TUBERCULOSIS DETECTION USING DEEP LEARNING AND IMAGE PROCESSING IN AI-POWERED WEB APPLICATION

A Project Report Submitted

in Partial Fulfilment of the Requirements

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BACHELOR OF TECHNOLOGY

in

Computer Science and Engineering

by

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to

DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

INDIAN INSTITUTE OF INFORMATION TECHNOLOGY

RAICHUR-584135, INDIA

May 2024

DECLARATION

I, **SIKANDER KATHAT** (**Roll Number: CS20B1020**), hereby declare that, this report entitled **"Tuberculosis Detection Using Deep Learning and Image Processing in AI-Powered Web Application"** submitted to Indian Institute of Information Technology Raichur towards partial requirement of **Bachelor of Technology** in **Computer Science and Engineering** is an original work carried out by me under the supervision of **Dr. Dubacharla Gyaneshwar** and has not formed the basis for the award of any degree or diploma, in this or any other institution or university. I have sincerely tried to uphold the academic ethics and honesty. Whenever an external information or statement or result is used then, that have been duly acknowledged and cited.

Raichur-584135 **Sikander Kathat**

May 2024

CERTIFICATE

This is to certify that the work contained in this project report entitled **"Tuberculosis Detection Using Deep Learning and Image Processing in AI-Powered Web Application"** submitted by **Sikander Kathat** (**Roll Number: CS20B1020**) to the Indian Institute of Information Technology Raichur towards partial requirement of **Bachelor of Technology** in has been carried out by him under my supervision and that it has not been submitted elsewhere for the award of any degree.

Raichur-584135 | Dr. Dubacharla Gyaneshwar
May 2024 | Project Supervisor

ABSTRACT

Tuberculosis (TB) remains a significant global health concern, necessitating efficient and accurate diagnostic methods for early detection and treatment initiation. Leveraging advancements in deep learning and medical imaging, this research focuses on developing a custom convolutional neural network (CNN) model based on the LeNet-5 architecture for automated TB detection from chest X-ray (CXR) images. The LeNet-5 architecture, known for its efficiency and effectiveness in image classification tasks, is adapted and fine-tuned to handle TB detection, demonstrating its suitability for medical image analysis. The study encompasses data collection, preprocessing, model training, and evaluation, with a specific emphasis on integrating image processing techniques to enhance model performance. Furthermore, a user-friendly web platform is developed to facilitate real-time TB screening, enhancing accessibility to diagnostic tools, particularly in resource-limited regions. Through comprehensive experimentation and analysis, the proposed approach demonstrates promising results, achieving high accuracy in TB detection while addressing challenges such as interpretability and scalability. This research contributes to the advancement of AI-powered TB detection systems, offering a scalable solution for early diagnosis and intervention in the fight against tuberculosis on a global scale.

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Chapter 1

Introduction

1.1 Background and Motivation

Despite improvements in medical research and healthcare infrastructure, tuberculosis (TB) continues to pose a serious danger to global health. Mycobacterium tuberculosis, the primary cause of tuberculosis (TB), is a disease that affects millions of people worldwide, especially in low- and middle-income nations. TB is one of the top 10 causes of death worldwide, according to the World Health Organization (WHO), underscoring the urgent need for efficient detection and treatment methods [4, 6, 7, 8, 10].

Timely intervention and mitigating the disease's spread are contingent upon early discovery of tuberculosis. Traditional diagnostic techniques, however, can be inaccurate and time-consuming, particularly in environments with limited resources. Because of its great sensitivity in identifying lung abnormalities linked to tuberculosis infection, chest X-ray (CXR) imaging is one of the main methods used for tuberculosis diagnosis. Unfortunately, subjectivity and even mistake might result from the specialized training and experience needed to evaluate CXR pictures [5, 11, 12].

A paradigm shift in medical image analysis has been brought about by the development of deep learning and artificial intelligence (AI). Deep convolutional neural networks (CNNs) have proven to be remarkably effective in a number of tasks, such as segmentation, object detection, and picture categorization. In an effort to get beyond the drawbacks of conventional diagnostic techniques, researchers have investigated the use of CNNs for automated TB identification from CXR pictures by utilizing the deep learning capabilities [13, 14, 15, 16].

In this study, we advance the field by creating a unique CNN model for TB identification from CXR pictures that is based on the LeNet-5 architecture. Yann LeCun et al.'s groundbreaking CNN architecture, LeNet-5, provides a small-but-strong framework for image classification problems. Our goal is to maximize LeNet-5's efficacy and efficiency in medical image analysis by modifying and optimizing it for tuberculosis diagnosis [1, 2, 3].

1.2 Problem Statement

Although deep learning-based methods show promise, there are still a number of obstacles in the way of tuberculosis identification. These include the absence of established evaluation measures for evaluating model performance, the requirement for reliable and accurate models that can handle heterogeneous and diversified information, and the restricted availability of AI-powered diagnostic tools, particularly in areas with limited resources [14, 15, 16, 17].

Furthermore, in order to guarantee patient safety and data privacy, the use of AI models in actual clinical settings necessitates regulatory approval and validation in addition to a smooth integration into current healthcare workflows and platforms. For AI-powered TB detection systems to be widely used and be effective, these issues must be resolved [10, 11, 12].

1.3 Objectives

The creation of a deep learning model for automated tuberculosis identification from CXR pictures is the main aim of this study, with the following particular objectives:

- Create a unique CNN model for TB diagnosis based on the LeNet-5 architecture.
- Apply image processing methods to raise the standard of input data and boost model output.
- Assess the created model's performance using benchmark datasets and common assessment measures.
- Incorporate the model into an approachable online platform for CXR image-based real-time tuberculosis screening.

By accomplishing these goals, we hope to further the development of AI-driven TB detection systems, which will eventually make early diagnosis and treatment initiation easier, especially in underprivileged areas.

1.4 Scope and Limitations

The creation and assessment of a deep learning model for TB diagnosis using CXR pictures is the specific focus of this study. Although the suggested paradigm might have consequences for other respiratory conditions like pneumonia, our focus is just on tuberculosis detection [14, 15, 16, 17].

We realize that our research has a number of limitations, including the use of publically accessible information, possible biases in the data, and the application of the established model to a variety of situations and populations. Furthermore, the model's performance can change based on parameters including comorbidities, illness severity, and picture quality.

Chapter 2

Related Works

2.1 Automated Detection of Tuberculosis

Using image processing techniques, Jan and Niazi [1] suggested an automated method for tuberculosis (TB) detection. Using chest X-ray (CXR) pictures, they trained a convolutional neural network (CNN) from scratch to distinguish between TB and normal instances. Furthermore, they used a variety of pre-trained CNN models to evaluate the effectiveness of their CNN architecture with transfer learning-based methods.

Munadi et al. [2] focused on image enhancement techniques for TB detection using deep learning. They evaluated the effect of different pre-processing approaches, including Unsharp Masking (UM) and High-Frequency Emphasis Filtering (HEF), on the performance of pre-trained CNN models. Their study highlighted the importance of image enhancement in improving classification accuracy.

