School of Information Technology and Engineering

Software Engineering Process, Tools & Methods– 'J' Component – 3rd Review

Title of the project: TUBERCULOSIS DETECTION WITH X-RAY IMAGES

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Abstract

Tuberculosis (TB) is a chronic lung disease that occurs due to bacterial infection and is one of the top 10 leading causes of death. It is transmitted by aerosol inhalation of the bacterium Mycobacterium tuberculosis (MTB) from an infected individual. During infection, a wide variety of pulmonary disease lesion presentations may concurrently present within the same host. Accurate and early detection of TB is very important, otherwise, it could be life-threatening. The latest World Health Organization (WHO) study on 2018 is showing that about 1.5 million people died and around 10 million people are infected with tuberculosis (TB) each year. Moreover, more than 4,000 people die every day from TB.

A number of those deaths could have been stopped if the disease was identified sooner. In this work, we have detected TB reliably from the chest X-ray images using image pre-processing, data augmentation, image segmentation, and deep-learning classification techniques. We also used a visualization technique to confirm that CNN learns dominantly from the segmented lung regions that resulted in higher detection accuracy.

1. Introduction

Tuberculosis (TB) is caused by bacteria (Mycobacterium tuberculosis) that most often affect the lungs. Tuberculosis is curable and preventable. TB is spread from person to person through the air. When people with lung TB cough, sneeze or spit, they propel the TB germs into the air. The risk of TUBERCULOSIS is immense for many, especially in developing nations where billions face energy poverty and rely on polluting forms of energy. The WHO estimates that over 4 million premature deaths occur annually from household air pollution-related diseases including pneumonia. Over 150 million people get infected with pneumonia on an annual basis especially children under 5 years old. In such regions, the problem can be further aggravated due to the dearth of medical resources and personnel. For example, in Africa's 57 nations, a gap of 2.3 million doctors and nurses exists. For these populations, accurate and fast diagnosis means everything. It can guarantee timely access to treatment and save much needed time and money for those already experiencing poverty.

2. Literature Survey

[1] Incorporating DL technique with Unsharp Masking (UM) and High-Frequency Emphasis Filtering (HEF) image enhancement, this paper uses EfficientNet-B4, ResNet-50 and ResNet-18 in order to train the TB images and improve the detection accuracy. The experiments showed that the accuracy of the proposed idea is very competitive. Moreover, in terms of the AUC and accuracy, we also thoroughly compared the results with previous works, the proposed idea achieved better results. The use of an image enhancement system to preprocess the TB images will thus allow the tested pre-trained network to learn better model. Future works will evaluate more image enhancement techniques in order to show a more significant effect of enhancement on DL models

[2] This work presents a transfer learning approach with deep Convolutional Neural Networks for the automatic detection of tuberculosis from the chest radiographs. The performance of nine different CNN models were evaluated for the classification of TB and normal CXR images. ChexNet model outperforms other deep CNN models for the datasets without image segmentation whereas DenseNet201 outperforms for the segmented lungs. The classification accuracy, precision, and recall for the detection of TB were found to be

96.47%, 96.62%, and 96.47% without segmentation and 98.6%, 98.57%, and 98.56% with segmentation respectively. It was also shown that image segmentation can significantly improve classification accuracy.

[3] As we all know, TB is a virulent infection disease, and several countries are suffering from a lack of resources, particularly developing countries. Therefore, every single positive case must be identified. The study introduced an approach to combined pretrained CNNs such as ResNet101, VGG19, and DenseNet201 with the XGBoost model to detect TB from CXR images.

[4] This work presents a workable solution for the detection of Tuberculosis from chest X-ray images. Starting from the observation that while existing approaches obtained an encouraging prediction performance, most of them have been evaluated on small and un-diverse datasets, we hypothesize that such a good performance might not hold for heterogeneous data sources, which originate from real world scenarios. Our model has been implemented based on two building blocks: deep convolutional neural networks with EfficientNet and Attention with Vision Transformer as the prediction engines, and effective transfer learning algorithms. One of the main advantages of EfficientNet is that the network family is compact as it is small in size and efficient, allowing us to incorporate various augmented techniques, e.g., Vision Transformer and Transfer Learning. An empirical evaluation on a considerably large dataset combined by using various datasets, which have been widely used in different papers, shows that our system obtains a better prediction performance compared to relevant studies. We conclude that the combination of EfficientNet with Vision Transformer and Learning brings in substantial improvement in performance compared to state- of the-art approaches.

[5] Diagnosis of Pulmonary infection through chest X-ray needs expertise. A diagnostic challenge to the physician is especially because diseases that mimic each other. The misdiagnosis may lead to inappropriate treatment which may risk the life of a patient. In this paper, we have proposed a novel framework to classify TB, Bacterial pneumonia, and Viral pneumonia in chest X-ray in by using the Neural Network classifier. The previous works in this field have accuracy less than ours because they took the height and width of the image into consideration but the depth information was lost. And in our framework, we have taken images at different angles and shifting the images horizontally and vertically and rescaling the it.

[6] A supervised deep learning model developed by using the training dataset from one population may not always have the same diagnostic performance in another population. Technical specification of CXR images, disease severity distribution, dataset distribution shift, and overdiagnosis should be examined before implementation in other settings.

[7] Computer aided diagnostic methods utilise radiographical data and machine learning algorithms for the early detection of several life-threatening diseases such as Tuberculosis, Pneumonia, COVID19 and Cardiovascular diseases. A robust automated system using non-invasive chest radiography that would be accessed by medical practitioners to detect subtle characteristics of pulmonary Tuberculosis is essential. The proposed scheme studies the effect of ELM and its variant in differentiating healthy and PTB patients in chest radiographs using integrated local texture descriptors. Both the classifiers with significant features are found to localize abnormalities by providing high classification sensitivity. The overall performance of ELM is found to be high. OSELM achieved the highest sensitivity in abnormality detection with minimal number of features.

[8] Efforts to develop effective and safe drugs for treatment of tuberculosis require preclinical evaluation in animal models. Alongside efcacy testing of novel therapies, effects on

pulmonary pathology and disease progression are monitored by using histopathology images from these infected animals. To compare the severity of disease across treatment cohorts, pathologists have historically assigned a semi-quantitative histopathology score that may be subjective in terms of their training, experience, and personal bias. Manual histopathology therefore has limitations regarding reproducibility between studies and pathologists, potentially masking successful treatments.

[9] This article compares the improved CNN model with the traditional machine learning algorithm as SVM [8], Naive Bayes classifier [9], CART decision tree and KNN [10], compares and analyzes its accuracy in tuberculosis classification. Table III shows the comparison of test accuracy of different algorithms

[10] The mixture of Gaussians performed best in the first stage of classification. It showed the lowest ratio of incorrectly classified pixels, which translates into few outlier pixels classified as bacilli. It picked up most of the bacilli with their length in the focal plane of an image; the relatively low percentage of correctly classified pixels (75.74%) was mainly due to inaccuracies in detecting object outlines. The MOG classifier performed best in the second stage of classification, using all features. Among the different feature sets, eccentricity and compactness produced the highest accuracy for all classifiers (Table II); the addition of Fourier features and moments increased specificity and reduced sensitivity for the Gaussian and MOG classifiers, and reduced overall performance for the PCA and KNN classifiers. The PCA classifier performed poorly on the linear Fisher mapped test set because it requires variance of features, which is removed by Fisher mapping. Fisher mapping improved specificity but reduced sensitivity for the other classifiers.

