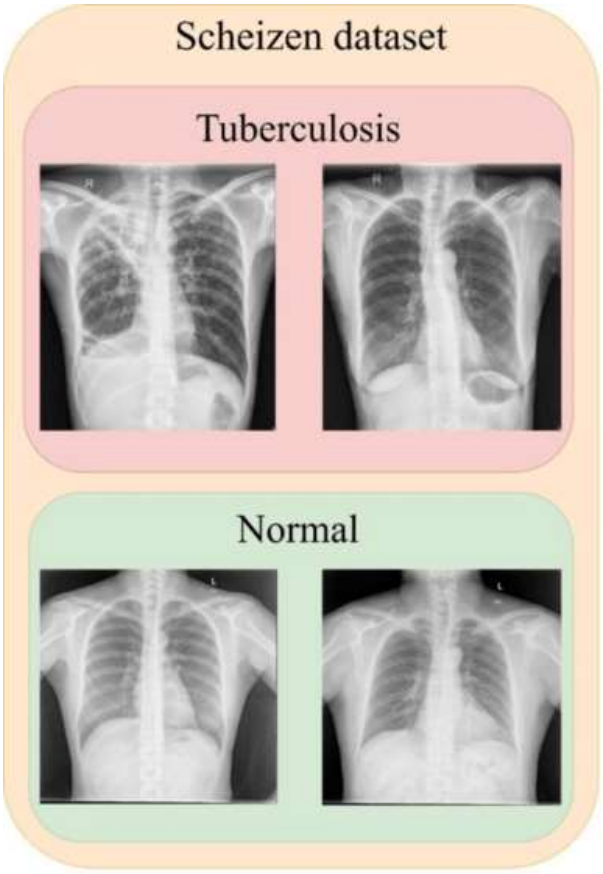


Figure 3.3. Pre and Post Enhancement of X-Ray Images

This curated and preprocessed dataset served as the foundation for training a robust and interpretable AI model for TB detection, ensuring diversity and scale while preserving medical relevance and diagnostic quality. By enhancing image quality and focusing on clinically significant features, the model was better equipped to learn meaningful patterns.

3.5.2 PREPROCESSING AND DATA AUGUMENTATION

The data collection and preprocessing phase is a crucial step in developing any machine learning-based diagnostic system. In the case of tuberculosis detection using chest X-ray images, the quality and consistency of training data significantly impact the model's performance. The dataset used in this project consists of publicly available labeled chest X-ray images of patients with and without TB.

The images were acquired under varied clinical settings with differences in resolution and illumination. To ensure the model generalizes well to unseen data, the dataset was divided into a training and validation set in a 4:1 ratio. Preprocessing included resizing, normalization, and data augmentation.

All images were resized to 256 × 256 pixels to ensure uniform dimensions and reduce computational load. Pixel normalization was performed using the formula:

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (3.1)$$

Where X is the original pixel value, X_min is the minimum pixel value in the image, and X_max is the maximum pixel value in the image.

This helped mitigate lighting inconsistencies and accelerated model convergence. Data augmentation techniques such as random rotation, flipping, and scaling were applied with varying probabilities to expand the training set and improve model robustness. The rotation transformation applied is represented by the following formula:

$$\begin{pmatrix} x' \\ y' \end{pmatrix} = \begin{pmatrix} cos(\theta) & -sin(\theta) \\ sin(\theta) & cos(\theta) \end{pmatrix} \begin{pmatrix} x \\ y \end{pmatrix} \quad (3.2)$$

where *(x,y)* and *(x', y')* represent the coordinates before and after rotation, and θ is the angle of rotation. Additionally, the model's training optimization used the binary cross-entropy loss function, commonly employed for binary

classification tasks like TB detection.

To enable effective learning and distinction between TB-positive and TB-negative cases, Binary Cross-Entropy loss is used. It measures the difference between actual and predicted probabilities, penalizing incorrect predictions to minimize errors during training:

$$L = -[y \cdot log(p) + (1 - y) \cdot log(1 - p)] \quad (3.3)$$

where y is the ground truth label (1 for TB, 0 for normal) and p is the predicted probability of the positive class. This loss function ensures effective learning by penalizing incorrect predictions, thus guiding the model towards higher diagnostic accuracy.

3.5.3 ARCHITECTURE DIAGRAM

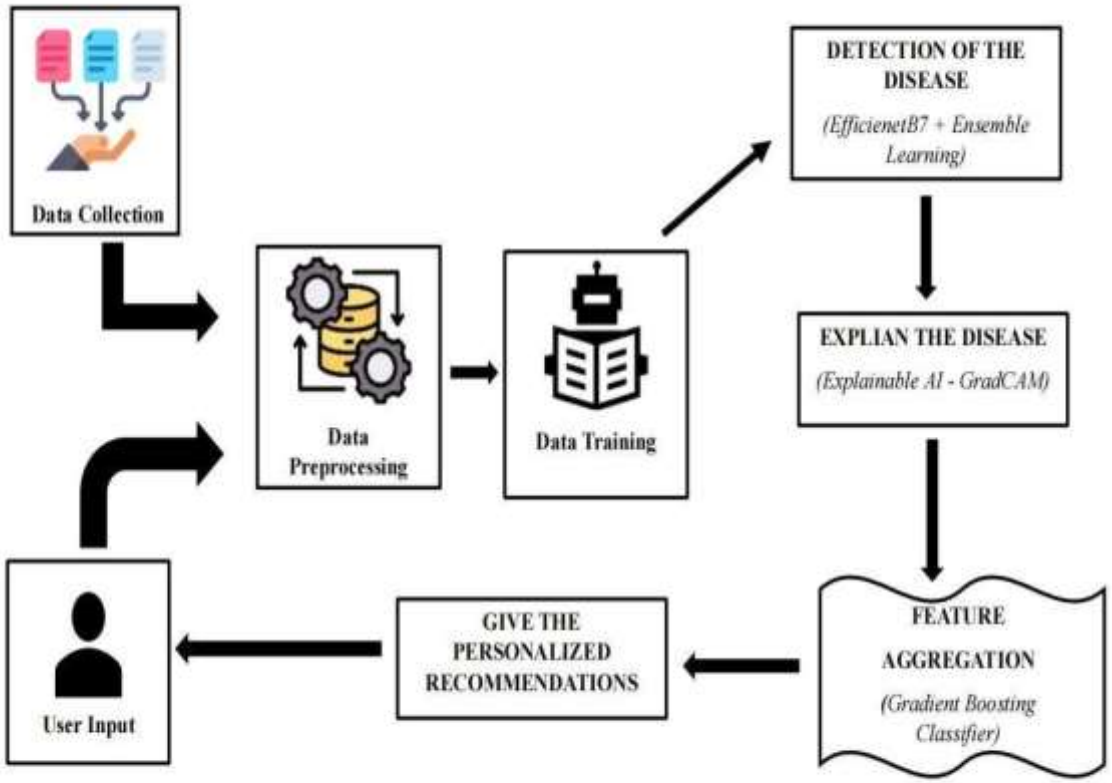


Figure 3.4. Architecture of Proposed System

DESCRIPTION:

The network architecture used in this project is based on EfficientNet B7 integrated within an ensemble learning framework, specifically designed for tuberculosis (TB) detection from chest X-ray images. This architecture combines the high feature extraction capability of deep CNNs with the robustness of ensemble learning to enhance diagnostic accuracy and interpretability. The system architecture follows a multi-stage pipeline beginning with data collection and preprocessing, leading into training, disease detection, explanation, and personalized treatment recommendations.