Showkatian et al. [3] developed a deep learning-based automatic detection system for TB disease on CXR images. They achieved high accuracy using a combination of deep CNN models, including Exception, ResNet50, and VGG16. Their study emphasized the significance of leveraging deep learning techniques for accurate and automated TB detection.

2.2 Image Enhancement Techniques

In their study, Munadi et al. evaluated the impact of different image enhancement algorithms on TB detection [2]. They compared the performance of pre-trained CNN models, such as EfficientNet-B4, ResNet-50, and ResNet-18, with various enhancement methods, including UM and HEF. Their results demonstrated the effectiveness of image enhancement in improving model accuracy and robustness.

Furthermore, Jan and Niazi analyzed the performance of their CNN architecture with and without image enhancement techniques [1]. They found that incorporating image enhancement, such as HEF, improved the model's ability to detect TB lesions in CXR images. Their study highlighted the importance of preprocessing techniques in medical image analysis.

2.3 Classification and Evaluation Techniques

In a comparative study, Jan and Niazi evaluated the performance of different classification metrics for TB detection [1]. They assessed metrics such as accuracy, sensitivity, precision, and area under the curve (AUC) to measure the effectiveness of their proposed CNN architecture. Their findings provided insights into the optimal evaluation metrics for TB detection systems.

Additionally, Munadi et al. compared the results of cross-validation and training-test set evaluation methods for TB classification [2]. They analyzed the performance of support vector machines (SVM) in both scenarios and observed higher accuracy in the training-test set approach. Their study emphasized the importance of proper evaluation techniques in assessing the performance of TB detection models.

2.4 Discussion

The related works highlight the advancements in automated TB detection using deep learning and image processing techniques. Studies have shown that leveraging pre-trained CNN models and image enhancement algorithms can significantly improve the accuracy and robustness of TB detection systems. Furthermore, the choice of classification and evaluation techniques plays a crucial role in assessing the performance of these systems. Future research may focus on exploring novel algorithms and methodologies to further enhance the efficiency and effectiveness of TB detection in medical imaging.

Chapter 3

Methodology

We will use the LeNet-5 deep learning model for TB detection for several reasons. Firstly, its architecture is well-suited for processing grayscale images, aligning with the nature of our chest X-ray dataset. Secondly, the LeNet-5 model has been widely used and studied in the field of computer vision, demonstrating its effectiveness in various image classification tasks. Additionally, its relatively simple architecture makes it computationally efficient, allowing for faster training times compared to more complex models. Furthermore, the interpretability of the model's features facilitates understanding and analysis of the learned representations, aiding in model evaluation and refinement.

3.1 LeNet-5 Architecture

LeNet-5 is well-suited for processing grayscale images of dimensions 32×32 pixels, making it suitable for our chest X-ray dataset. Its architecture comprises two convolutional layers followed by max-pooling layers, facilitating feature extraction from the input images. Additionally, three fully connected layers are integrated into the network for high-level feature extraction and classification. Rectified Linear Units (ReLU) serve as activation functions after each convolutional and fully connected layer, introducing non-linearity into the model and enabling it to learn complex patterns from the input data. Notably, the final layer of the LeNet-5 architecture consists of two neurons representing the classes: TB detected or not detected, allowing for binary classification of the chest X-ray images.

The LeNet-5 architecture, illustrated in Figure 3.1, outlines the network's convolutional and fully connected layers.

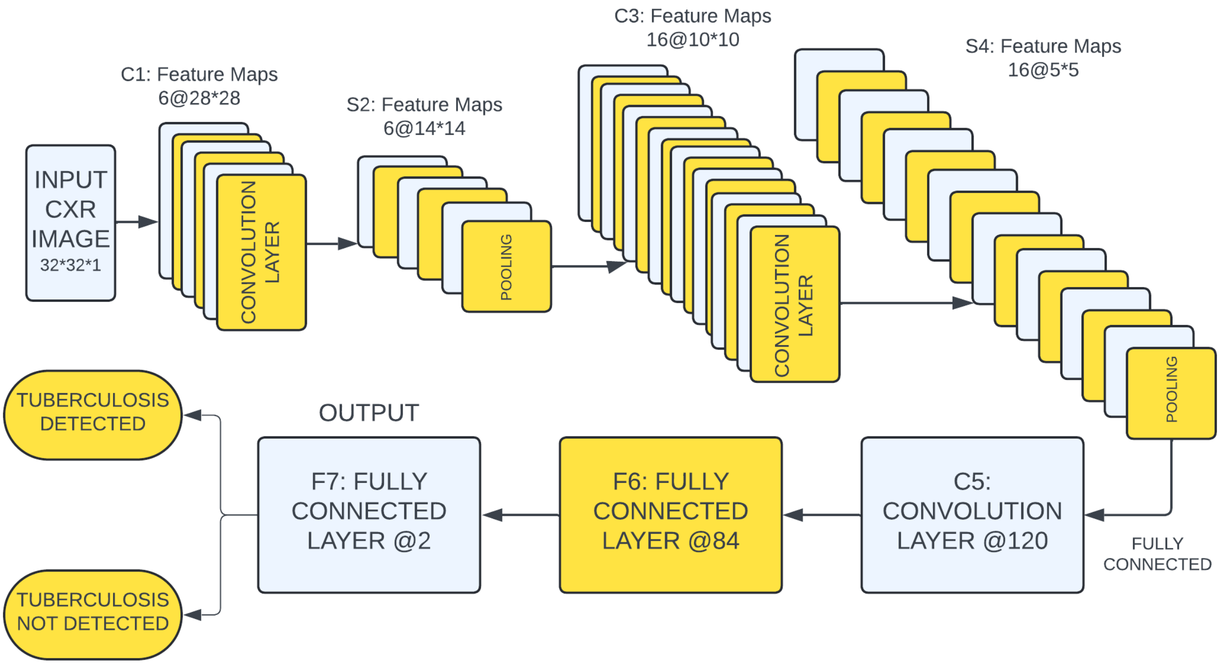

Figure 3.1: LeNet-5 Architecture

Table 3.1 provides a detailed description of each layer's parameters, including the number of filters/neurons, filter size, stride, feature map size, and activation function

Table 3.1: LeNet-5 Layers Description

Layer	**No. of Filters/Neurons**	**Filter Size**	**Stride**	**Feature Map Size**	**Activation Function**
Input	-	-	-	$32 \times 32 \times 1$	-
Conv1	6	5×5	1	$28 \times 28 \times 6$	ReLU
MaxPool1	-	2×2	2	$14 \times 14 \times 6$	-
Conv2	16	5×5	1	$10 \times 10 \times 16$	ReLU
MaxPool2	-	2×2	2	$5 \times 5 \times 16$	-
Conv3	120	5×5	1	$1 \times 1 \times 120$	ReLU
Flatten	-	-	-	120	-
FC1	84	-	-	84	ReLU
FC2	2	-	-	2	-

3.2 Dataset Used

Chest X-ray images from a variety of sources, mostly downloaded from Kaggle, make up the dataset used in this study. These photos are divided into groups according to their size and subject.