[11] This work provides a proof of concept on how image processing techniques can be applied to automatically detect bacilli in microscopic images of sputum treated with the ZN stain. This staining procedure introduces several strange objects in the detection process as opposed to the Auramine staining process. Even with simple techniques for acquisition of images and classification of objects, the results are close to previously reported attempts.

[12] In this paper they propose a novel study for automatic diagnosis of TB based on image classification and plasmonic ELISA. This research study has two research contributions. First, it integrates a biosensing mechanism (i.e., plasmonic ELISA) with computational intelligence to detect TB. Second, it compares the classification performance of various types of classifiers. The results of applying the classifiers on the testing dataset (25% of the whole dataset) show high accuracy rate (>94%) despite blurriness in the images. The bagged tree method uses random forest classifier with decision tree learners. We have varied the number of learners (100 – 300 learners) in our simulations but observed no significant change in the predictive performance.

[13] The best-performing classifier had an AUC of 0.99, which was an ensemble of the AlexNet and GoogLeNet DCNNs. The AUCs of the pretrained models were greater than that of the untrained models (P, .001). Augmenting the dataset further increased accuracy (P values for AlexNet and GoogLeNet were .03 and .02, respectively). The DCNNs had disagreement in 13 of the 150 test cases, which were blindly reviewed by a cardiothoracic radiologist, who correctly interpreted all 13 cases (100%). This radiologist-augmented approach resulted in a sensitivity of 97.3% and specificity 100%.

[14] A scheme to segment and classify TB bacilli from ZN-stained images is presented. The bacilli are segmented by thresholding the hue component by choosing an appropriate range adaptively based on the input image. The beaded structure of the bacilli is obtained by segmenting the saturation

component. The presence of beaded structure and thresholds chosen for thread length, thread width and area parameters are used to identify valid single bacillus. Results presented for various images showed that the scheme performs well in spite of the variations in the images.

[15] We have presented a ConvNet model that uses VGG16 for classifying CXR images to identify patients suffering from TB. Previous research on CXR classification applied complex models for lung segmentation prior to training the model using Support Vector Machines. We show that VGG16 can use the raw data to classify the results with comparable accuracy without any form of pre-processing done in the previous research. To further increase the accuracy VGG16 was reapplied on a subset of data after performing augmentation to see if we could achieve a higher accuracy. Results indicated that accuracy increases when VGG16 is applied on augmented images.

[16] This work presents an advanced neural network architecture optimized for tuberculosis diagnosis. We can train this specialized architecture from scratch and achieve good results compared to other publications, while reducing the computational, memory and power requirements significantly. We also analyzed the output with saliency maps and grad-CAMs and found that saliency maps offer a good visual explanation of the network decision. Saliency maps were interpreted by an expert radiologist (one of the authors, D.P.) and were found to highlight areas where tuberculosis was visible in many cases.

[17] The developed algorithm detects the TB bacilli automatically. This automated system reduces fatigue by providing images on the screen and avoiding visual inspection of microscopic images. The system has a high degree of accuracy, specificity and better speed in detecting TB bacilli. The method is simple and inexpensive for use in rural/remote areas in the emerging economies. Segmentation algorithm is developed to automate the process of detection of TB using digital microscopic images of different subjects.

[18] The algorithm recognized AFB under wide latitudes of staining, magnification and resolution (Figure 2). In Figure 2a,b nearly all visible bacilli were color-labeled as TB objects (green); conglomerations were labeled possible objects (blue). In Figure 2c,d the single typical TB bacillus was clearly recognized alongside a minor artifact. In Figure 2e,f, all AFB were recognized. In a challenge tissue slide (image not shown), the single TB bacillus was successfully detected without artifacts.

[19] The obtained results allow to conclude that the bacilli segmentation in the digital image by using the proposed methodology has up to 92% effectiveness, under different color and contrast image conditions. For normalized images, the method provides up to 98% effectiveness. The bacilli detection can be performed based on these segmentation results, helping to identify the bacilli by shape and size. In order to increase the robustness of the system, it is necessary to perform preprocessing tasks to eliminate such variability by standardizing the RGB components of the image. In addition, it is necessary to consider the image resolution in order to obtain adequate segmentation results.

[20]	An automatic detection of tuberculosis for lung images is presented in this paper. The location of tuberculosis within the lung varies with the stage of infection and age of patient. The X-ray images contain variable lung shapes, a static model is not sufficient to describe the lung regions. In our method, linearly align all training masks to a given input CXRs by using rigid registration. The average mask computed on a subset of most similar training masks is used an approximate lung model for the input CXR. An approximate model is segmented using the watershed segmentation. Moreover, to improve the accuracy of the segmentation results noise and contrast is improved by using wiener filter and histogram equalization. The proposed method is evaluated by JSRT and MC dataset. We compare the global thresholding and active contour method of image segmentation with proposed algorithm and found that the accuracy of the proposed method is 60% compared with active contour and global thresholding

3. Methodology

Introduction of Tensor flow

TensorFlow is an open-source software library developed by Google for building and training machine learning models. It is one of the most popular machine learning libraries used today, and is widely used in a variety of fields, including computer vision, natural language processing, and deep learning.

TensorFlow is designed to be flexible, allowing developers to create and train a wide range of machine learning models, from simple linear models to complex deep neural networks. It provides a high-level API for building and training models, as well as lower-level APIs for more fine-grained control over model development.

One of the key features of TensorFlow is its ability to perform distributed training, allowing developers to train models on large datasets using multiple machines. TensorFlow also includes a suite of tools for visualizing and debugging models, as well as tools for deploying models in production environments.

TensorFlow is a powerful and versatile library for machine learning, offering a wide range of tools and capabilities for building and training models.