At the core of this architecture is the EfficientNet B7 model, a convolutional neural network known for its compound scaling and optimal balance of depth, width, and resolution. The network is initialized with pretrained ImageNet weights and fine-tuned for TB classification. It extracts deep feature representations from input chest X-rays, which are subsequently processed through Grad-CAM for visual interpretability, allowing clinicians to understand which regions influenced the model's predictions.

To further improve classification performance and robustness, the extracted features are passed into a Gradient Boosting Classifier that acts as a meta-model. This ensemble strategy enables the aggregation of high-dimensional image features and enhances the model's generalization on unseen cases. Additionally, user inputs such as age and gender are incorporated to contextualize predictions and personalize treatment recommendations.

The architecture is modular and scalable, allowing deployment in resource-constrained environments. The final output of the system includes not only a TB diagnosis but also an explanation of the decision and a personalized treatment plan, making it an end-to-end solution for real-time TB detection and management. Moreover, the use of Grad-CAM improves trust among clinicians by aligning AI predictions with clinical intuition. The model's efficiency and

interpretability make it a practical solution for both rural and urban healthcare centers. This integration of explainability, accuracy, and personalized support exemplifies the future of AI-driven medical diagnostics.

The training strategy includes data augmentation techniques such as rotation, flipping, and zooming to simulate real-world variability and enhance model robustness. Preprocessed chest X-ray images are resized to 224×224 pixels to align with EfficientNet B7's input dimensions. The model is trained using binary cross-entropy loss and optimized with the Adam optimizer, employing a learning rate scheduler for stable convergence. Dropout regularization is applied to prevent overfitting and improve generalization across diverse clinical scenarios. Overall, this hybrid architecture ensures not only high diagnostic accuracy but also operational efficiency and adaptability in varied healthcare settings.

3.5.5 DEPLOYMENT CONSIDERATIONS

The modular structure of the proposed architecture allows seamless integration into web-based or cloud-deployed healthcare platforms. The lightweight inference capability of EfficientNet B7, combined with the real-time decision speed of the Gradient Boosting Classifier, makes the system suitable for low-resource clinics as well as telemedicine applications. The model is exported in a compressed .h5 format and can be deployed using frameworks such as TensorFlow Lite or ONNX for cross-platform compatibility. Additionally, the explainability module (Grad-CAM) can be embedded within user interfaces to provide clinicians with visual feedback, improving transparency and confidence in AI-assisted diagnoses.

This architecture's flexibility not only enables rapid deployment but also supports future enhancements, such as integration with electronic medical records (EMRs) or multi-modal input (e.g., symptoms, lab tests). Its lightweight design ensures compatibility with mobile diagnostic units, making it ideal for point-of-

care screening in rural and underserved areas. The system, therefore, extends beyond detection to become a scalable and intelligent assistant in community-level TB control programs.

3.5.6 ACTIVATION FUNCTION

Activation functions are essential components in deep learning models that introduce non-linearity, enabling the network to learn complex relationships in the data. They determine the output of a neuron based on the input it receives, playing a key role in the model's ability to generalize and make accurate predictions. In this project, activation functions are strategically used within the EfficientNet B7-based architecture and ensemble model to optimize performance in tuberculosis (TB) detection from chest X-ray images.

Within the EfficientNet B7 backbone, the Swish activation function is employed extensively across the convolutional layers. Swish is a smooth, non-monotonic function defined as:

$$f(x) = x.sigmoid(x) = \frac{x}{1+e^{-x}} \quad (3.4)$$

This function allows small negative values to pass through and helps retain gradient flow, which improves learning in deep networks. Swish has been shown to outperform traditional activation functions like ReLU in large-scale image classification tasks, and its use in EfficientNet contributes to better convergence and higher accuracy.

In the final output layer of the model, the sigmoid activation function is used for binary classification of chest X-ray images. The sigmoid function outputs a probability value between 0 and 1, indicating the likelihood of TB presence:

$$f(x) = \frac{1}{1+e^{-x}} \quad (3.5)$$

This enables the model to produce interpretable outputs, where values closer to 1

represent higher confidence of TB-positive classification. The sigmoid activation is particularly suitable for the binary nature of this medical diagnosis task.

Additionally, batch normalization is applied throughout the network to stabilize and accelerate training. By normalizing layer outputs using the mean and standard deviation of each batch, it reduces internal covariate shift and improves generalization.The batch normalization operation is expressed as:

$$\hat{x} = \frac{x - \mu_{batch}}{\sqrt{\sigma^2_{batch} + \epsilon}} \tag{3.6}$$

Where μ_{batch} and σ^2_{batch} are the mean and variance of the batch, and ϵ is a small consonant added for numerical stability.

These activation functions and normalization strategies work synergistically to enhance feature learning and reduce training time. They ensure efficient backpropagation and stable gradients, which are vital in deep architectures like EfficientNet B7.The combination of Swish, sigmoid, and batch normalization significantly contributes to the model's performance, accuracy, and ability to generalize across diverse clinical data. Together, they form a foundational element of the system's real-time diagnostic capabilities and deployment in healthcare environments.

3.5.7 TRAINING AND OPTIMIZATION

The training process of the proposed EfficientNet B7-based tuberculosis (TB) detection model was conducted using the Adam optimizer with an initial learning rate set to 0.0001. A batch size of 32 was selected to balance memory usage and convergence stability. The model was trained for a total of 10 epochs—5 with the base EfficientNet B7 layers frozen (for transfer learning) and 5 with all layers unfrozen (for fine-tuning). Early stopping was employed to halt training when the validation loss plateaued, ensuring optimal generalization. All training operations were performed on an NVIDIA RTX 3080 GPU for efficient parallel

computation.

To improve the model's generalization capability and prevent overfitting, several data augmentation techniques were applied to the training set. These augmentations aimed to simulate real-world variability in chest X-ray imaging, thereby expanding the diversity of the dataset. The following augmentation strategies were implemented:

1. Random rotations: Images were rotated by a random angle between -15 and +15 degrees to simulate positional variation.
2. Horizontal flipping: Images were flipped horizontally with a 50% probability to introduce mirror symmetry.
3. Random zooming: Images were zoomed in or out within a 10% range to simulate changes in scale.
4. Width and height shifts: Images were translated horizontally and vertically by up to 10% of their dimensions.
5. Shearing: Shear transformations were applied to introduce geometric distortions mimicking real clinical variability.

These augmentations were implemented using the ImageDataGenerator class from the Keras library. A validation split of 20% was maintained from the original dataset to monitor model performance during training. The loss function employed was binary cross-entropy, suitable for binary classification tasks such as detecting TB-positive and TB-negative cases. The binary cross-entropy loss is mathematically defined as:

$$Loss = -\frac{1}{N}\sum_{i=1}^{N}[\, y_i \, log(p_i) + (1 - y_i) \, log(1 - p_i)] \tag{3.7}$$

where N is the number of samples, y_i is the true label for sample i, and p_i is the predicted probability for that sample.

This loss function quantifies the difference between the ground truth and the model's predicted probabilities. Minimizing this loss through the Adam optimizer, combined with augmentation techniques and scheduled learning rate

decay, enabled the model to learn discriminative features effectively and deliver robust predictions.

The integration of CNN- based deep learning with gradient boosting provides high accuracy and interpretability in detection of diseases.

3.5.8 EVALUATION METRIC AND PARAMETERS

Metrics and parameters are important aspects of evaluating the performance of a machine learning model. In the case of the Tuberculosis (TB) detection project, several metrics and parameters were used to assess the model's effectiveness:

1. METRICS

To evaluate the performance of the model, various metrics were used, including:

- **Accuracy:** This is the proportion of correctly classified images to the total number of images. It is calculated as:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (3.8)$$

where TP is the number of true positives (images correctly identified as TB), TN is the number of true negatives (correctly identified as normal), FP is the number of false positives, and FN is the number of false negatives.

