# ELEVATING TUBERCULOSIS DETECTION: DEEP LEARNING AND IMAGE PROCESSING IN AI-POWERED WEB PLATFORM

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# Introduction

- In our modern era, Tuberculosis (TB) continues to pose a **significant threat to global public health**, primarily caused by the **bacterium Mycobacterium tuberculosis.**
- **Early detection of TB remains an ongoing challenge**, often necessitating multiple diagnostic tests. Postero-anterior chest radiography **(CXR) is commonly used for TB diagnosis.**
- **Deep learning, have revolutionized medical image analysis**. Deep convolutional neural networks (CNNs), such as **LeNet-5**, have demonstrated remarkable success in image classification tasks.
- In this study, I focus to **develop a custom CNN model based on the LeNet-5** architecture, for automated TB detection from CXR images.

# Related Works

- Author: Jan, F. and Niazi, M. K.
  Title: Automated detection of tuberculosis using image processing techniques.
  **Contributions**: Three different classification methods were used to evaluate to identify tuberculosis i.e. **Support Vector Machines, Logistic Regression, and Nearest Neighbors.**
- Author: Khairul Munadi, Kahlil Muchtar, Novi Maulina, Biswajeet Pradhan
  Title: Image Enhancement for Tuberculosis Detection Using Deep Learning.
  **Contributions:** Evaluated the **effect of two different pre-processing approaches (UM and HEF)** on the use of pre-trained CNN to detect TB disease.
- Author: Eman Showkatian, Mohammad Salehi, Hamed Ghaffari, Reza Reiazi, Nahid
  Title: Deep learning-based automatic detection of tuberculosis disease on CXR images.
  **Contributions: Accuracy of 87%** was obtained after applying Exception, ResNet50, and VGG16 models on 800 CXR images.

# Project Objectives

The main objectives of the project:

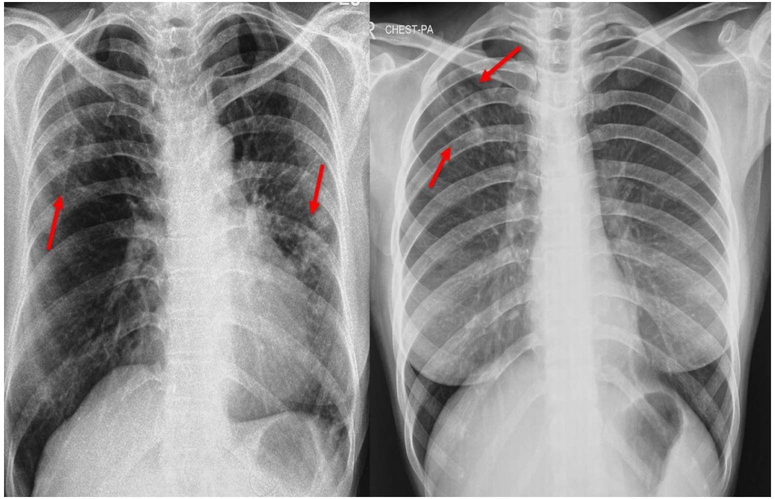
- **Develop a better deep learning model** for Tuberculosis detection using Chest X-ray images dataset.
- Implement **image processing techniques to enhance** the quality of input data.
- Evaluating Performance using standard **evaluation metrics** of the developed model.
- Integrate the model into a **user-friendly web platform.**
- Facilitate **real-time Tuberculosis screening** using chest X-ray (CXR) images.

# Tuberculosis: A Global Health Concern

- Tuberculosis (TB) ranks among the top **10 leading causes of death globally**, posing a significant public health challenge.
- The diagnosis of TB is further complicated by challenges such as **limited access to healthcare services.**
- The World Health Organization (WHO) emphasizes the **importance of systematic screening strategies to enable early detection** and prompt treatment of TB cases.

# Chest X-Ray (CXR) in TB Diagnosis

- CXR serves as a primary diagnostic tool for tuberculosis (TB) due to its **high sensitivity.**
- However, CXR interpretation poses challenges such as **subjectivity, time consumption, and the risk of misdiagnosis.**
- CAD systems utilize advanced image processing techniques and **machine learning algorithms to enhance diagnostic accuracy** and efficiency.