An overview of the datasets utilized may be seen in the table 3.2 below.:

Table 3.2: Overview of Chest X-ray Dataset

Dataset	$N_{\text{normal images}}$	$N_{\text{tb images}}$	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

Each dataset includes the overall count of TB-infected photos as well as a specified number of normal (non-TB) images. The 512 $\times$ 512 pixel dimension of the photographs offers enough resolution for activities involving analysis and classification.

3.3 Data Preprocessing

Chest X-ray images were gathered from Kaggle, a popular platform for datasets. These images were then preprocessed to ensure consistency and quality across the dataset. Preprocessing steps typically include resizing images to a uniform size, adjusting brightness and contrast, and removing noise.

3.4 Model Training

The LeNet-5 model, a convolutional neural network architecture, was chosen for TB detection. Training of the model was conducted using Anaconda Spyder IDE, a popular integrated development environment for Python programming. During training, the model learns to identify patterns and features in the X-ray images that are indicative of tuberculosis

3.5 Integration into AI-powered Web Platform

After training, the model was integrated into an AI-powered web platform. This involved using Python for backend development, PHP for server-side scripting, and XAMPP Server for hosting the web application. Integration allows users to upload chest X-ray images to the web platform for automatic TB detection.

Chapter 4

Experimental Setup

4.1 Dataset Description

There were 4200 chest X-ray pictures in the training and testing dataset. Out of them, 3500 photos were normal chest X-rays and 700 were TB-positive, meaning they showed signs of tuberculosis.

In addition, two key elements were emphasized to give a visual depiction of the dataset's composition:

The distribution of class types in the dataset is shown in Figure 4.1. To help comprehend the balance between the classes and any imbalances, this graphic provides insights into the proportion of TB-positive and normal chest X-ray images.

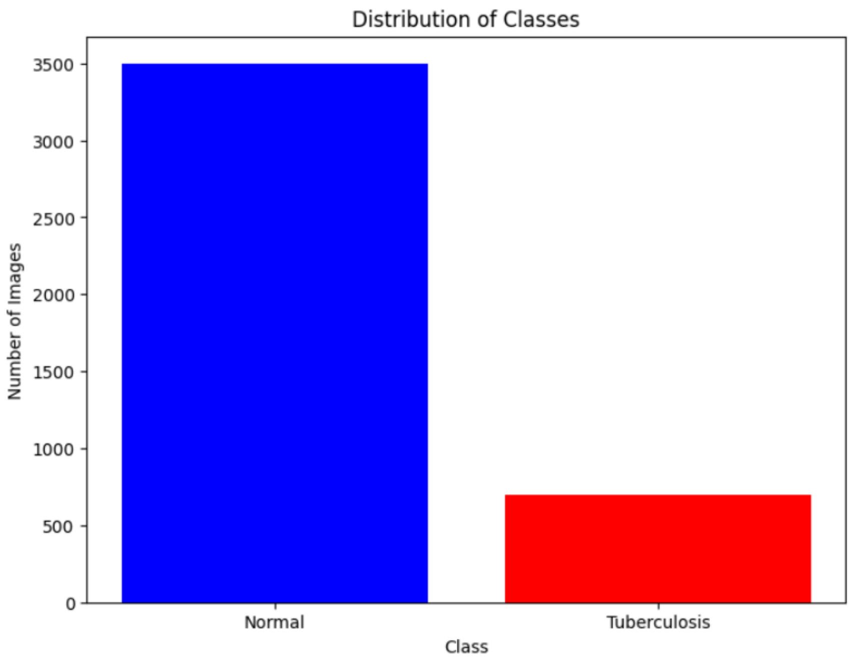

Figure 4.1: Distribution of Class types

A variety of sample images from each class type—TB-positive and normal chest X-rays—are shown in Figure 4.2. These sample photographs highlight the visual distinctions between normal chest X-ray images and TB-positive images, providing informative examples of the content contained in the dataset. They give an indication of the traits that machine learning models pick up on during training.

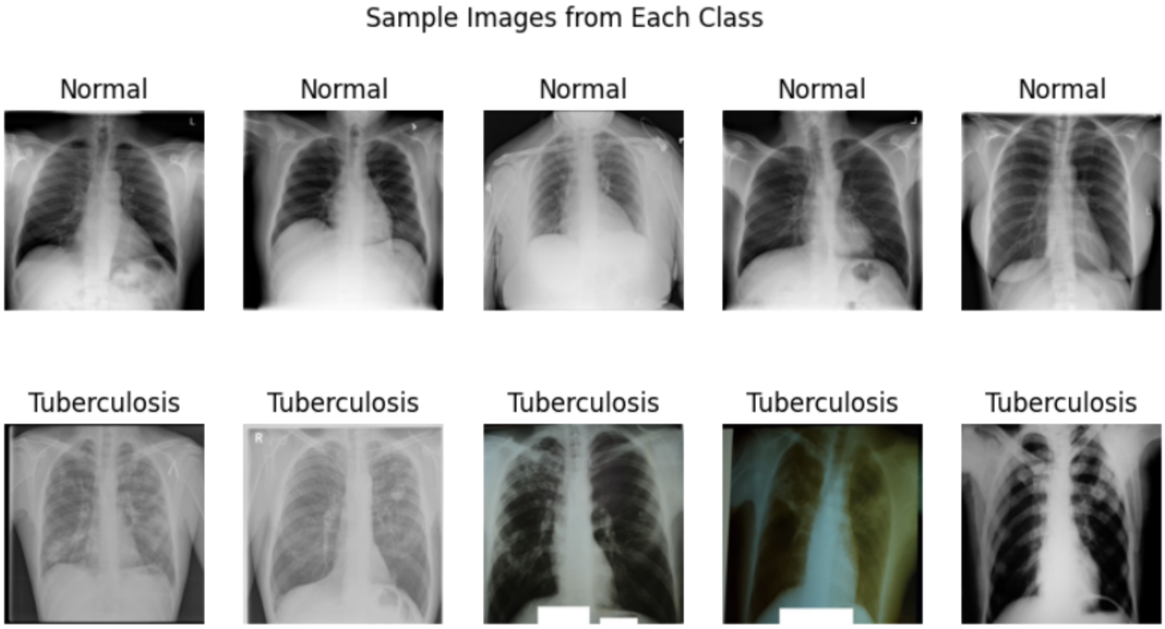

Figure 4.2: Sample images of Class types

4.2 Data Splitting

A methodical splitting procedure was applied to the dataset in order to guarantee an objective assessment of the model's performance. It was separated into three subsets, each with a specific function in the model-development process: the training, validation, and testing sets.

The training set, which made up 70% of the dataset, was essential to the model's training. To find patterns in the input data and improve the model's parameters, this subset was employed. The model may be trained to efficiently distinguish between normal chest X-ray images and TB-positive images by providing it with a vast and varied collection of training examples.

15% of the dataset was the validation set, which was used to track the model's performance during training and adjust its hyperparameters. Any indications of overfitting or underfitting could be found and fixed to guarantee optimal performance by routinely assessing the model on the validation set.