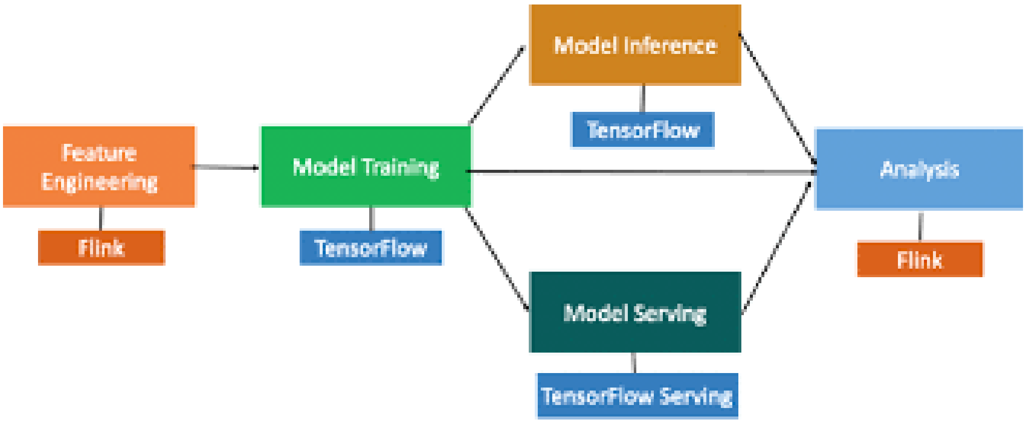
Methods used in TensorFlow

TensorFlow provides a variety of methods for building and training machine learning models. Here are some of the most commonly used methods in TensorFlow:

- **Data Loading and Pre-processing:** TensorFlow provides methods for loading and pre-processing data, such as the TensorFlow data API, which can be used to efficiently load large datasets and perform data transformations.
- **Model Creation:** TensorFlow provides a high-level API called Keras, which can be used to create and train a wide range of machine learning models, including feedforward neural networks, convolutional neural networks, and recurrent neural networks.

- **Model Training:** TensorFlow provides a variety of methods for training machine learning models, including gradient descent optimization algorithms like Stochastic Gradient Descent (SGD), Adam, and Adagrad.
- **Model Evaluation:** TensorFlow provides methods for evaluating the performance of machine learning models, such as computing accuracy, precision, recall, and F1 score.
- **Visualization:** TensorFlow provides tools for visualizing models, such as TensorBoard, which can be used to visualize the model architecture, training progress, and performance metrics.
- **Deployment:** TensorFlow provides methods for deploying trained models in production environments, such as the TensorFlow Serving API, which can be used to serve models over a network.

These are just a few of the methods provided by TensorFlow. TensorFlow is a very versatile library and provides many other methods and features for building and training machine learning models.



TensorFlow method using tuberculosis detection with x - ray images

TensorFlow is an open-source machine learning framework that can be used to build and train deep learning models. It provides tools for building, training, and deploying machine learning models, making it a popular choice for applications such as tuberculosis detection using X-ray images.

Tuberculosis is a bacterial infection that primarily affects the lungs. One way to detect tuberculosis is by analysing X-ray images of the lungs, looking for signs of the infection such as nodules or cavities.

To use TensorFlow for tuberculosis detection with X-ray images, you would typically follow these steps:

- Collect a dataset of X-ray images of the lungs that have been labeled as either "positive" or "negative" for tuberculosis.
- Pre-process the images to prepare them for analysis. This might involve resizing the images, adjusting the contrast and brightness, and normalizing the pixel values.

- Use TensorFlow to build a deep learning model that can classify the X-ray images as either positive or negative for tuberculosis. This might involve using a convolutional neural network (CNN) architecture, which is well-suited to image classification tasks.
- Train the model on the labelled dataset, using techniques such as stochastic gradient descent to adjust the model's parameters to improve its accuracy.
- Evaluate the model's performance on a separate test dataset, to ensure that it is able to generalize well to new, unseen data.
- Deploy the trained model in a real-world application, such as a medical diagnostic tool that can assist radiologists in detecting tuberculosis from X-ray images.
- By using TensorFlow to build and train a deep learning model for tuberculosis detection, it is possible to create an accurate and reliable tool for diagnosing this potentially life-threatening disease.

4. Experiments

Feature	Computer-aided Detection	Tensorflow	CNN
Training Data	Labeled X-ray images	Labeled X-ray images	Labeled X-ray images
Implementation Complexity	Low/Moderate	High	High
Performance	High accuracy and specificity	High accuracy and specificity	High accuracy and specificity
Speed	Fast (near-instantaneous results)	Fast (depending on hardware and software)	Fast (depending on hardware and software)
Customization	Limited (algorithm-based)	Highly customizable	Highly customizable

Hardware Requirements	Moderate	High	High
Cost	Moderate	High	High
Maintenance	Low	High	High
Accuracy	83.2%	94%	80%

5. Result and Analysis

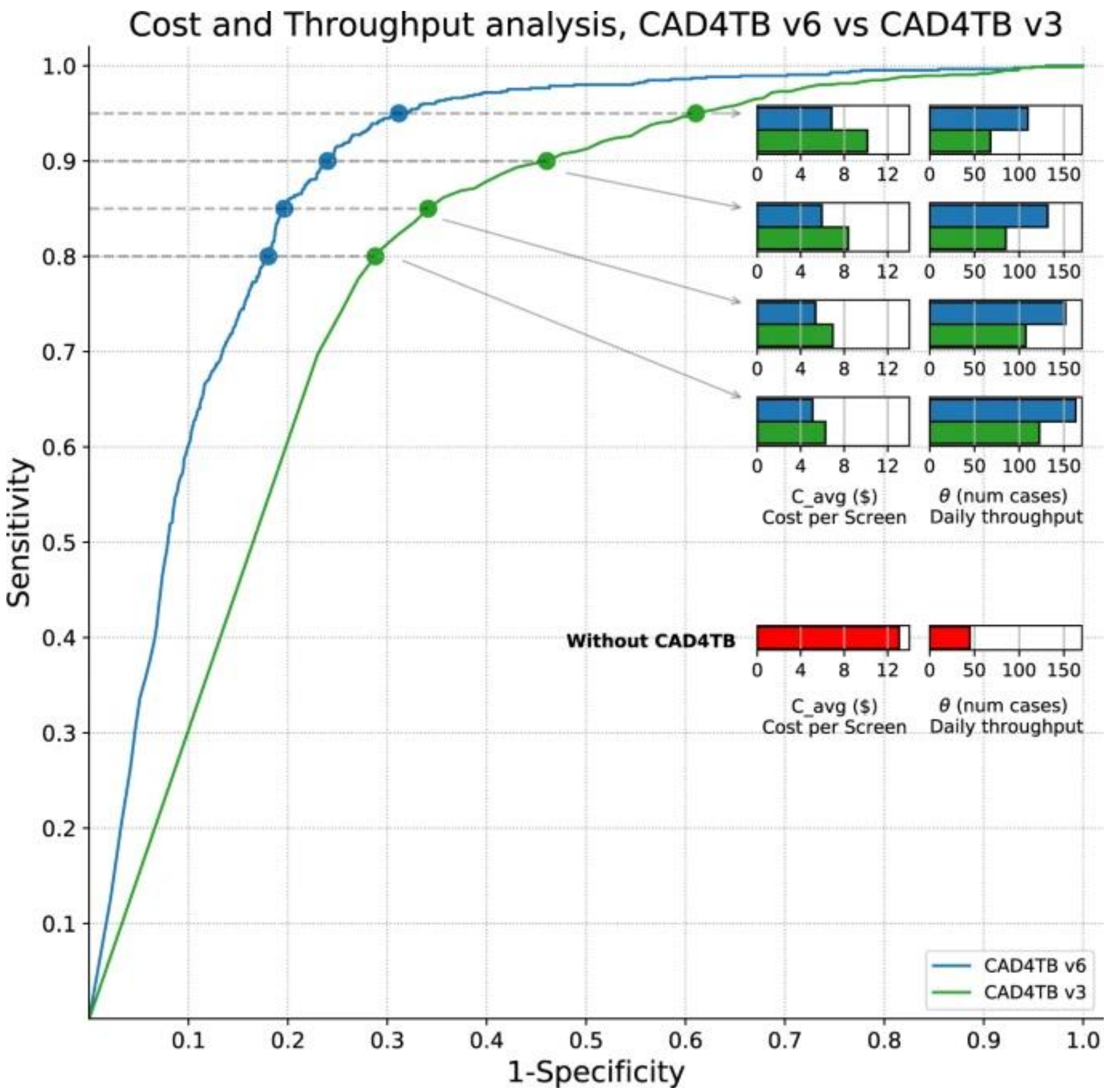
TensorFlow machine algorithm gives higher accuracy than others. Which is 94%. But CAD gives 83.2% and CNN gives 80%.