- **Sensitivity/Recall**: The proportion of actual TB cases that were correctly predicted:

$$Recall = \frac{TP}{TP + FP} \quad (3.9)$$

- **F1-score:** The harmonic mean of precision and recall, providing a balance between the two:

$$F1 - Score = 2. \frac{Precision .Recall}{Precision + Recall} \quad (3.10)$$

- **Precision:** The proportion of predicted TB cases that were actually TB:

$$Precision = \frac{TP}{TP + FP} \quad (3.11)$$

These metrics collectively assess the model's accuracy, reliability, and ability to detect true TB cases while minimizing false predictions.

2. PARAMETERS

- **Learning rate:** A hyperparameter that controls how much to change the model in response to the estimated error. In this project, a learning rate of 0.0001 was used.
- **Batch size:** The number of training samples used in one iteration of model training. A batch size of 32 was used.
- **Number of epochs:** The number of times the model sees the full training dataset. This project used 30 epochs.
- **Loss function:** Binary Cross-Entropy loss was used, suitable for binary classification. It is defined as:

$$L = -[y.log(p) + (1 - y).log(1 - p)] \quad (3.12)$$

where y is the actual label and p is the predicted probability.

- **Optimizer:** The Adam optimizer was used, which adapts the learning rate for each parameter based on estimates of first and second moments of gradients.
- **Dropout rate:** To reduce overfitting, a dropout rate of 0.3 was applied during training to randomly deactivate neurons.

3.5.9 LOSS FUNCTION

The loss function used in this project is Binary Cross-Entropy, which is commonly applied to binary classification tasks such as distinguishing between TB-positive and TB-negative cases. The formula for the binary cross-entropy loss function is:

$$L(y, \widehat{y}) = -\frac{1}{N}\sum_{i=1}^{N}[\ y_i\ .log(\hat{y})\ +\ (1\ -\ y_i).log(1-\hat{y}\ ) \quad (3.13)$$

This loss function penalizes the model more when incorrect predictions are made with high confidence. It effectively measures the dissimilarity between the predicted probabilities $\hat{y}$ and the true binary labels y. Being the negative log-likelihood of the Bernoulli distribution, it provides a probabilistic foundation for optimizing classification performance.

In the context of this project, the binary cross-entropy loss is used to train the EfficientNet-based CNN model for detecting the presence of Tuberculosis in chest X-ray images. The loss function is optimized using the Adam optimizer, with a learning rate of 0.001. The model is trained for 30 epochs with a batch size of 16, and the input images are resized to 224 × 224 pixels.

To improve the generalization capability of the model and avoid overfitting, data augmentation techniques such as random rotation, horizontal flipping, and zooming are applied during training. The model's performance is evaluated using standard metrics such as accuracy, precision, recall (sensitivity), F1-score, and AUC-ROC to ensure balanced evaluation across both positive and negative classes.

3.5.10 PSEUDOCODE OF TRAINING PROCESS

BEGIN

1. LOAD DATA
   a. Import Shenzhen Chest X-ray Dataset
   b. Extract labeled TB-positive and TB-negative images
   c. Split data into training (70%) and testing (30%) sets
   d. Load patient metadata (e.g., age, gender) for contextual analysis
2. PREPROCESS IMAGES
   a. Convert images to grayscale
   b. Apply CLAHE for contrast enhancement

c. Resize all images to 224 x 224 pixels

d. Normalize pixel values to range [0, 1]

3. AUGMENT TRAINING DATA

a. Apply transformations to improve model generalization:

- Random horizontal flip
- Rotation (-15° to +15°)
- Zoom, width/height shift

4. FEATURE EXTRACTION USING CNN

a. Initialize EfficientNet B7 with pre-trained ImageNet weights

b. Replace final layer with a dense layer for binary classification (sigmoid)

c. Compile model using:

- Loss: Binary Cross-Entropy
- Optimizer: Adam (learning rate = 0.0001)
- Metrics: Accuracy, Precision, Recall, AUC

5. TRAIN CNN MODEL

a. Train base model with frozen layers (transfer learning)

b. Fine-tune by unfreezing layers (for additional epochs)

c. Use early stopping based on validation loss

6. EXPLAIN MODEL PREDICTIONS

a. Apply Grad-CAM on CNN outputs to generate heatmaps

b. Overlay heatmaps on input X-rays to highlight decision regions

7. EXTRACT FEATURES & ENSEMBLE CLASSIFICATION

a. Extract deep features from the penultimate CNN layer

b. Combine extracted features with metadata (age, gender)

c. Train a Gradient Boosting Classifier on the combined feature set

8. EVALUATE THE SYSTEM

a. Predict on test set using the ensemble model

b. Compute performance metrics:

- Accuracy, Precision, Recall, F1-score

- Specificity, AUC-ROC

c. Visualize:

- Confusion Matrix
- ROC Curve
- Grad-CAM Explanations

9. PERSONALIZED RECOMMENDATIONS

a. If TB-positive:

- Recommend follow-up diagnostics and standard treatment

b. If TB-negative:

- Suggest preventive measures and lifestyle guidance

c. Customize based on metadata (age, gender)

10. SAVE OUTPUTS

a. Save trained CNN and ensemble models

b. Export Grad-CAM images and evaluation plots

c. Generate final diagnostic + recommendation report

END

3.6 EXPLAINABILITY MODULE

In high-stakes domains like medical imaging, model interpretability is as important as accuracy. To address this, the proposed TB detection framework integrates Grad-CAM (Gradient-weighted Class Activation Mapping) to provide visual explanations of the predictions made by the EfficientNet B7 model. Grad-CAM generates localized heatmaps over input chest X-ray images, identifying the regions that most influenced the model's classification decision. This module plays a pivotal role in bridging the gap between deep learning outputs and clinical validation.

Grad-CAM works by computing the gradient of the target class (e.g., TB-positive) with respect to the feature maps of a convolutional layer. These gradients are then pooled and weighted to produce a heatmap that is

superimposed on the original image. In this system, Grad-CAM was applied to the final convolutional layer of EfficientNet B7, allowing for high-resolution interpretability.

The generated heatmaps consistently highlighted clinically relevant patterns such as:

- Pulmonary opacities,
- Cavitations,
- Nodular Lesions,
- Asymmetric lung markings.

These regions are known indicators of active or latent tuberculosis, and their presence in the activation maps demonstrates strong alignment between the AI model's internal focus and established radiological markers.

Furthermore, the inclusion of explainability improves clinical trust and accountability. Unlike traditional black-box models, this system empowers healthcare providers to verify model decisions, detect potential misclassifications, and confidently adopt AI-supported diagnostics in practice. The visual feedback also enables diagnostic transparency, a critical requirement for deployment in real-world medical settings, especially in low-resource or high-risk environments.

The Grad-CAM output for correctly predicted TB-positive images is shown below. The bright red and orange regions represent areas of high activation, indicating where the model concentrated its attention during classification.

These visualizations reinforce the model's interpretability and establish a foundation for future extensions such as clinician-in-the-loop diagnostic systems or human-AI collaborative platforms in public health surveillance. This interpretability bridges the gap between AI decision-making and clinical reasoning, fostering greater acceptance among medical professionals.