Lastly, the testing set, which made up the last 15% of the dataset, was used to evaluate the model's performance on data that had not yet been seen. It was maintained apart from the training and validation sets. This subgroup offered a practical assessment of the model's applicability and generalization capacity in real-world situations.

Figure 4.3 shows the distribution of TB-positive and normal chest X-ray pictures throughout the dataset subsets to give an indication of how the dataset categories are distributed visually.

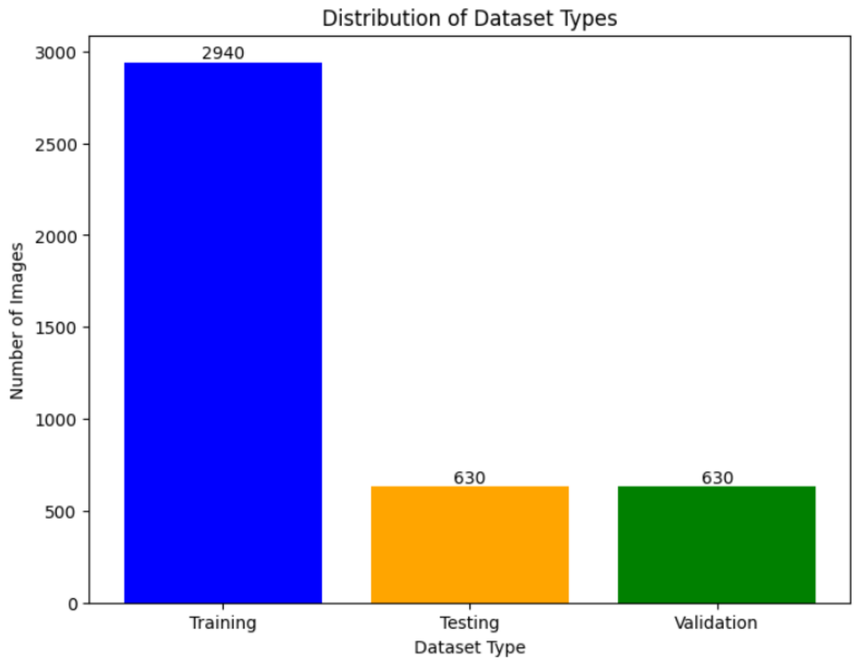

Figure 4.3: Distribution of Dataset types

4.3 Data Preprocessing

A number of preprocessing techniques were used to improve the quality of the photos and maximize the learning process prior to feeding them into the model. The purpose of these carefully thought-out preparation methods was to guarantee consistency and uniformity in the dataset, which would enhance the performance of the model.

First, the photos were resized to a common 32x32 pixel size. This ensured that the image dimensions were consistent and allowed for more effective processing. In order to standardize the input dimensions across all photographs and allow the model to learn from the dataset efficiently, resizing was an essential step.

After scaling, the photos' pixel values were adjusted using normalization techniques. Normalization facilitates the stabilization of the training process and accelerates convergence during model optimization by scaling the pixel values to a standard range, usually between 0 and 1.

To improve the dataset's variability and the resilience of the model, data augmentation techniques were also used. These methods included random horizontal flipping and random rotation up to 15 degrees, which introduce variances in the training data without changing the fundamental properties of the images.

These preparation processes ensured that the dataset was ready to be input into the model for training. This thorough preprocessing made that the model was fed high-quality, consistent input data, which allowed for optimal learning and enhanced the model's ability to identify tuberculosis from chest X-ray pictures.

4.4 Model Training

Using the preprocessed dataset, the LeNet-5 model was trained using a batch size of 32 and the Adam optimizer with a learning rate of 0.001. The model iteratively adjusted its parameters to minimize a predetermined loss function throughout the training phase. By doing this, it methodically improved its ability to distinguish between normal and TB-positive chest X-ray images, a crucial duty in medical diagnosis.

Notably, the Anaconda Spyder IDE was used for the model training process, which made for an environment that was ideal for efficient development and experimentation.

4.5 Model Evaluation

In order to gauge the model's capacity for generalization and avoid overfitting, its performance was assessed on the validation set following training. Performance metrics were computed to measure the efficacy of the model in tuberculosis detection, including accuracy, precision, recall, and F1-score. The following chapter will go into more information about this part.

4.6 Model Saving

The weights and architecture of the model were saved using the Python PyTorch package in a local directory for later usage after it had been trained and assessed. This makes it possible to quickly implement the trained model in the online application, where it can identify tuberculosis (TB) in real time on freshly uploaded chest X-ray images from users.

Chapter 5

Results and Discussions

5.1 Result

A few common evaluation matrices served as the basis for the model's evaluation. The formula for each evaluation matrix is displayed in Figure 5.1.

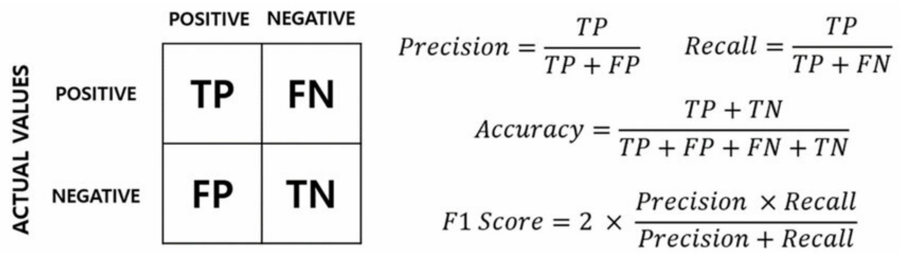

Figure 5.1: Evaluation Matrices Formula

5.1.1 Training and Validation Accuracy

Over 50 epochs, the training and validation accuracy are displayed in Figure 5.2. The graphic makes it evident that accuracy nearly becomes constant after more than 50 epochs. Thus, the model has only been sufficiently trained for more than 10 epochs.

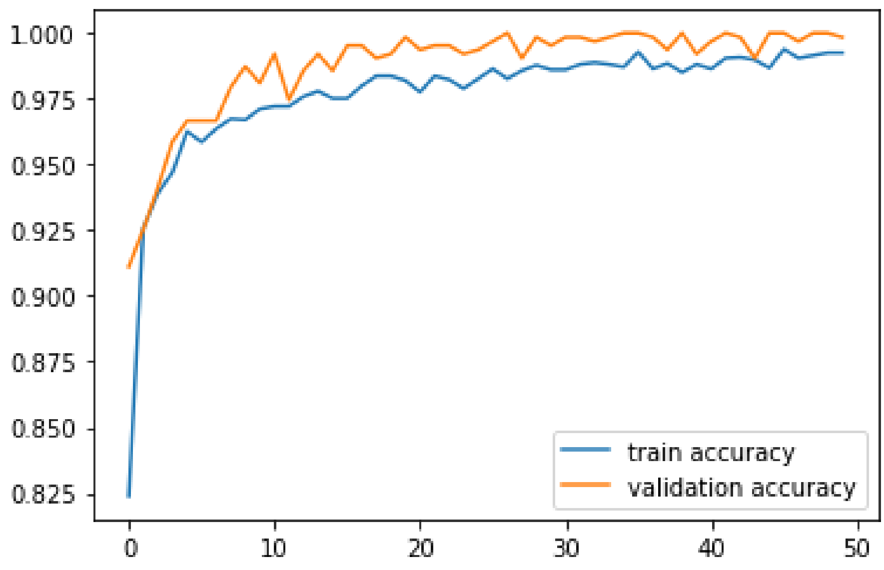

Figure 5.2: Plot of Training and Validation Accuracy over 50 Epochs

Over ten epochs, the training and validation accuracy is shown in Figure 5.3. The accuracy of the model increases with each training period, as shown by the constant growth in both curves. High accuracy on training and validation datasets indicates that the model is learning to correctly categorize normal chest X-ray images and tuberculosis.