Cost Analysis:

However, computer-aided detection may be less expensive than developing a custom deep learning model using TensorFlow and CNN.

CAD software is commercially available and can be purchased or licensed from various vendors, which may offer different pricing models depending on factors such as the size and complexity of the dataset, the number of users, and the level of support required. While the cost of CAD software may still be significant, it may be more affordable than developing and training a custom deep learning model from scratch.

On the other hand, developing and training a custom deep learning model using Tensorflow and CNN requires specialized expertise in deep learning and may involve significant time and resources for data acquisition, pre-processing, and model development. Additionally, the cost of hardware, software, and personnel required for developing and training a custom model can be high.



[Reference: https://www.nature.com/articles/s41598-020-62148-y]

Time Taken:

Computer-Aided Detection - Faster

CNN and TensorFlow - Slower than CAD

In general, both CAD and deep learning models can provide fast and accurate results when used for tuberculosis detection. However, the specific speed and performance of each approach will depend on the specific implementation and use case, and may require careful optimization and tuning to achieve optimal performance.

6. Testing

Dataset:

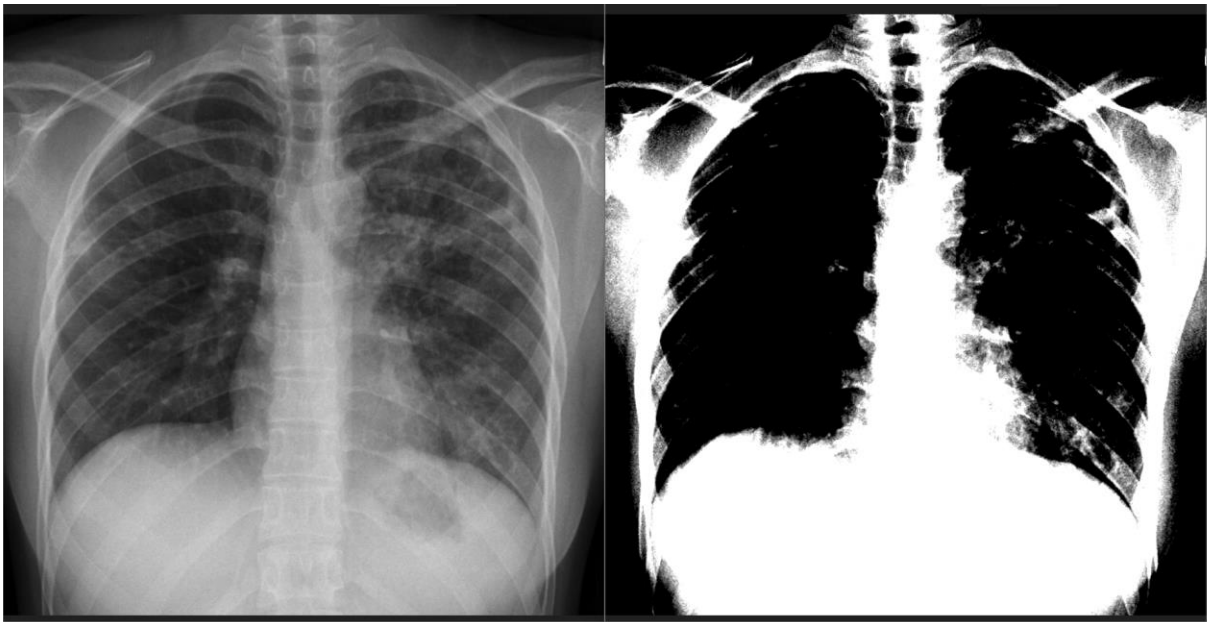
https://paperswithcode.com/dataset/shenzhen-hospital-x-ray-set

https://data.lhncbc.nlm.nih.gov/public/Tuberculosis-Chest-X-ray-Datasets/Montgomery-County-CXR-Set/MontgomerySet/index.html

Pre-processing:

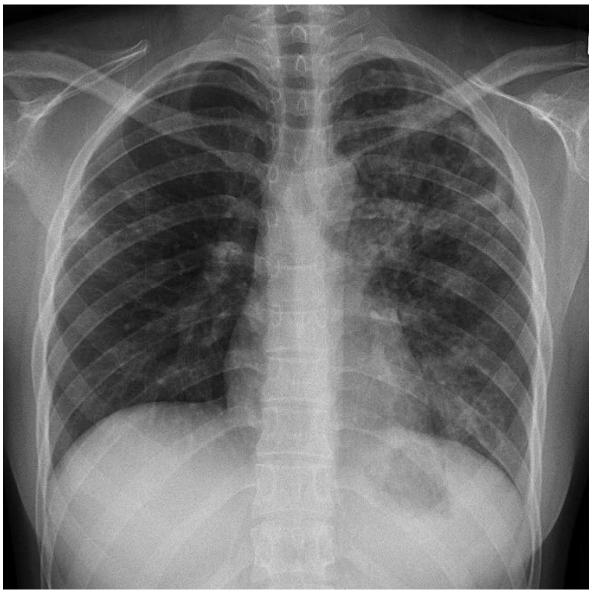
https://github.com/GokulChandar17/TB_detection_using_CNN_TensorFlow/tree/main/TB_detection/Tuberculosis_preprocessing