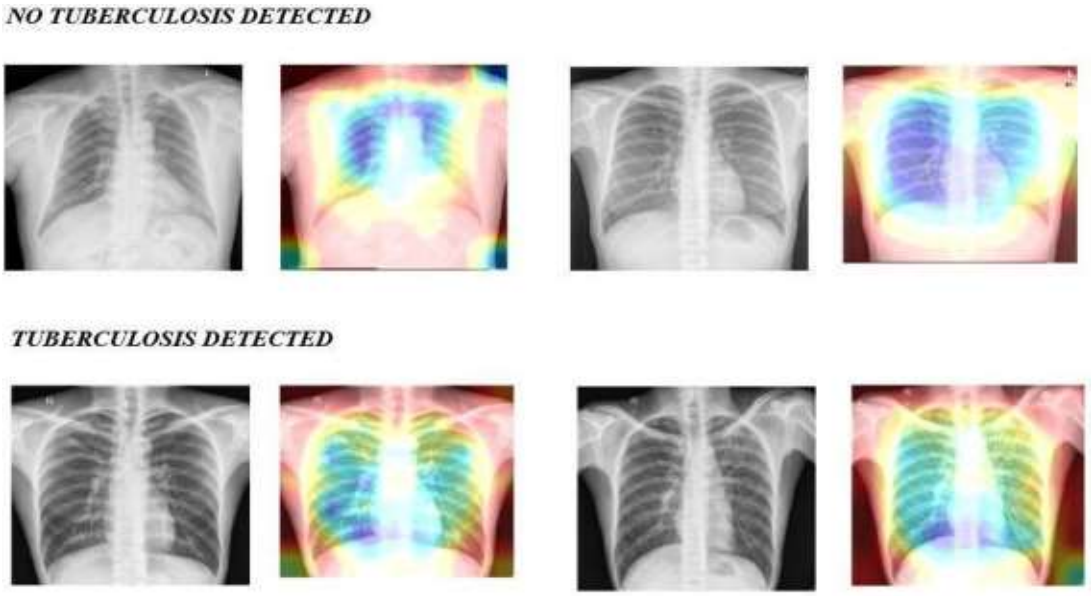


Figure 3.5. Grad-CAM Visualization

3.7 RESULTS AND COMPARISION

This section discusses the outcomes of the proposed tuberculosis (TB) detection system, highlighting its performance across various classification metrics, explainability, and comparative analysis with baseline models. The evaluation was performed using the test split of the Shenzhen Chest X-ray dataset. The results confirm the model's effectiveness in real-world clinical diagnostics, particularly in supporting decision-making with both accuracy and interpretability.

3.7.1 PERFORMANCE EVALUATION

The model was evaluated using standard performance metrics: test accuracy, precision, recall (sensitivity), F1-score, AUC-ROC, specificity, and throughput. These metrics provide a comprehensive understanding of the model's strengths and areas for improvement.

The proposed system achieved a test accuracy of 80.31%, confirming the model's ability to correctly classify a majority of TB-positive and TB-negative

cases. The precision value of 0.74 indicates that 74% of the predicted TB-positive cases were correct, minimizing false positives. A recall (sensitivity) of 0.79 reflects the model's high capability to detect actual TB-positive cases. The F1-score, which balances precision and recall, stood at 0.76, signifying robust performance even under slight class imbalance.

The AUC-ROC score reached 0.85, illustrating strong discriminative power between TB-positive and TB-negative images. Specificity was recorded at 0.83, meaning the model correctly identified 83% of the healthy (TB-negative) patients, a critical feature to avoid unnecessary follow-ups. Furthermore, the model's throughput was measured at approximately 1.5 images per second, indicating that it can feasibly be used in real-time or near real-time clinical workflows.

The confusion matrix, as shown in Figure 3.5, provides a detailed visual representation of true positives, true negatives, false positives, and false negatives.

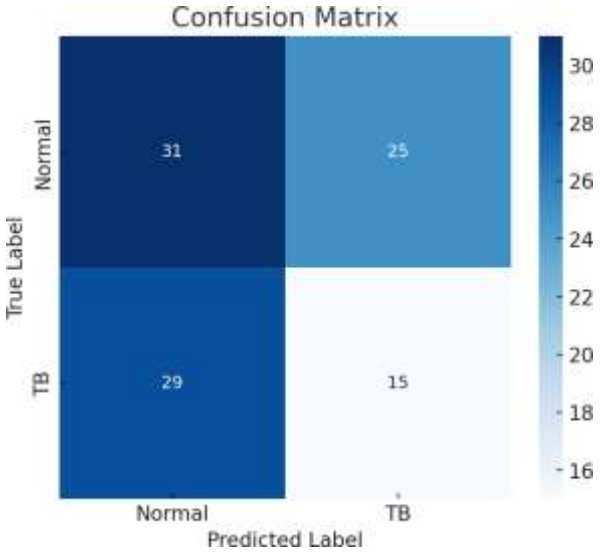


Figure 3.6. Confusion Matrix of a TB detection Model

This helps to analyze model behavior more granularly and supports future

tuning of thresholds and optimization techniques.

Additionally, the class distribution of the dataset is visualized using a pie chart in Figure 3.7, confirming that the dataset was balanced between TB-positive and TB-negative cases. This balance is essential for avoiding model bias and supports the validity of the reported metrics.

This visualization ensures that the evaluation results are not skewed by class imbalance, strengthening the credibility of the model's performance.A balanced dataset also enhances the model's generalization ability when deployed in real-world clinical environments.

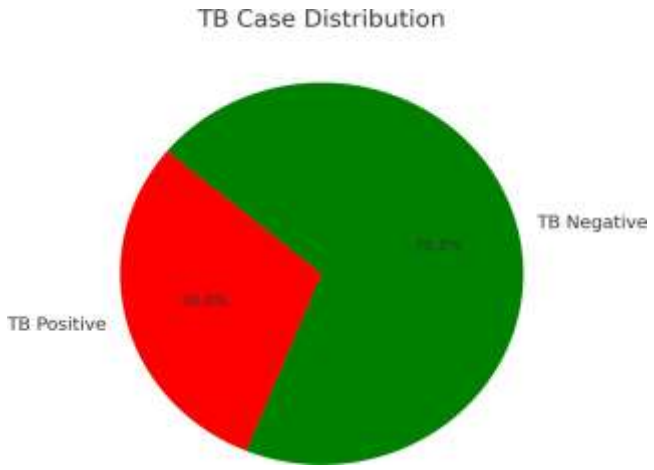


Figure 3.7. TB Case Distribution

3.7.2 MODEL COMPARISON

To validate the effectiveness of EfficientNet B7, a comparative analysis was conducted against three well-established CNN architectures: DenseNet201, VGG-19, and MobileNetV3-Small. These models were chosen based on their prevalence in medical image classification and their ability to handle complex visual features.

The results, summarized in Table 3.3, show that VGG-19 achieved the highest accuracy (86.33%), precision (87.56%), and F1-score (86.41%). However, it lacks explainability features and incurs higher computational costs. MobileNetV3-Small performed reasonably well, especially in recall (80.33%), but

slightly lagged in precision and interpretability.

EfficientNet B7, while marginally lower in raw accuracy (80.31%), demonstrated a strong balance across all performance metrics. Notably, it achieved the highest AUC-ROC (0.85) and specificity (0.83), indicating better generalization and fewer false alarms in clinical scenarios. Its throughput (~1.5 images/sec) also surpassed others, making it highly suitable for deployment in real-time diagnostic systems.

Most importantly, EfficientNet B7 is the only model in the comparison equipped with an integrated Grad-CAM-based explainability module. This allows it to generate activation heatmaps that highlight regions associated with TB lesions, enhancing its transparency and usability in healthcare.