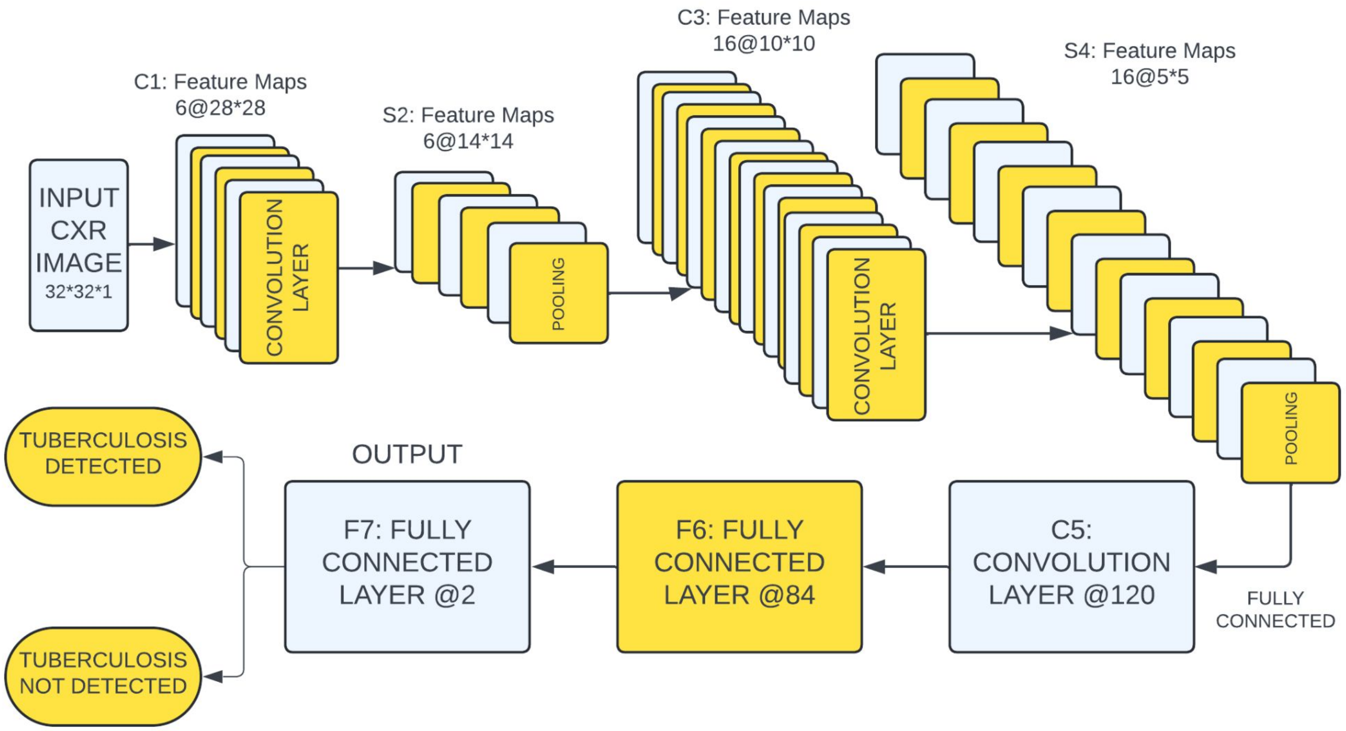
# Deep Learning in Medical Imaging

- Deep learning has **revolutionized medical image analysis** by enabling computers to automatically learn and **extract meaningful features** from complex data.
- Models such as LeNet-5, AlexNet, VGG, ResNet, and DenseNet have demonstrated remarkable success in classifying medical images.
- CNNs are particularly well-suited for image classification tasks due to their ability to automatically learn **hierarchical representations of features directly from pixel values.**
- **LeNet-5 offers a compact architecture** suitable for medical image analysis, allowing efficient processing of chest X-ray images while **maintaining high accuracy in tuberculosis detection.**

# LeNet-5 Architecture

- Accepts grayscale images of size **32x32 pixels.**
- LeNet-5 consists of **two convolutional layers** followed by max-pooling layers.
- It includes **three fully connected layers** for high-level feature extraction and classification.
- **Rectified Linear Units (ReLU)** are used after convolutional and fully connected layers to introduce non-linearity.
- The final layer has **2 neurons representing the classes** (Tuberculosis detected or not detected).