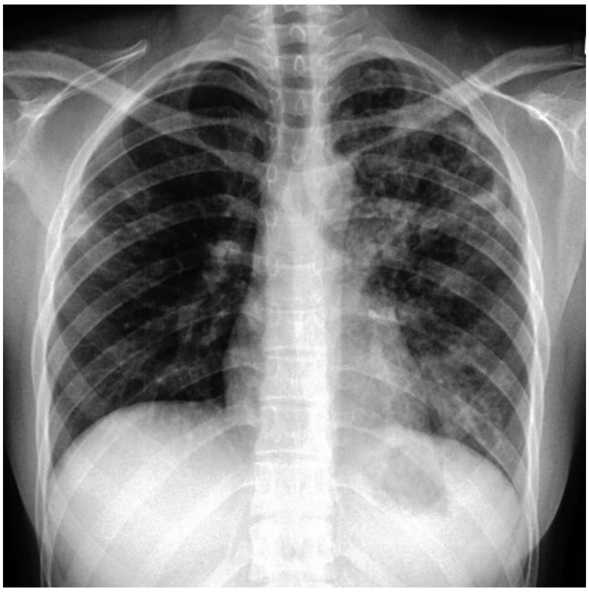
Image Enhancement:



ORIGINAL IMAGE ENHANCED IMAGE

Histogram Equalization:





ORIGINAL HISTOGRAMISED IMAGE

Image Filtration:

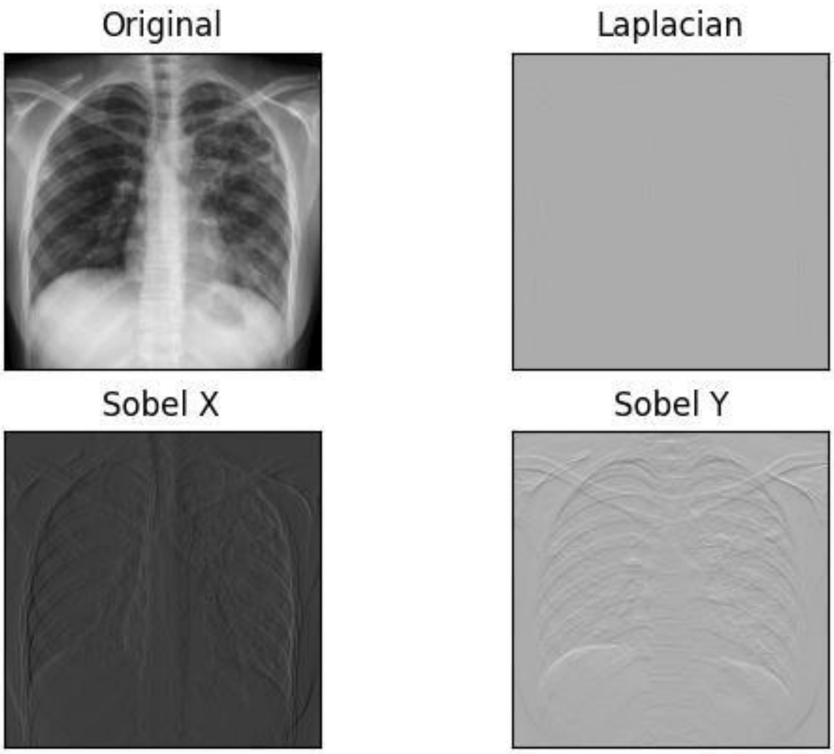
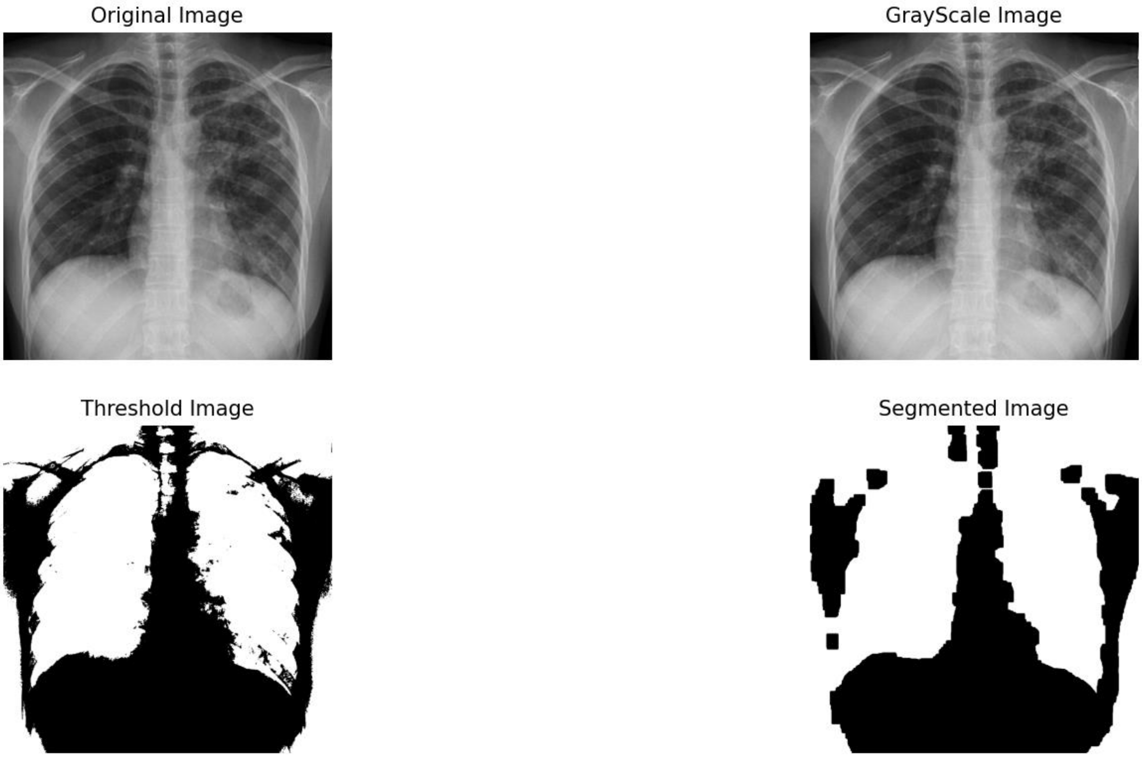
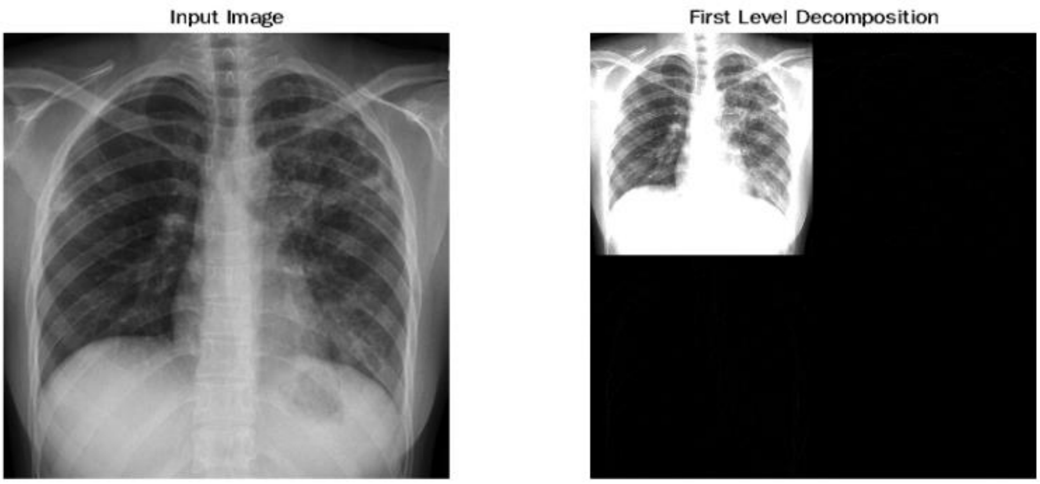