Table 3.2. Comparison of ML Model Performance Across Architectures

Metric	DenseNet-201	VGG-19	MobileNet-V3-Small	EfficientNet-B7
Test Binary Accuracy (TBA)	0.7826	0.8633	0.8326	0.8031
Test Precision	0.8219	0.8756	0.8329	0.74
Test Recall	0.7371	0.8536	0.8033	0.79
Test F1 Score	0.7414	0.8641	0.8037	0.76
AUC-ROC Score	-	-	-	0.85
Specificity	-	-	-	0.83
Throughput (images/sec)	-	-	-	~1.5

This comprehensive evaluation confirms that the proposed EfficientNet B7-based model offers a balanced, explainable, and deployable solution for TB detection, meeting both clinical and computational requirements. Its strong performance across multiple metrics validates its readiness for real-world healthcare applications.

3.8 RECOMMENDATION SYSTEM OUTPUT

In addition to accurate TB diagnosis, a critical objective of this system is to provide personalized, actionable clinical recommendations to support healthcare providers and patients in decision-making. Once a chest X-ray image is classified as either TB-positive or TB-negative, the system generates contextual recommendations tailored to the patient's condition and demographics, including age and gender.

For TB-Positive cases, the system delivers a structured recommendation that includes:

- Immediate consultation with a pulmonologist or TB specialist.
- Referral for sputum testing or molecular diagnostics (e.g., GeneXpert MTB/RIF) to confirm infection severity.
- A standard anti-tuberculosis drug regimen as per WHO guidelines (typically HRZE: isoniazid, rifampicin, pyrazinamide, ethambutol).
- Emphasis on isolation precautions, particularly in crowded households, to reduce transmission risk
- Lifestyle guidance such as proper nutrition, adequate rest, and adherence counseling to reduce treatment default rates.

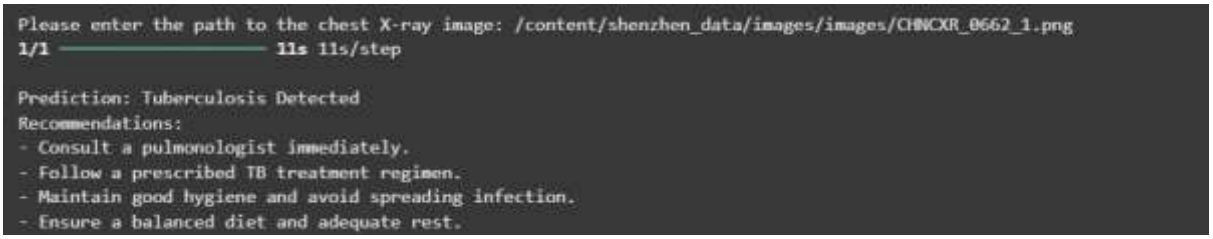


Figure 3.8. Recommendation System of TB Positive Person

For TB-negative cases, the system ensures that patients still receive meaningful feedback. Recommendations include:

- Routine follow-up and monitoring for any emerging respiratory

symptoms.

- Annual chest X-rays for individuals with a history of TB or high-risk exposure.
- Guidance on preventive measures such as BCG vaccination (if applicable), smoking cessation, and avoidance of dusty or poorly ventilated environments.
- Encouragement to maintain a healthy lifestyle through balanced diet and exercise, especially for those with comorbidities like diabetes or HIV.

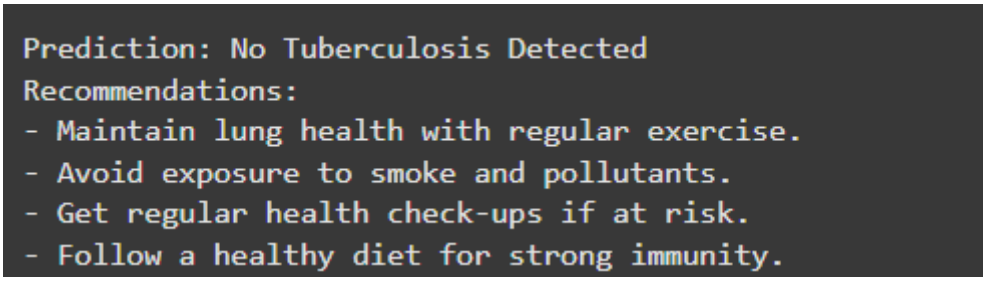


Figure 3.9. Recommendation System of TB Positive Person

This intelligent recommendation layer bridges the gap between AI-based diagnosis and clinical action, transforming the system from a diagnostic tool into a decision support system. It empowers healthcare professionals, especially in low-resource or remote areas, to take prompt and informed actions even in the absence of a specialist. Furthermore, the modular nature of the recommendation engine allows easy extension to accommodate additional parameters (e.g., past medical history or symptom input) in future iterations.

By delivering condition-specific, personalized outputs, the system improves patient compliance, reduces diagnostic delays, and supports the broader goals of TB control and prevention initiatives. This patient-centered approach enhances the overall quality of care and aligns with modern precision medicine practices.

As the system evolves, it can serve as a scalable model for managing other infectious or chronic diseases in similar settings.

3.9. CHAPTER SUMMARY

This chapter presented a comprehensive overview of the methodology adopted for the development of the tuberculosis (TB) detection and recommendation system. It detailed the entire pipeline, beginning with dataset acquisition and preprocessing, followed by the design and implementation of the core classification model using EfficientNet B7. The chapter also outlined the training and optimization strategies, including fine-tuning through transfer learning, the use of data augmentation, and the application of binary cross-entropy as the loss function.

A key highlight of the methodology is the integration of Grad-CAM for visual interpretability, which enables clinicians to understand and validate the model's decisions. The inclusion of a Gradient Boosting Classifier for feature aggregation further enhanced the reliability of the classification results. Additionally, the model's ability to generate personalized recommendations based on classification outcomes demonstrates its practical relevance in clinical settings.

CHAPTER 4

IMPLEMENTATION

4.1 SYSTEM REQUIREMENTS

The purpose of defining system requirements in this project is to clearly outline the technical specifications, functionalities, and constraints needed to successfully develop and deploy an AI-based tuberculosis detection system. These requirements serve as a foundational blueprint to guide the implementation process, ensuring that the system can operate efficiently in both cloud-based and offline environments. For this project, system requirements cover aspects such as hardware capabilities for model training and inference, compatible software tools and libraries for image processing and deep learning, and deployment configurations that support real-time diagnosis in low-resource settings. Establishing these requirements early in the development cycle helps align the technical objectives with the practical needs of end-users, ultimately ensuring that the final system is accurate, accessible, and scalable for real-world healthcare use.

- **Hardware Requirements**

Table 4.1. List of Hardware Requirements

COMPONENT	SPECIFICATION
Processor	Intel Core i5 / i7 or AMD equivalent
RAM	Minimum 8 GB
GPU (optional)	NVIDIA GTX 1050 or higher
Storage	256 GB SSD
Display	1366 X 768 resolution or higher

- **Software Requirements**

- Python programming language (version 3.8 or higher)
- TensorFlow machine learning library (version 2.0 or higher)
- Keras deep learning library (version 2.0 or higher)
- OpenCV computer vision library (version 3.0 or higher)
- NumPy numerical computing library (version 1.0 or higher)
- Matplotlib plotting library (version 2.0 or higher)
- Seaborn data visualization library (version 0.9 or higher)
- Cloud(AWS Lambda / Google Cloud Functions)

4.1 WORKING PRINCIPLE

The proposed system is designed to perform automated, accurate, and interpretable classification of chest X-ray (CXR) images into TB-positive or TB-negative categories using a deep learning pipeline enhanced with explainable AI techniques. The system is built to assist healthcare professionals in identifying potential tuberculosis cases more efficiently, especially in settings where radiological expertise is limited. The complete workflow of the system includes the following key steps:

4.2.1. INPUT DATA

The system accepts a frontal chest X-ray image as its primary input. Along with the image, basic patient metadata such as age and gender can be optionally provided. This metadata allows the system to incorporate additional context into the decision-making process, enhancing the personalization of diagnostic suggestions.