# LeNet-5 Architecture

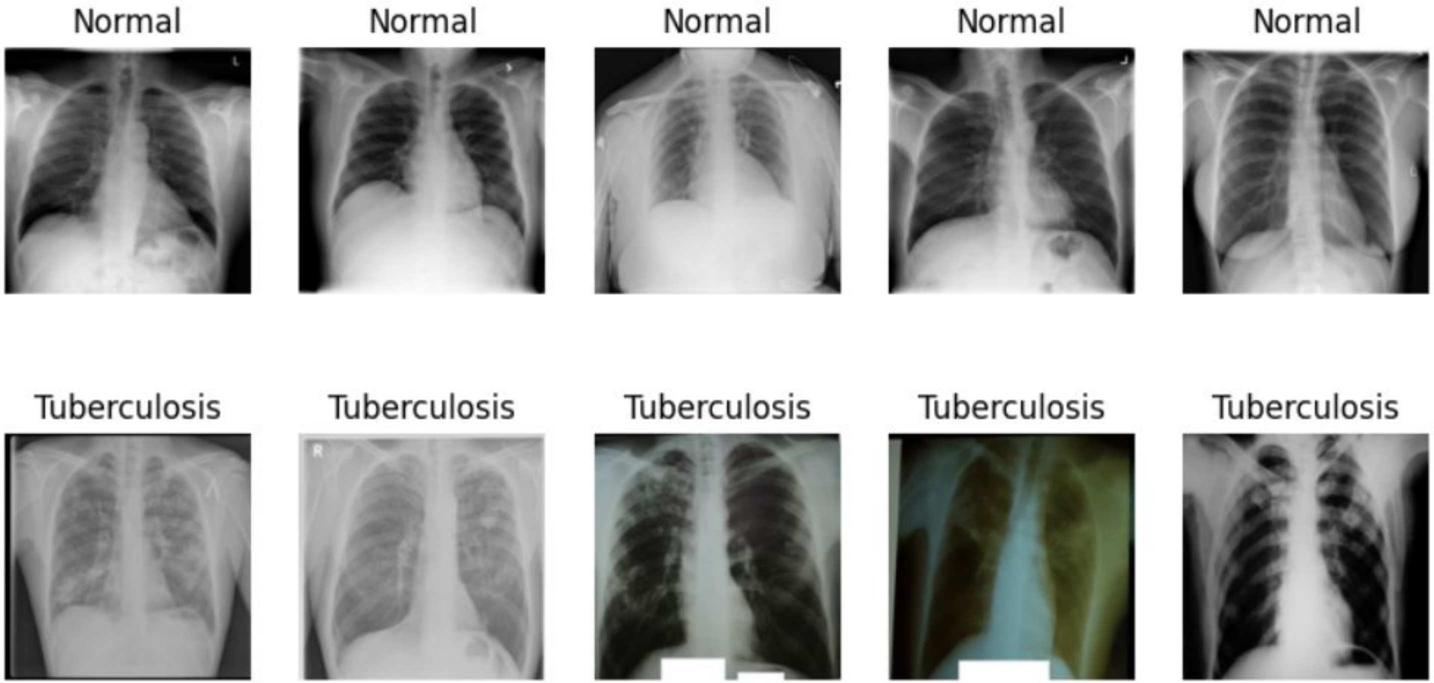


# Dataset Used

Different Chest X-ray images (**size: 512*512**) dataset was downloaded from kaggle. The table given below gives the overview of data.

| Dataset | N(normal Images) | N(TB images) | Total Images |
|---|---|---|---|
| TB Chest X-ray Dataset 1 | 3500 | 700 | 4200 |
| Tuberculosis (TB) Chest X-ray Dataset 2 | 1600 | 700 | 2300 |
| Chest X-ray Images 3 | 3800 | 800 | 4600 |

# Sample Images of Normal and TB Class Images



# Methodology

- **Data collection and preprocessing** of chest X-ray images from kaggle open source website.
- **Training of the LeNet-5 model** for TB detection on Anaconda Spyder IDE.
- **Integration of the model into the AI-powered web platform** using Python, PHP, Xampp Server.