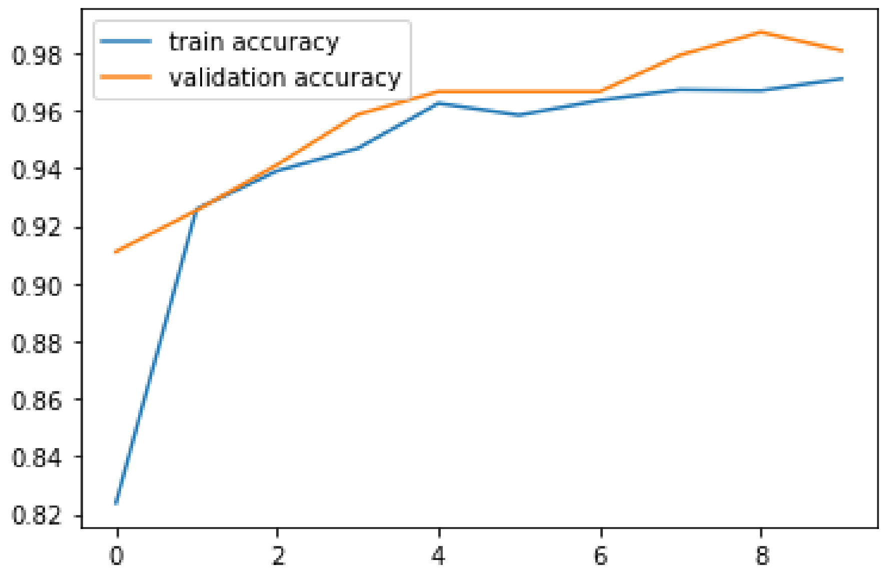

Figure 5.3: Plot of Training and Validation Accuracy over 10 Epochs

5.1.2 Training and Validation Loss

Ten epochs of training and validation loss are shown in Figure 5.4. As the model is trained, the plot displays the progressive decline in both training and validation loss. The convergence of the loss curves shows that the model is successfully learning from the training data and generalizing well to previously unseen validation data.

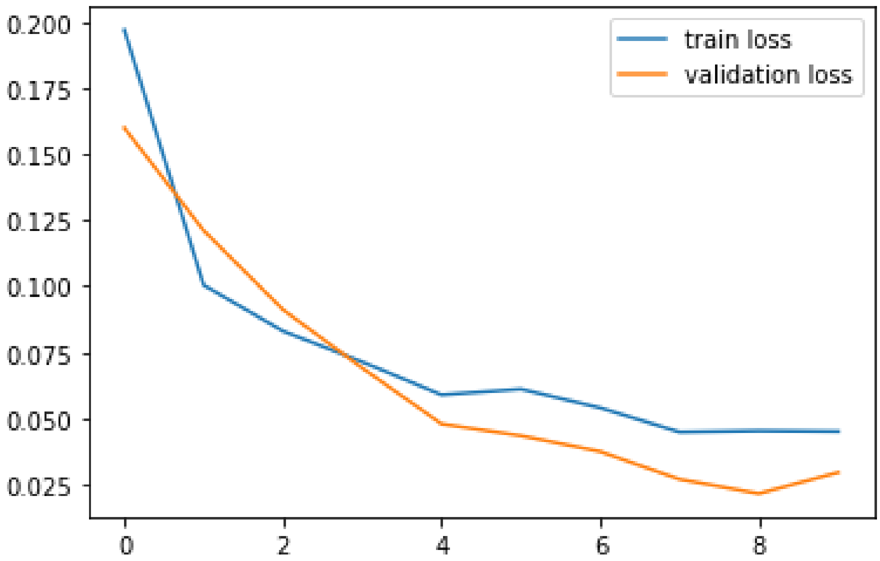

Figure 5.4: Plot of Training and Validation Loss over 10 Epochs

A precision matrix comparison between the Training and validation datasets is displayed in Figure 5.5. The precision on the validation datasets is 0.91, while it was 0.95 after training.

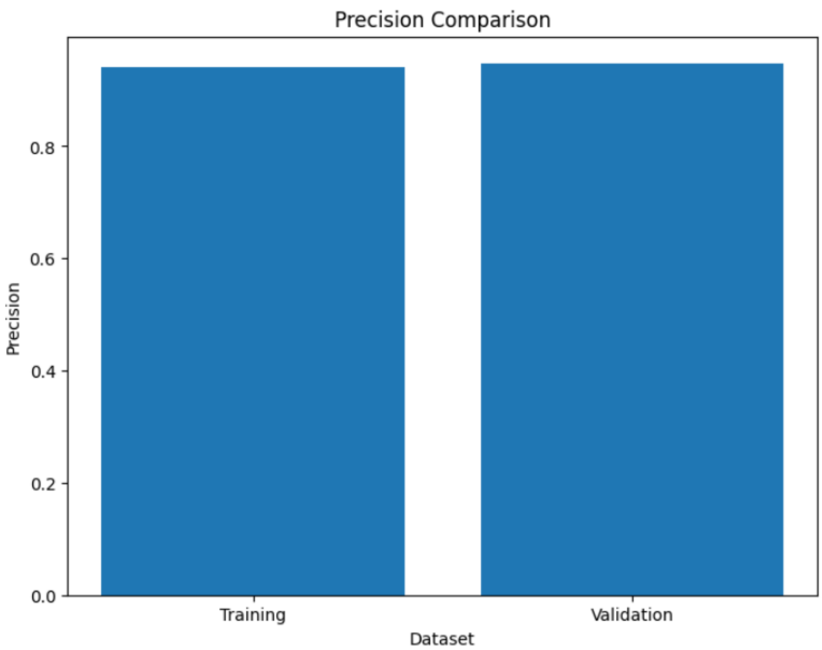

Figure 5.5: Precision Matrix Plot

A recall matrix comparison between the Training and validation datasets is displayed in Figure 5.6. Recall for the training dataset is 0.96, while recall for the validation datasets is 0.80.