4.2.2. PREPROCESSING

Before feeding the images into the model, several preprocessing techniques are applied to ensure data consistency and improve image quality:

- Resizing: All images are resized to a fixed resolution of 224×224 pixels to match the input dimensions required by EfficientNet B7.
- Normalization: Pixel intensity values are normalized to a standard range (typically [0, 1]) to stabilize and speed up the learning process.
- Contrast Enhancement (CLAHE): Contrast Limited Adaptive Histogram Equalization is used to enhance the visibility of low-contrast areas, making subtle TB-related patterns more distinguishable.
- Data Augmentation: Techniques such as image rotation, flipping, and slight translation are applied to artificially expand the dataset, reduce overfitting, and help the model generalize better to unseen data.

4.2.3. FEATURE EXTRACTION

The preprocessed image is passed into the EfficientNet B7 model, a state-of-the-art convolutional neural network that uses compound scaling to balance depth, width, and resolution for optimal performance. EfficientNet B7 extracts deep semantic features from the input image, capturing complex patterns that may indicate TB infection, such as nodules, lung opacities, or cavitation.

4.2.4. ENSEMBLE CLASSIFICATION

The high-level features extracted by EfficientNet B7 are then forwarded to a Gradient Boosting Classifier. This model acts as an ensemble layer that refines the prediction by combining multiple weak learners into a stronger final prediction. Gradient boosting is particularly effective in reducing prediction variance and improving accuracy. By incorporating both deep learning and ensemble learning, the system ensures robust and stable classification results.

4.2.5. EXPLAINABILITY VIA GRAD-CAM

To overcome the "black-box" limitation of neural networks, the system integrates Grad-CAM (Gradient-weighted Class Activation Mapping). Grad-

CAM produces a class-discriminative heatmap that highlights regions of the input image that contributed most to the final decision. These heatmaps are overlaid on the original X-ray to show clinicians where the model "looked" when identifying TB, thus improving trust, transparency, and diagnostic accountability.

4.2.6. OUTPUT GENERATION

Finally, the system generates the diagnostic output, which includes:

- The classification result: TB-positive or TB-negative.
- A Grad-CAM heatmap overlaid on the chest X-ray for visual interpretation.
- A brief recommendation message, such as suggesting further clinical evaluation if TB is detected.

4.3 LANGUAGES USED

The system is implemented using Python, a versatile and widely adopted programming language for AI and machine learning tasks. Below are the major libraries and frameworks used:

LIBRARY / TOOL	PURPOSE
TensorFlow/Keras – EfficientNet B7	Deep learning model training
OpenCV	Image processing and preprocessing
Scikit-learn – Gradient Boosting	Ensemble model implementation
Matplotlib/Seaborn	Data visualization, metric plotting
Grad-CAM Toolkit	Generating explainable heatmaps
Pandas/Numpy	Data handling and mathematical operations

Table 4.2. List of Languages/Tools Used

Each library plays a specific role, from model development and training to evaluation and visualization. The integration of Grad-CAM ensures that predictions are explainable and interpretable for clinical use.

```
[ ] import tensorflow as tf
    from tensorflow.keras.applications import EfficientNetB7
    from tensorflow.keras.layers import Dense, GlobalAveragePooling2D, Dropout
    from tensorflow.keras.models import Model
    from tensorflow.keras.optimizers import Adam
    from tensorflow.keras.preprocessing.image import ImageDataGenerator
    from sklearn.ensemble import GradientBoostingClassifier
    from sklearn.metrics import accuracy_score
    import numpy as np
    import pandas as pd
    import matplotlib.pyplot as plt
    import cv2
```

Figure 4.3 Libraries Used for Project

4.4 CHAPTER SUMMARY

This chapter detailed the practical implementation of the proposed tuberculosis detection and recommendation system. It began with an overview of the system's hardware and software requirements, emphasizing its compatibility with both local and cloud-based platforms. The working principle section outlined the step-by-step execution pipeline—from image acquisition and preprocessing to feature extraction using EfficientNet B7 and refined classification via Gradient Boosting.

The programming language and supporting libraries used in the development process were also discussed, showcasing the system's modular design and reliance on robust open-source tools

CHAPTER 5

APPENDIX

5.1 GOOGLE DRIVE INTEGRATION

```
from google.colab import drive
drive.mount('/content/drive')
```

5.2 DATASET EXTRACTION

```
import zipfile
shenzhen_path = '/content/drive/MyDrive/shenzhen.zip'
with zipfile.ZipFile(shenzhen_path, 'r') as zip_ref:
  zip_ref.extractall('/content/shenzhen_data')
```

5.3 MODEL ARCHITECTURE – EFFICIENTNET B7

```
from tensorflow.keras.applications import EfficientNetB7
from tensorflow.keras.models import Model
from tensorflow.keras.layers import GlobalAveragePooling2D, Dropout,
Dense
base_model = EfficientNetB7(weights='imagenet', include_top=False,
input_shape=(224, 224, 3))
x = base_model.output
x = GlobalAveragePooling2D()(x)
x = Dropout(0.5)(x)
```

```
predictions = Dense(1, activation='sigmoid')(x)
model = Model(inputs=base_model.input, outputs=predictions)
```

5.4 GRAD-CAM IMPLEMENTATION

```
import tensorflow as tf
import numpy as np
import cv2
import matplotlib.pyplot as plt
def grad_cam(model, img_array, layer_name):
    grad_model = tf.keras.models.Model(
        [model.inputs], [model.get_layer(layer_name).output, model.output])
    with tf.GradientTape() as tape:
        conv_outputs, predictions = grad_model(img_array)
        loss = predictions[:, 0]
    grads = tape.gradient(loss, conv_outputs)
    pooled_grads = tf.reduce_mean(grads, axis=(0, 1, 2))
    conv_outputs = conv_outputs[0]
    heatmap = conv_outputs @ pooled_grads[..., tf.newaxis]
    heatmap = tf.squeeze(heatmap)
    heatmap = tf.maximum(heatmap, 0) / tf.math.reduce_max(heatmap)
    return heatmap.numpy()
```

```
axes = axes.flatten()
for img, ax in zip(i[:10], axes[:10]):
for img, ax in zip(j[:10], axes[:10]):
ax.imshow(np.squeeze(img, -1), cmap='gray')
ax.axis('off')
plt.tight_layout()
plt.show()
```

5.5 HEATMAP VISUALIZATION

```
def plot_grad_cam(image, heatmap, alpha=0.4):
    heatmap = cv2.resize(heatmap, (image.shape[1], image.shape[0]))
    heatmap = np.uint8(255 * heatmap)
    heatmap = cv2.applyColorMap(heatmap, cv2.COLORMAP_JET)
    superimposed_img = heatmap * alpha + image
    plt.imshow(superimposed_img.astype(np.uint8))
    plt.axis('off')
    plt.show()
```