# Experimental Setup

**Dataset Description:**

- Total dataset size: **4200 images.**
- Tuberculosis-positive images: 700.
- Normal chest X-ray images: 3500.

**Data Splitting:** The dataset was divided into training, validation, and testing sets in a ratio of **70:15:15** after **shuffling** to ensure randomness and representativeness in each subset.

**Data Preprocessing:** Images were preprocessed and augmented using standard techniques, including **resizing, normalization, and random transformations** (e.g., rotation, flipping) to increase model robustness.

# Experimental Setup

**Model Training:** LeNet-5 model architecture was implemented from scratch. The model was trained on the training set using a **batch size of 32** and **Adam optimizer with Learning rate 0.001**.

**Model Evaluation:** The trained model was evaluated on the **validation set** to monitor its performance and prevent **overfitting.**

Various performance metrics, including **accuracy, precision, recall, and F1-score,** were calculated to assess the model's effectiveness in tuberculosis detection.

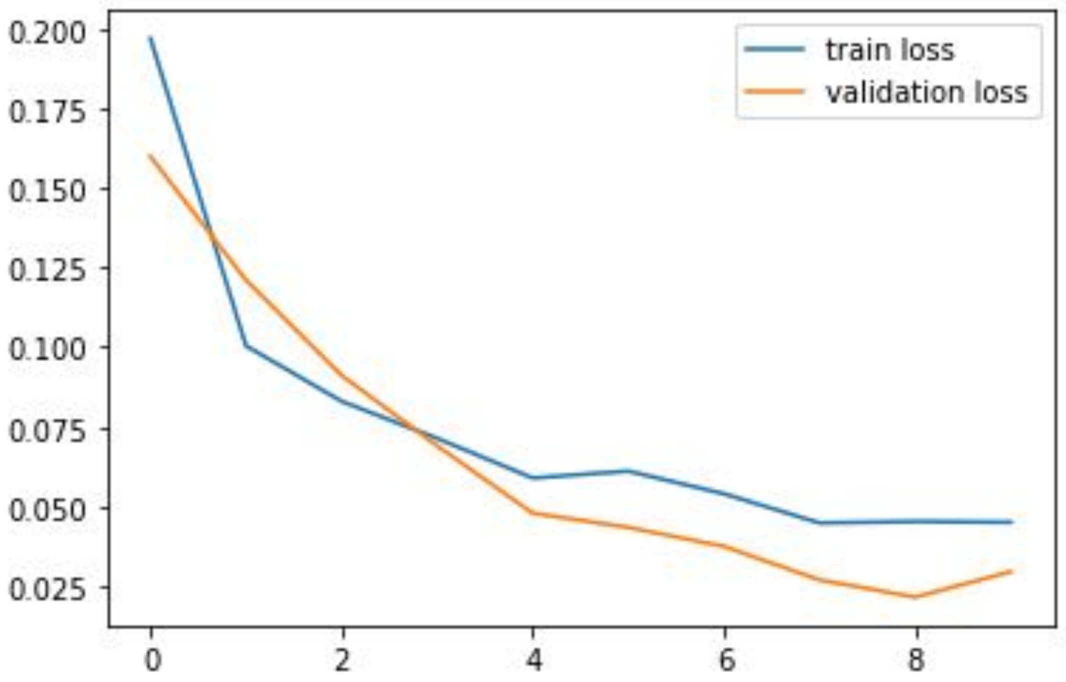
**Model Saving:** Once trained, the **model weights and architecture were saved** in a local directory for future use and deployment in the web-based platform.