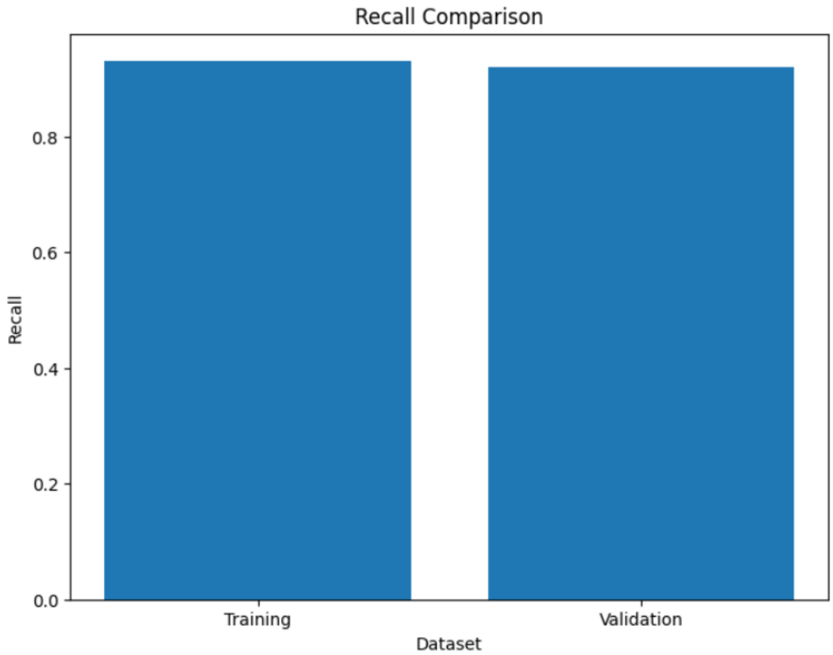

Figure 5.6: Recall Matrix Plot

An F1 score matrix comparison between the Training and validation datasets is displayed in Figure 5.7. On validation datasets, the F1 score was 0.87, while the training F1 was 0.95.

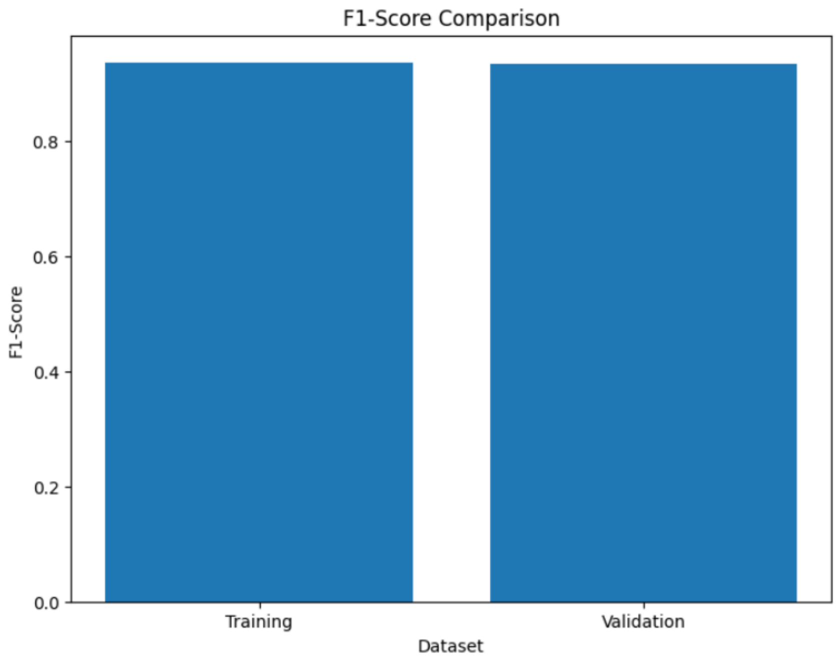

Figure 5.7: F1 score Matrix Plot

5.1.3 Confusion Matrix

Figure 5.8 presents a comprehensive analysis of the model's classification performance through the confusion matrix plot. It provides insights into the model's accuracy in identifying TB-positive and normal chest X-ray pictures by visualizing the distribution of true positive, true negative, false positive, and false negative predictions. Correct classifications are represented by diagonal elements, and incorrect classifications are shown by off-diagonal elements.

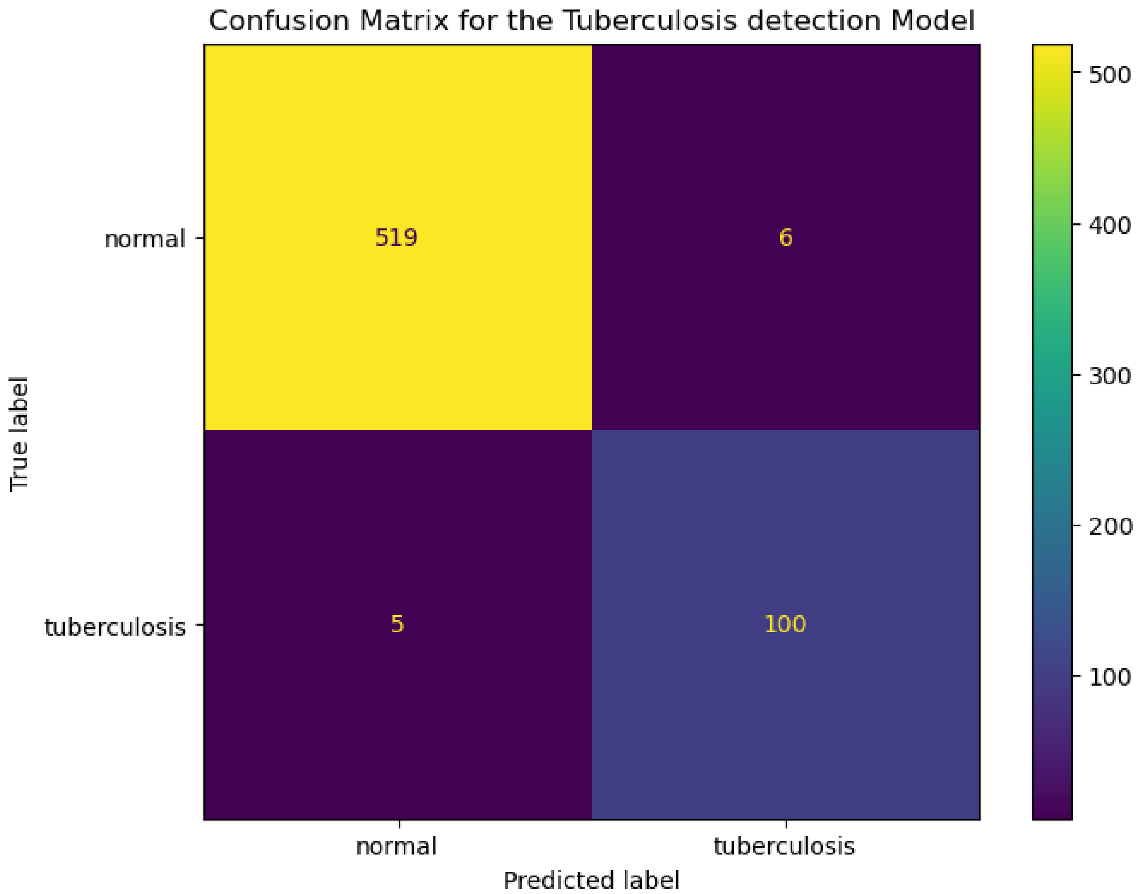

Figure 5.8: Confusion Matrix Plot

5.2 Comparative Analysis

Figure 5.9 examined how well different models performed using a dataset of eight hundred photographs. With 87% accuracy, ResNet50 and VGG16 were the exception. DenseNet121 also had respectable accuracy, although training took longer because to its intricate architecture. LeNet-5 is an effective option for TB detection jobs because it notably attained the greatest accuracy while requiring less training time when compared to other models.