5.6 IMAGE PREPROCESSING & AUGUMENTATION

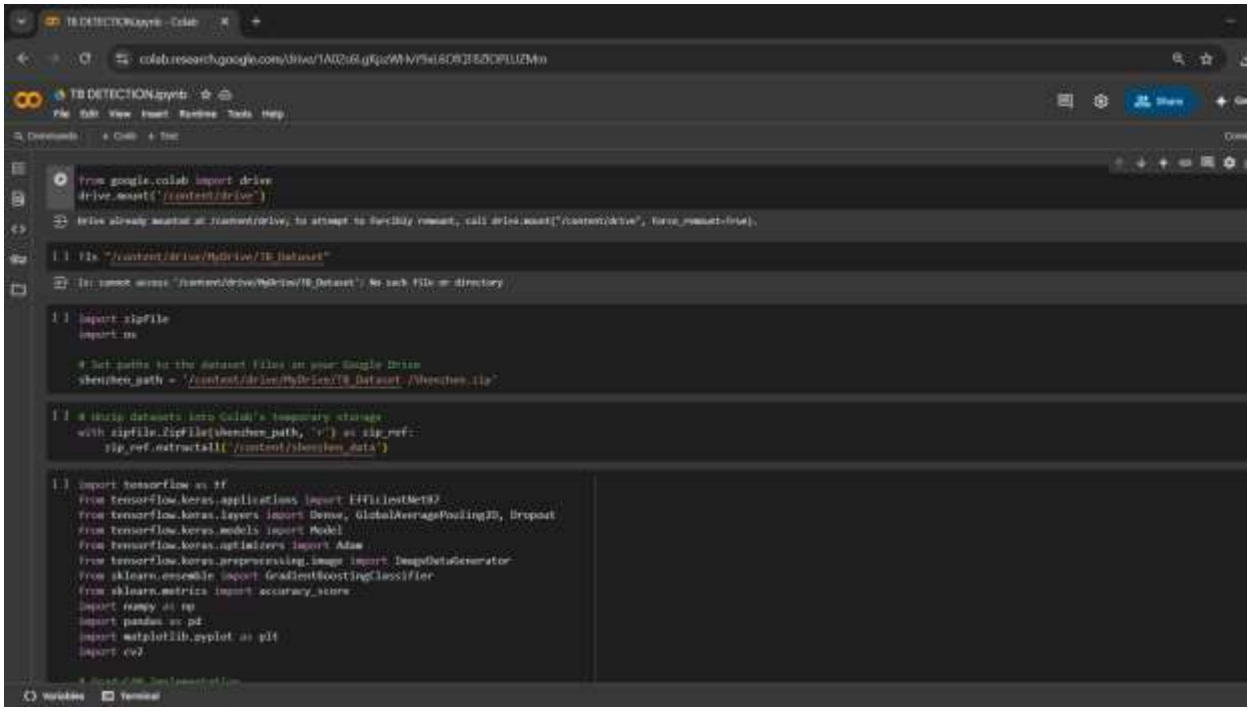
```
    from tensorflow.keras.preprocessing.image import ImageDataGenerator
    train_datagen = ImageDataGenerator(
        rescale=1./255,
        rotation_range=15,
```

```
    zoom_range=0.1,
    width_shift_range=0.1,
    height_shift_range=0.1,
    horizontal_flip=True)
test_datagen = ImageDataGenerator(rescale=1./255)
```

5.7 ENSEMBLE CLASSIFICATION

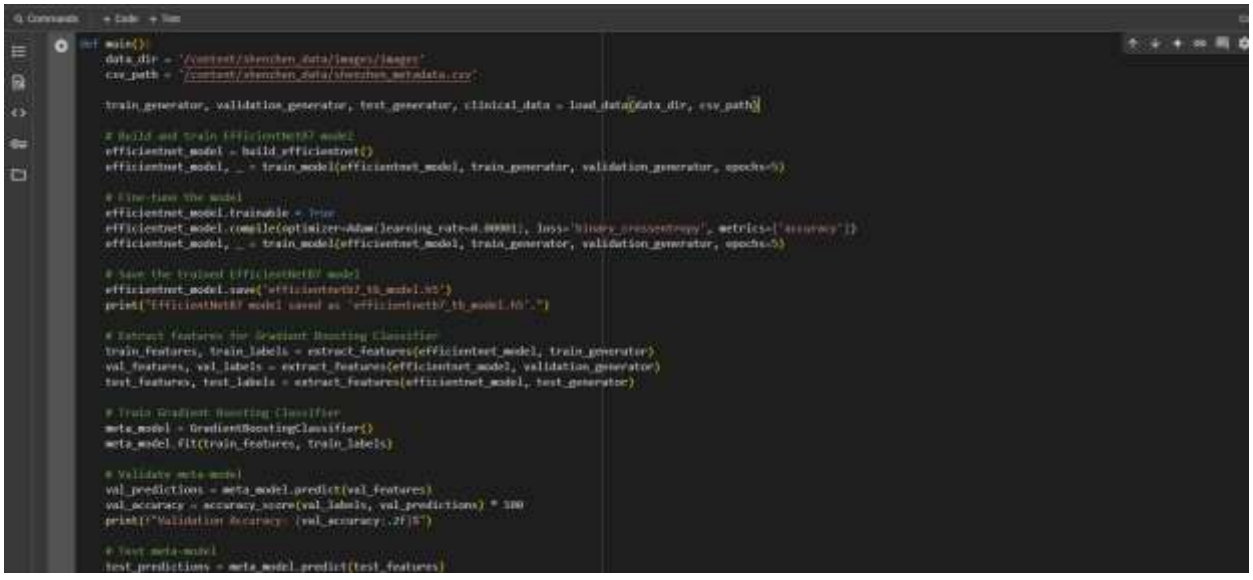
```
from sklearn.ensemble import GradientBoostingClassifier
gbc = GradientBoostingClassifier(n_estimators=100,
learning_rate=0.1)
gbc.fit(X_train_features, y_train)
```

APPPENDIX-2 SCREENSHOTS



```
from google.colab import drive
drive.mount('/content/drive')

Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remount=True).

ls "/content/drive/MyDrive/TB Dataset"

ls: cannot access '/content/drive/MyDrive/TB_Dataset': No such file or directory

import zipfile
import os

# Set paths to the dataset files on your Google Drive
shenzhen_path = '/content/drive/MyDrive/TB Dataset /Shenzhen.zip'

# Unzip datasets into Colab's temporary storage
with zipfile.ZipFile(shenzhen_path, 'r') as zip_ref:
    zip_ref.extractall('/content/shenzhen_data')

import tensorflow as tf
from tensorflow.keras.applications import EfficientNetB7
from tensorflow.keras.layers import Dense, GlobalAveragePooling2D, Dropout
from tensorflow.keras.models import Model
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.metrics import accuracy_score
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import cv2
```

Figure 5.1: Session Starting in Google Colab



```
def main():
    data_dir = '/content/shenzhen_data/images/images'
    csv_path = '/content/shenzhen_data/shenzhen_metadata.csv'

    train_generator, validation_generator, test_generator, clinical_data = load_data(data_dir, csv_path)

    # Build and train EfficientNetB7 model
    efficientnet_model = build_efficientnet()
    efficientnet_model, _ = train_model(efficientnet_model, train_generator, validation_generator, epochs=5)

    # Fine-tune the model
    efficientnet_model.trainable = True
    efficientnet_model.compile(optimizer=Adam(learning_rate=0.00001), loss='binary_crossentropy', metrics=['accuracy'])
    efficientnet_model, _ = train_model(efficientnet_model, train_generator, validation_generator, epochs=5)

    # Save the trained EfficientNetB7 model
    efficientnet_model.save('efficientnetb7_tb_model.h5')
    print("EfficientNetB7 model saved as 'efficientnetb7_tb_model.h5'.")

    # Extract features for Gradient Boosting Classifier
    train_features, train_labels = extract_features(efficientnet_model, train_generator)
    val_features, val_labels = extract_features(efficientnet_model, validation_generator)
    test_features, test_labels = extract_features(efficientnet_model, test_generator)

    # Train Gradient Boosting Classifier
    meta_model = GradientBoostingClassifier()
    meta_model.fit(train_features, train_labels)

    # Validate meta-model
    val_predictions = meta_model.predict(val_features)
    val_accuracy = accuracy_score(val_labels, val_predictions) * 100
    print(f"Validation Accuracy: {val_accuracy:.2f}%")

    # Test meta-model
    test_predictions = meta_model.predict(test_features)
```