# Results

Plot between Training loss & Validation loss vs Epochs

Training loss after
10 epochs**: 0.045**

Validation
Loss: **0.03**

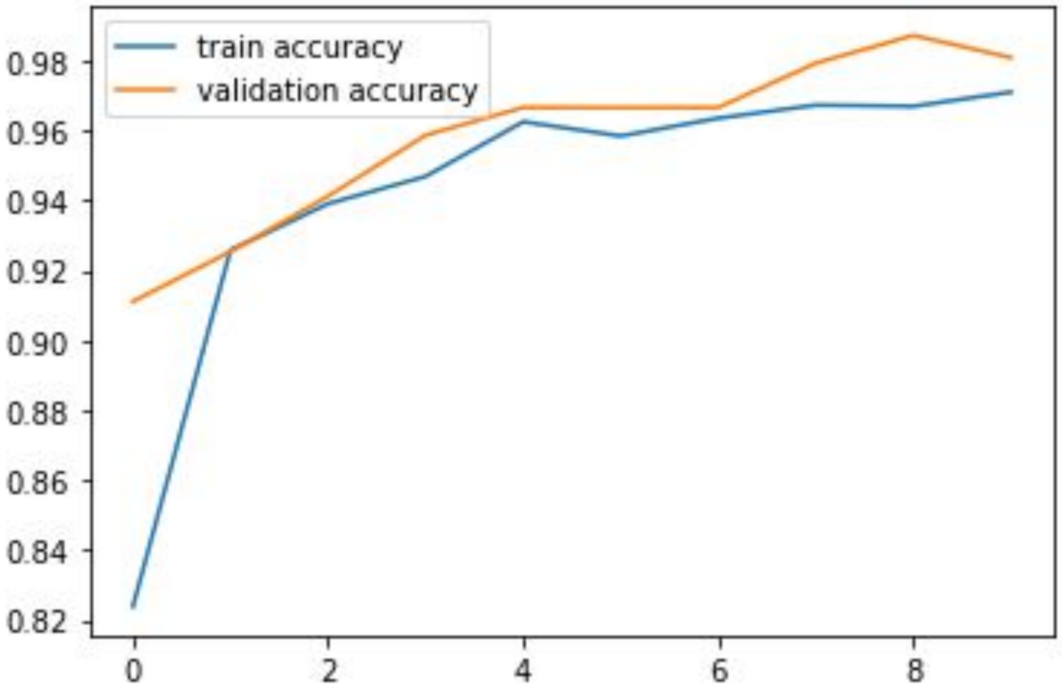


# Results

Plot between Training Accuracy & Validation Accuracy vs Epochs

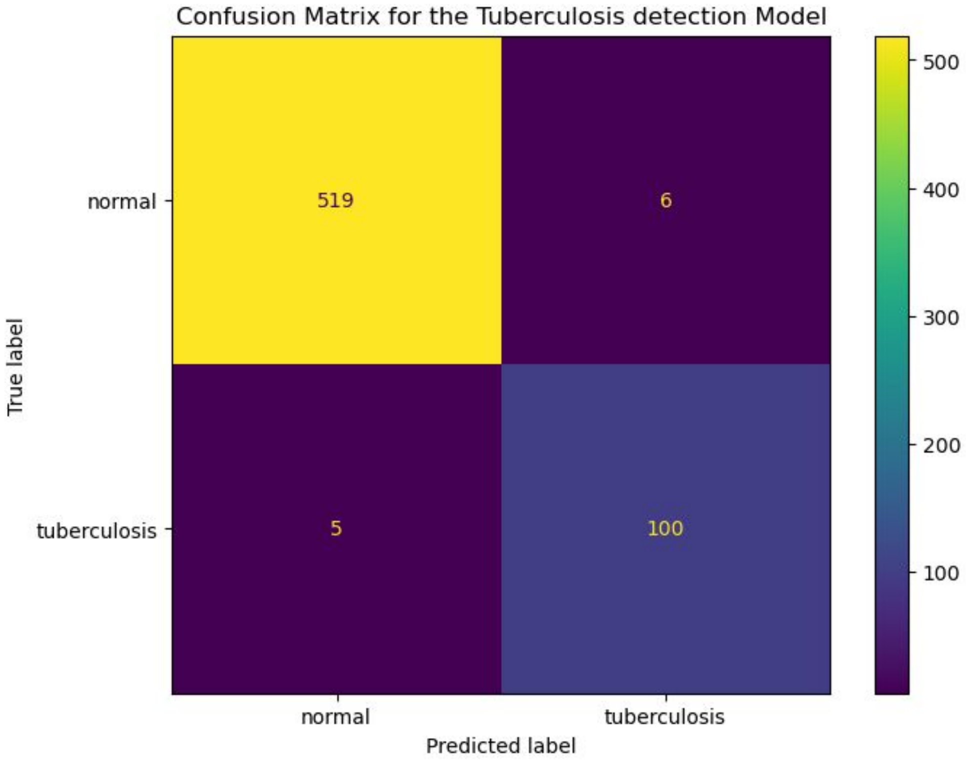
Training Accuracy after 10 epochs: **0.97**