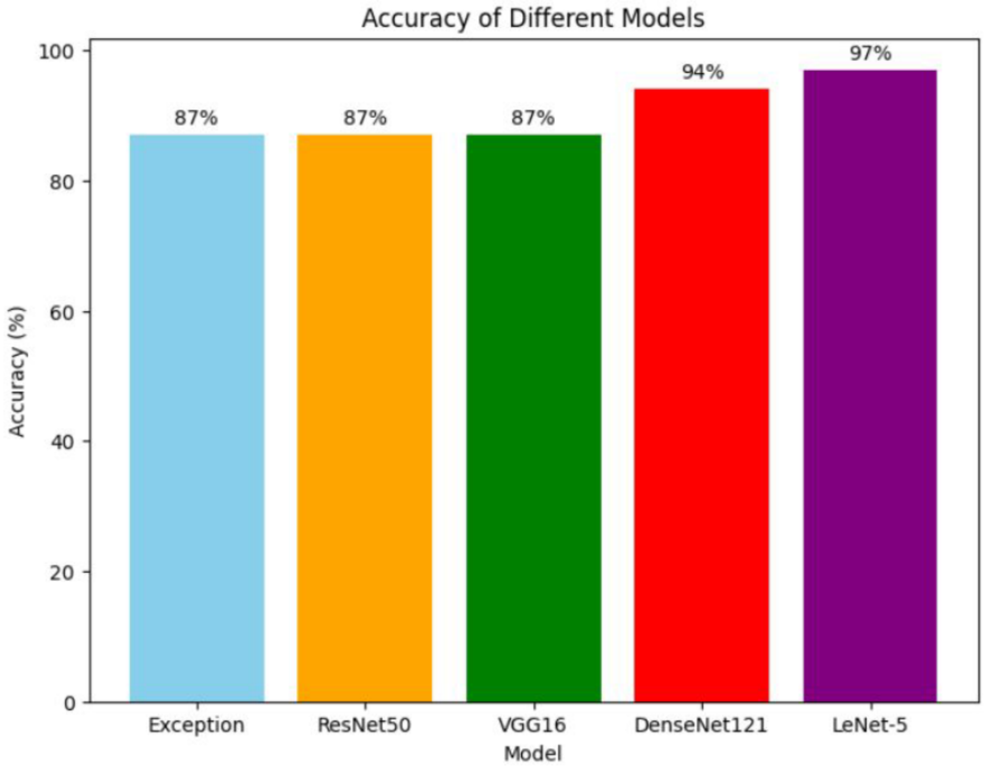

Figure 5.9: Plot for comparison between different models

Chapter 6

Web Platform Development

6.1 Platform Features

1. **User Authentication:** Through a login page where users can either register if they are new to the site or log in with their credentials, our platform ensures secure access. In order to maintain data integrity and privacy, user authentication requests are handled by a SQL database.

2. **Intuitive Navigation:** Our website's home page has an easy-to-use menu with links to Home, Services, AI Model, About Us, Contact Us, and Logout. Users can access various aspects of the platform with ease thanks to the user-friendly navigation.

3. **TB Detection Service:** By selecting the Detect Tuberculosis option on the home page, users can start the tuberculosis detection procedure. They are taken to a page where they can upload a chest X-ray (CXR) image as a result of this action. To find out if TB is present in an uploaded image, our software applies a locally saved, pre-trained AI model to it.

4. **Future Work:** Our platform is always changing, and we have future plans to add COVID-19 and pneumonia detection to our list of services. More details regarding these impending features are available on the "Services" page, giving users an idea of what the platform will be able to do in the future.

6.2 Backend Infrastructure

- **PHP and Python:** For backend development, our platform uses Python and PHP, which guarantees effective data processing and a smooth interface with the AI model.
- **XAMPP Server:** Users can use their web browsers to access our services locally thanks to the platform, which is hosted on the XAMPP server. Reliability and seamless performance are guaranteed by this configuration.

6.3 Frontend Design

- **HTML and CSS:** Our platform's frontend is made with HTML and CSS, which results in an aesthetically pleasing and intuitive user interface. Our website provides a seamless browsing experience from the login page to the home page.