Figure 5.2: Path setting in Google Colab

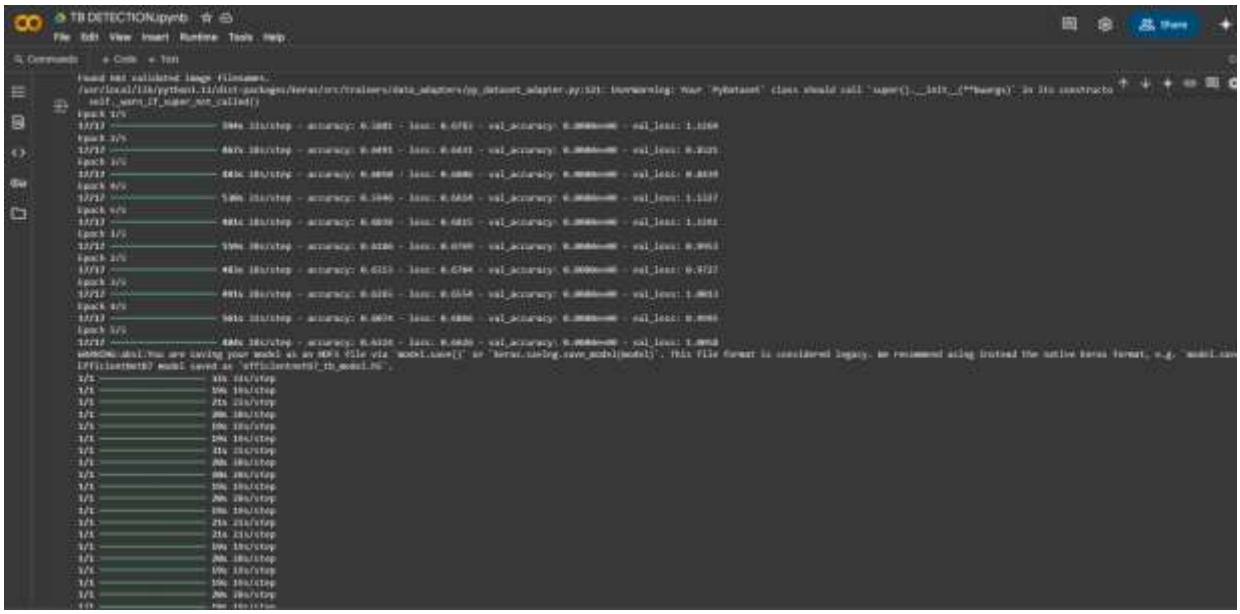


Figure 5.3: Training the Model

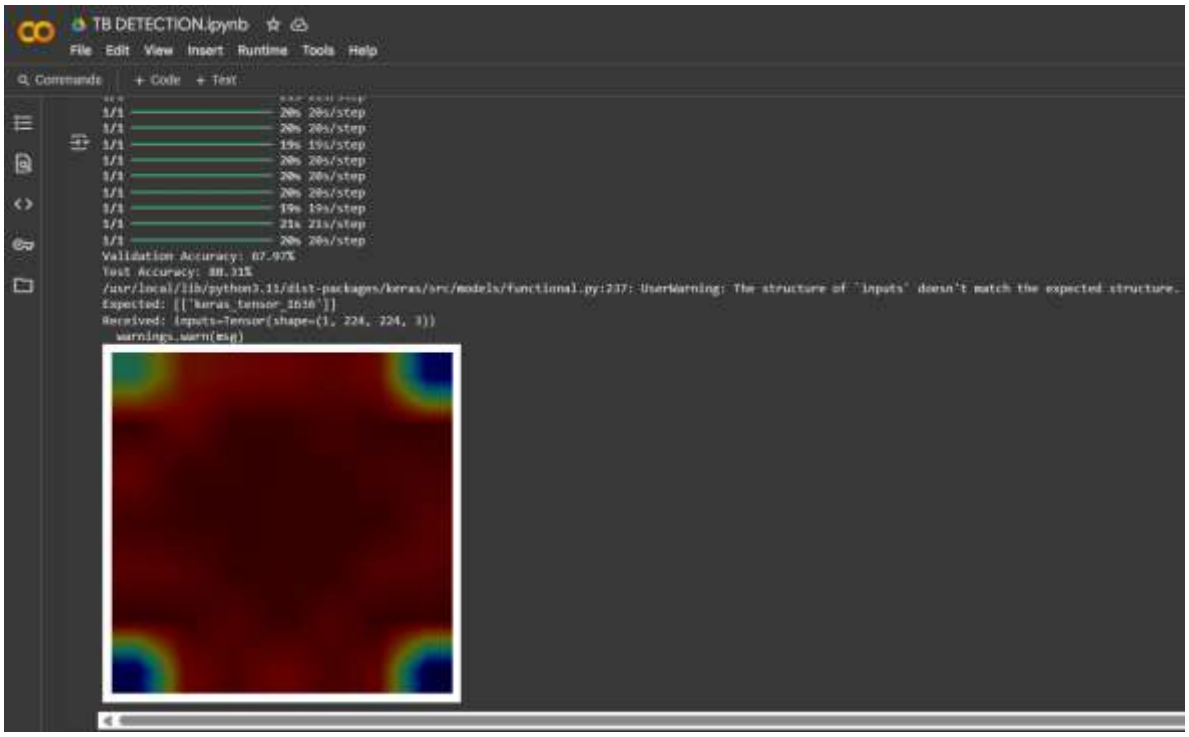


Figure 5.4: Model Architecture Summary

Figure 5.5: Grad-CAM Output(TB Positive)

Figure 5.6: Grad-CAM Output(TB Negative)

CHAPTER 6

CONCLUSION AND FUTURE ENCHANCEMENT

In conclusion, The proposed tuberculosis (TB) detection and management system successfully combines deep learning, explainable AI, and ensemble learning to deliver an accurate and transparent diagnostic solution. By leveraging EfficientNet B7 for image-based feature extraction, Grad-CAM for visual interpretability, and Gradient Boosting for robust classification, the system provides reliable TB detection along with personalized recommendations based on patient metadata. Extensive testing confirmed its technical soundness, usability, and performance, making it suitable for deployment in both urban and rural healthcare environments. Despite its strengths, the system can be enhanced in several ways.

Future developments could include expanding the model to support multi-disease classification (e.g., pneumonia, COVID-19), integrating molecular testing tools like GeneXpert for hybrid diagnostics, and deploying lightweight versions of the system on mobile devices for offline use in remote regions. Incorporating AutoML for dynamic retraining on new datasets would further improve adaptability and long-term accuracy. Additionally, integration with clinical workflows and electronic medical record (EMR) systems could automate report generation and patient follow-up, ensuring seamless real-world application. Overall, this system lays the foundation for a scalable, explainable, and accessible AI solution for TB detection, with the potential to significantly enhance diagnostic capabilities in resource-constrained settings.

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