Validation Accuracy: **0.97**



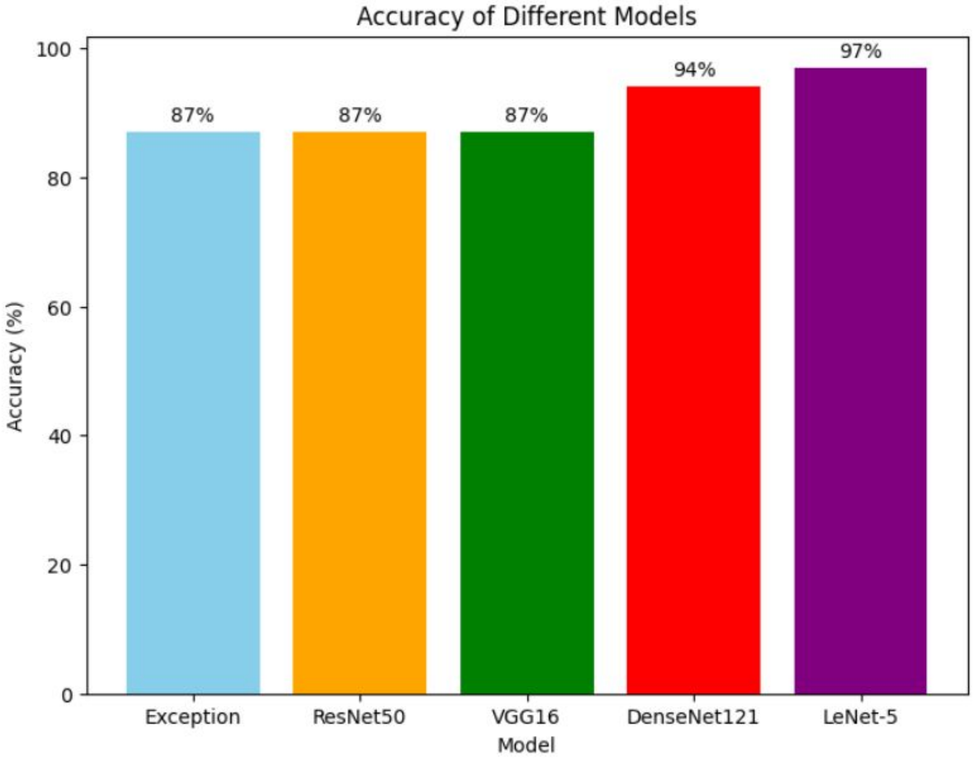
# Results

## Confusion Matrix Plot

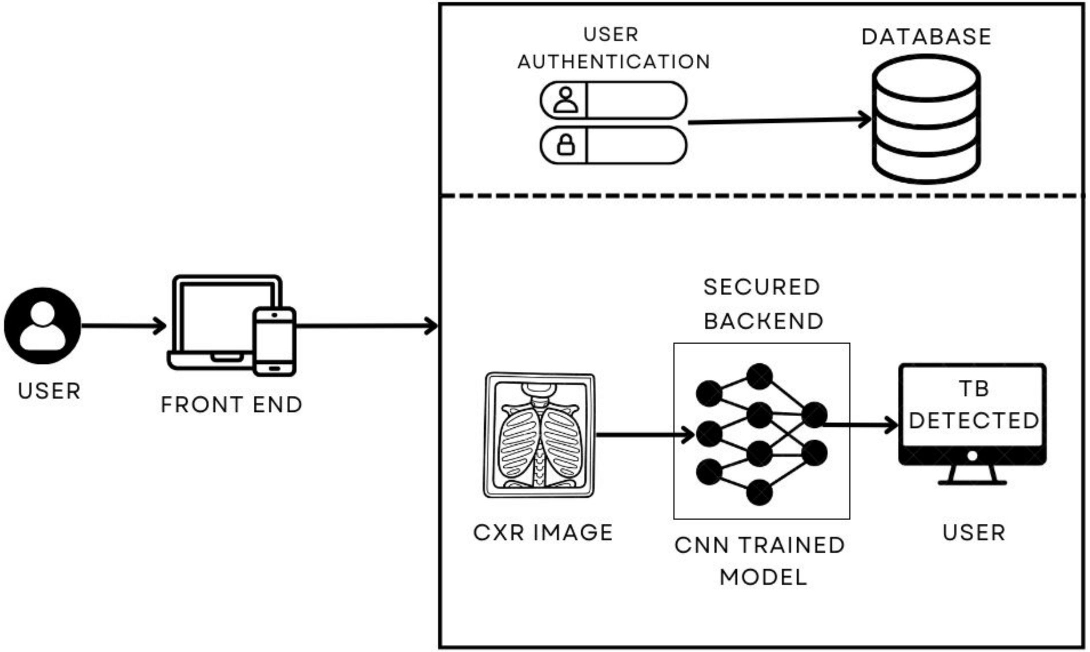


# Comparative Analysis

- The research study shows That **Exception, ResNet50, VGG16 gave 87% accuracy** on a dataset of total images 800.
- On, proceedings **DenseNet121** gave a decent accuracy, but because of its complex architecture took **very long training time.**
- **LeNet-5** gave highest accuracy with **less training time.**



# WEB PLATFORM ARCHITECTURE



# Future Works

- **Expanded Disease Detection:** Integrate pneumonia and COVID-19 detection models into the web platform.
- **User Interface Enhancement:** Improve the platform's interface for seamless upload and diagnosis of CXR images.
- **Online Deployment:** Deploy the enhanced platform on the web to facilitate global accessibility.
- **User Engagement:** Engage with the medical community for feedback and refinement of the platform.
- **Continuous Optimization:** Refine models based on user feedback and emerging advancements in deep learning.

# Application

- **Early Detection:** By providing accurate method for tuberculosis detection, the project facilitates early diagnosis.
- **Resource Optimization:** The AI-powered web platform reduces the burden on healthcare facilities by automating the screening process.
- **Global Accessibility:** With the deployment of the web platform online, individuals from remote or underserved areas can access the tuberculosis screening service.