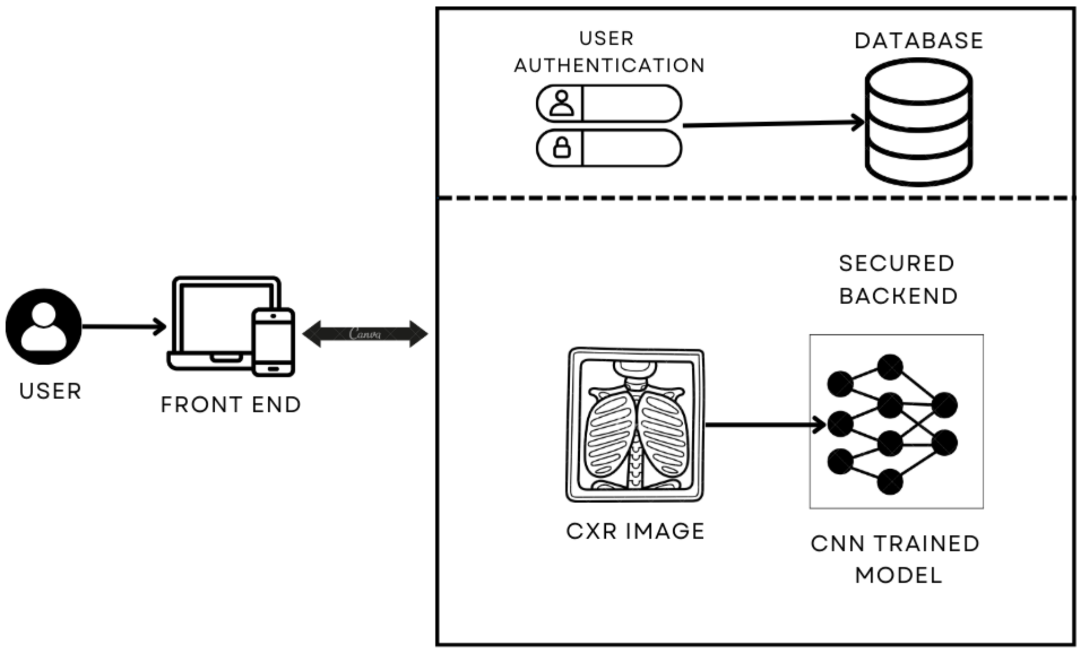

Figure 6.1: Architecture of Web Application

6.4 User Interface Screenshots

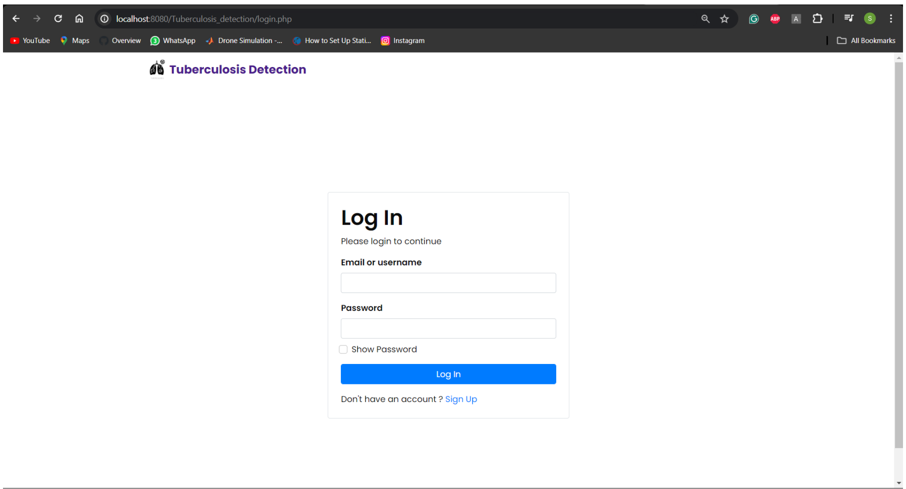

Figure 6.2: Login Page

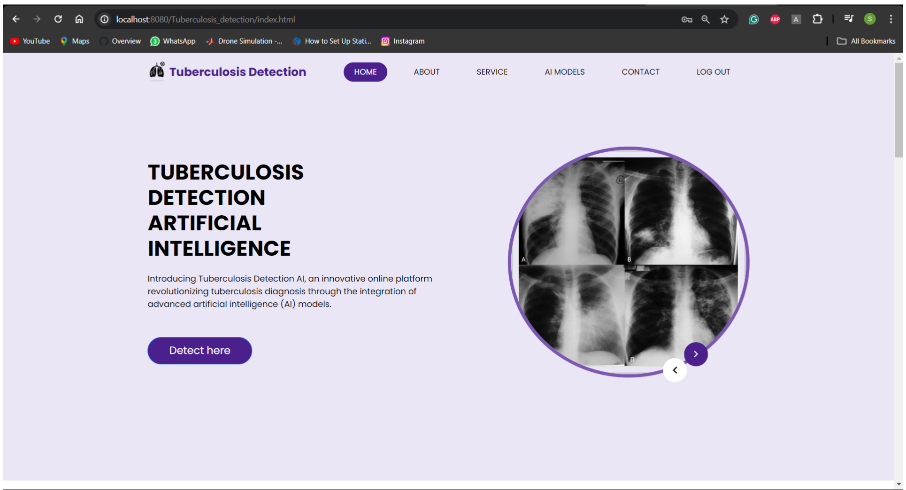

Figure 6.3: Main Page

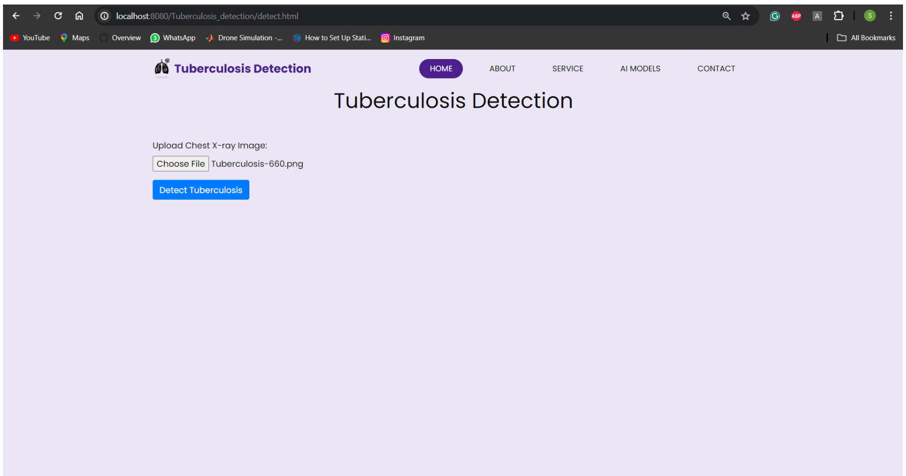

Figure 6.4: TB Detection on Tuberculosis Positive Image

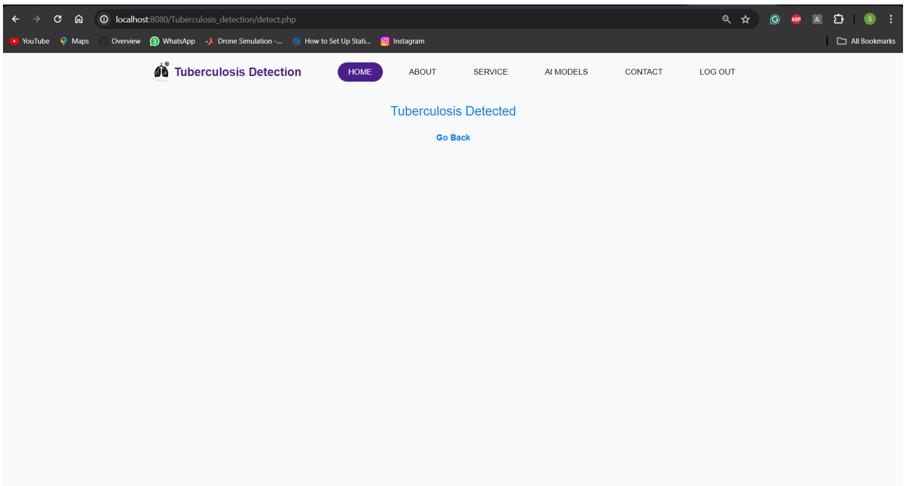

Figure 6.5: Result on TB Positive Image by Website

Chapter 7

Conclusion

This project's successful completion represents a critical turning point in medical diagnosis. We have developed an effective and user-friendly early screening tool by utilizing the LeNet-5 deep learning technique to establish an AI-powered web platform for tuberculosis detection. Users can now check for early detection of tuberculosis with an astounding accuracy rate over 95% with just a chest X-ray image upload.

I see the platform continuing to improve public health outcomes all throughout the world as we bring it online. By enabling early diagnosis and response, this platform will aid in the global fight against tuberculosis and ultimately improve treatment outcomes and lower transmission rates. Additionally, we are laying the groundwork for a healthier future where cutting-edge technologies are used for medical diagnostics by utilizing AI technology.

To sum up, this study shows how AI-driven solutions may be used to solve urgent healthcare issues, which is a major advancement in the field of medical diagnostics. Our commitment to utilizing technology for the benefit of society and providing significant support to global health projects does not waver as we work to improve and broaden our platform.

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