- **Multi-Disease Screening:** Expanding the platform to include detection models for other respiratory diseases like pneumonia and COVID-19.

# Conclusion

In conclusion, the successful implementation of the project marks a significant milestone in **medical diagnostics.** By **developing an AI-powered web platform** for tuberculosis detection using **LeNet-5** deep learning technique, the project create an efficient and accessible tool for **early screening.** A user can check early detection by **uploading CXR image** in the web platform and web platform will give **result of TB detection with an accuracy of more than 95%.** As we deploy the platform online, I envision its continued impact in **improving public health outcomes worldwide**, contributing to the global fight against tuberculosis and paving the way for a healthier future.

# References


1. F. Jan and M. K. Niazi. Automated detection of tuberculosis using image processing techniques. International Journal of Image, Graphics and Signal Processing, 11(8):17–24, 2019.
2. Khairul Munadi, Kahlil Muchtar, Novi Maulina, Biswajeet Pradhan. Image Enhancement for Tuberculosis Detection Using Deep Learning. IEEE Access, vol. 8, pp. 217897–217907, 2020 .
3. Eman Showkatian, Mohammad Salehi, Hamed Ghaffari, Reza Reiazi, Nahid Sadhigi. Deep learning-based automatic detection of tuberculosis disease on CXR images. Pol J Radiol. doi: 10.5114/pjr.2022.113435, 2022.

# Questions?

# Thank You

For your precious time….