Image Segmentation:

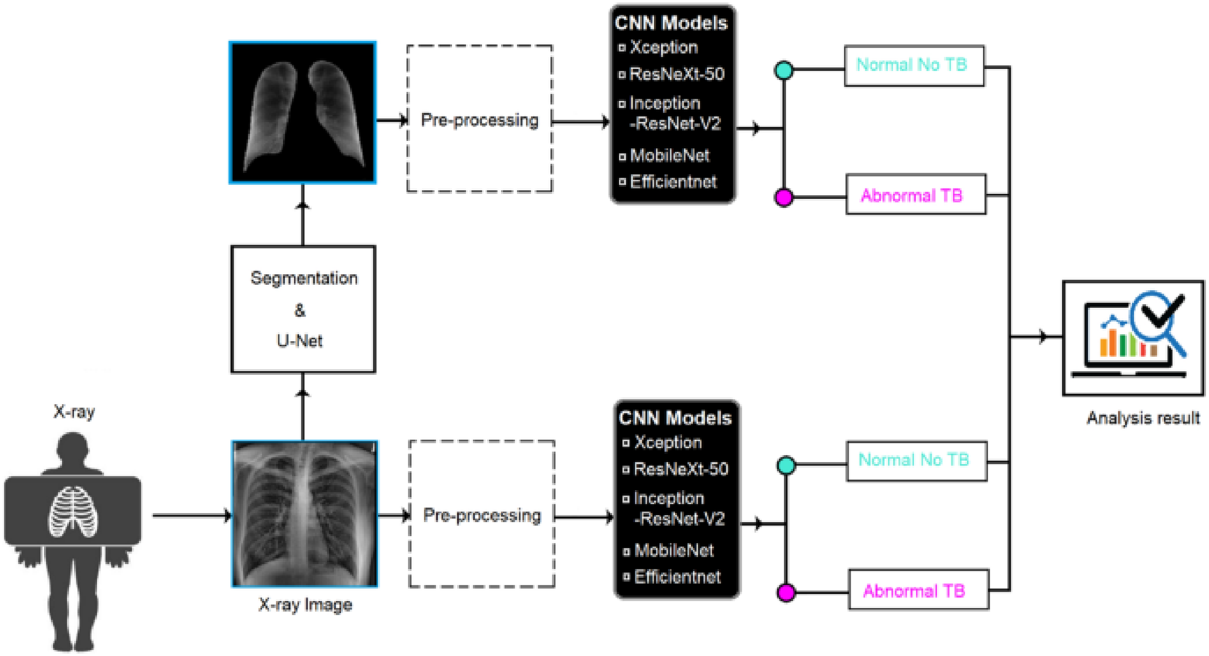


Feature Extraction:

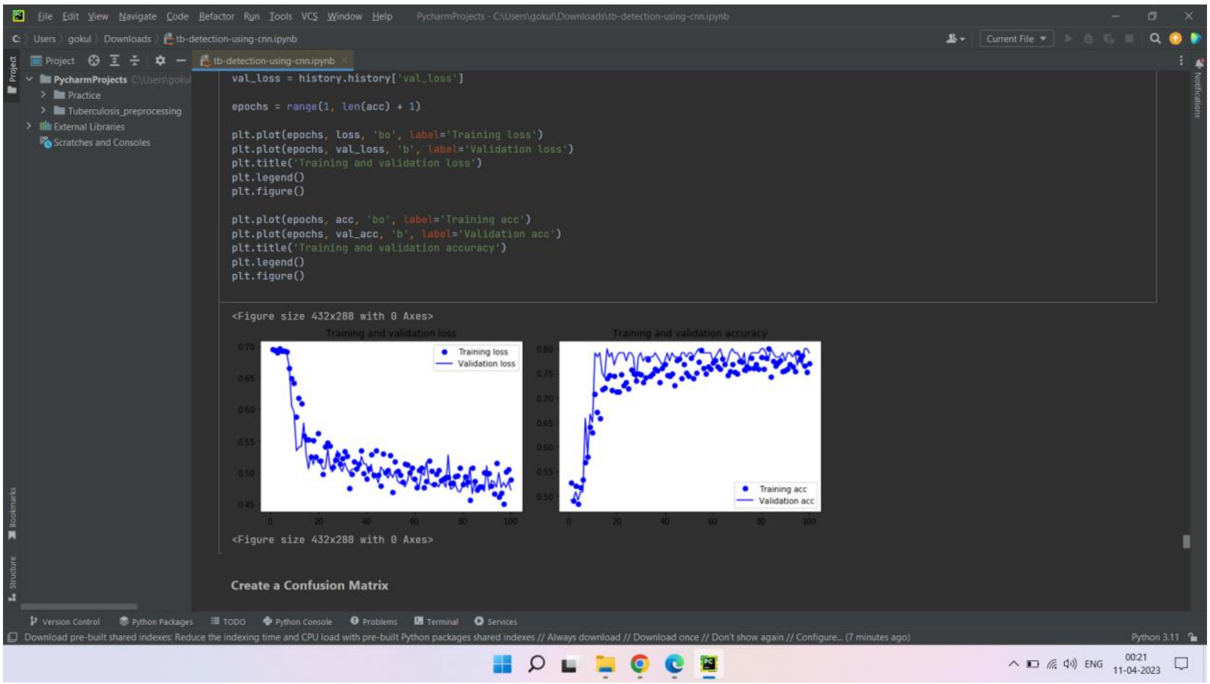


Tuberculosis Detection using CNN:

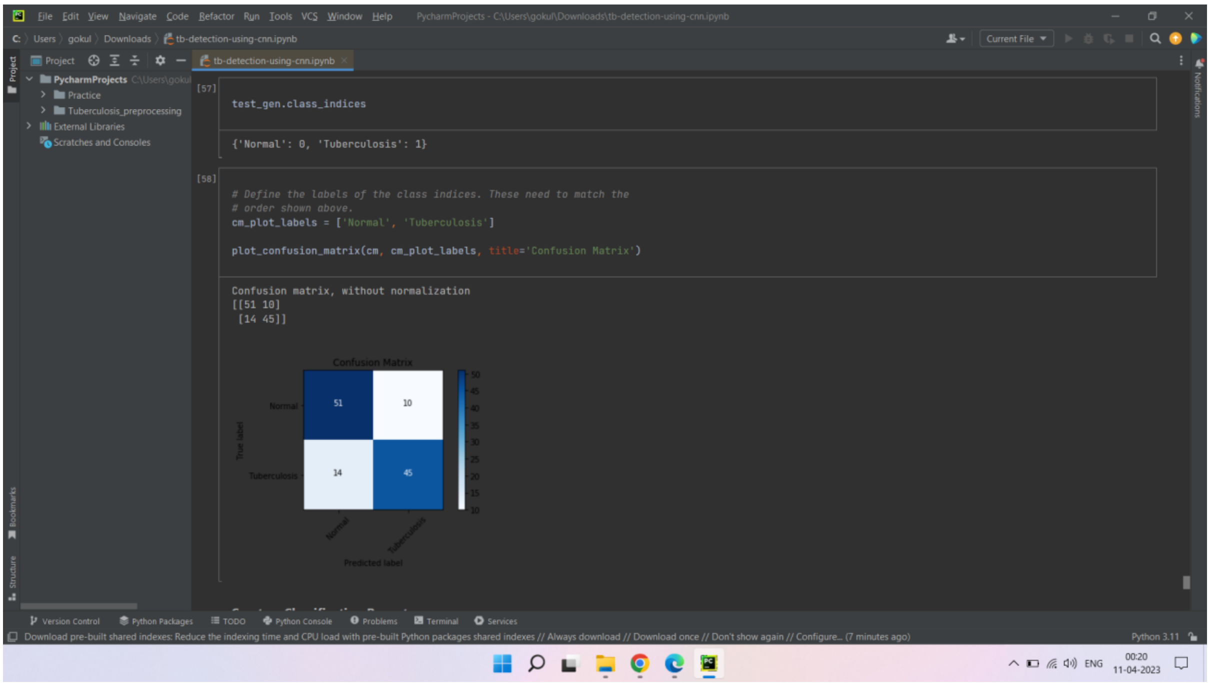
https://www.kaggle.com/code/gokul20mis0332/tb-detection-using-cnn



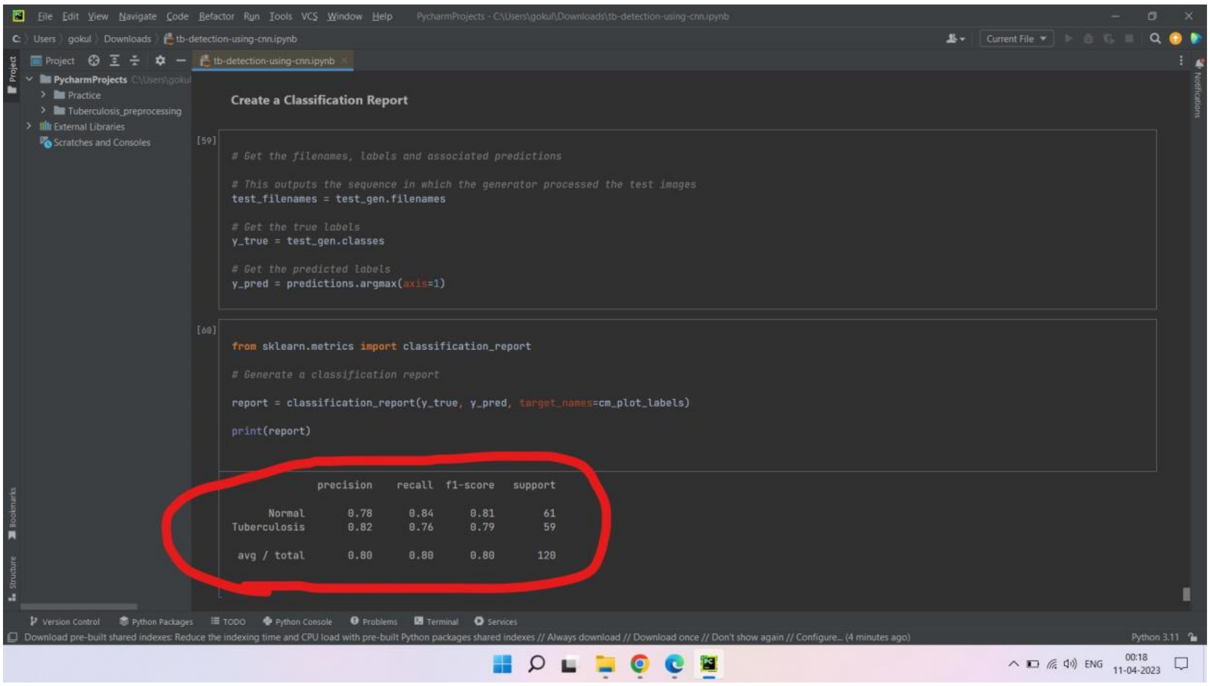
Training curves:



Confusion Matrix:



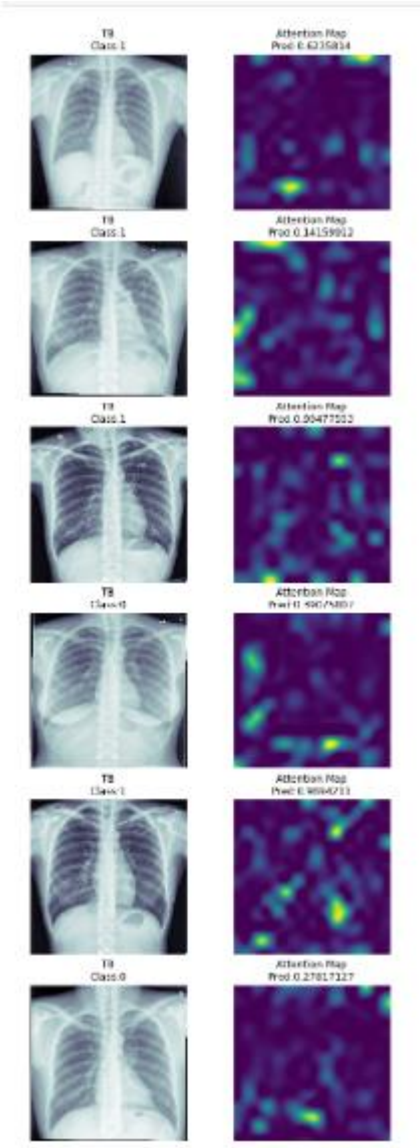
Accuracy:



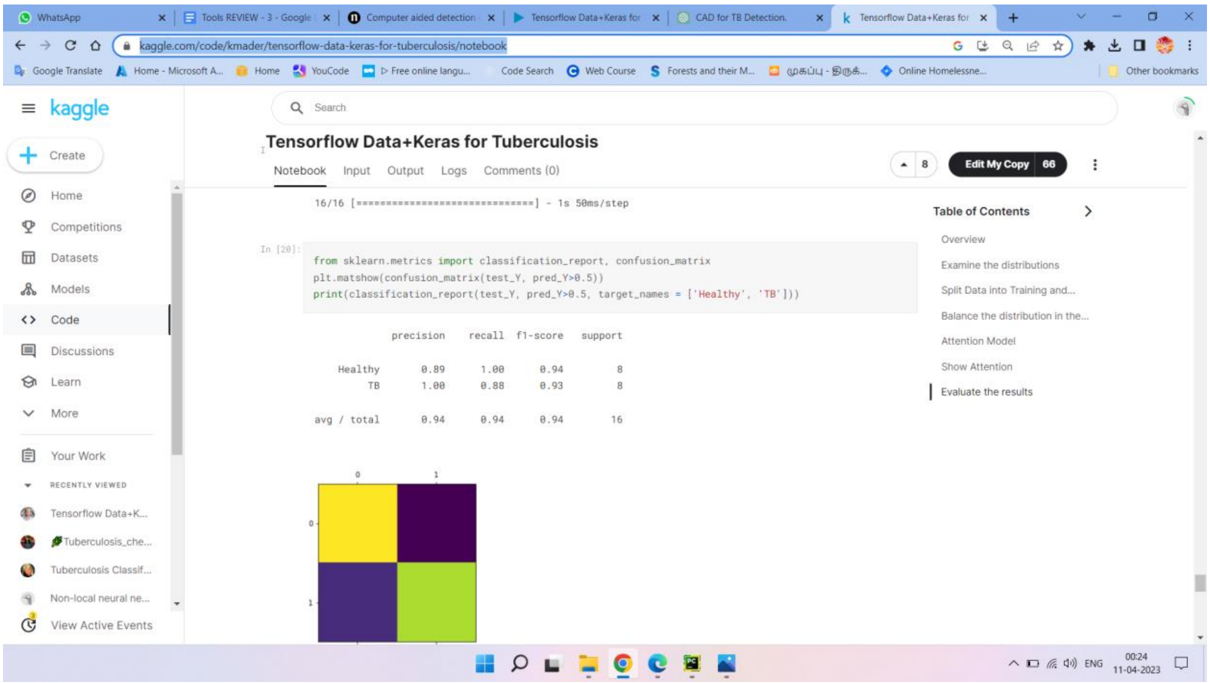
Tuberculosis Detection using TensorFlow:

https://www.kaggle.com/code/gokul20mis0332/tensorflow-data-keras-for-tuberculosis

Attention matrix:



Acuuracy:



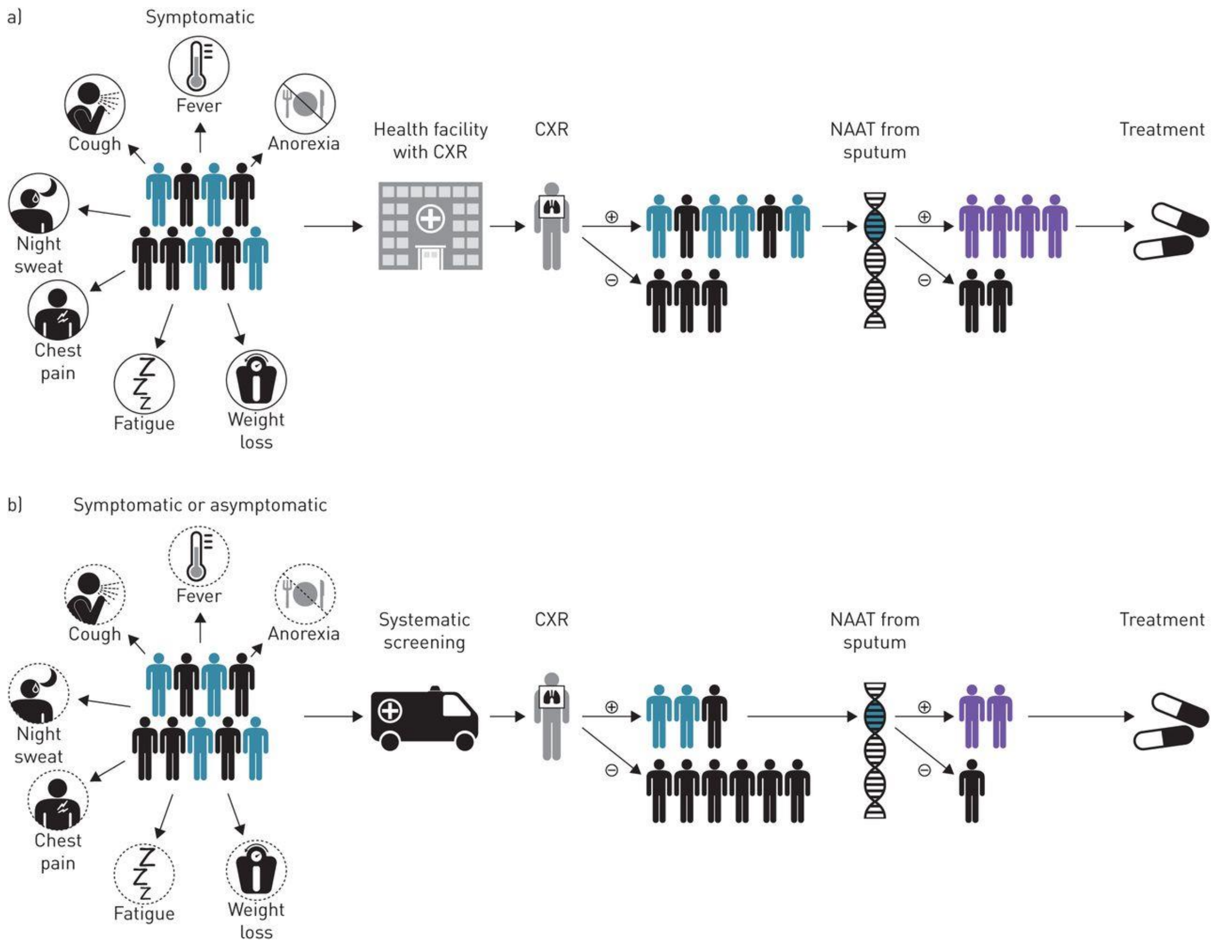
Tuberculosis Detection using Computer-Aided Detection:

Computer-aided detection (CAD) is a technology that uses software algorithms and machine learning techniques to assist radiologists in detecting and interpreting medical images. In the case of tuberculosis (TB) detection, CAD can be used to aid in the interpretation of chest X-rays, which are commonly used to diagnose TB.

CAD for TB detection typically involves a two-step process. First, the chest X-ray image is analyzed by the CAD software, which applies a set of algorithms to detect abnormal patterns or areas of concern on the image. These algorithms may include edge detection, texture analysis, and pattern recognition techniques.

Next, the software generates a report or "heat map" highlighting the areas of the image that are most likely to indicate TB. This report is then reviewed by a radiologist, who makes the final determination as to whether the patient has TB.

CAD for TB detection has several potential benefits, including improved accuracy and speed of diagnosis, reduced inter-observer variability, and increased sensitivity for detecting early-stage TB. However, it is important to note that CAD is not a substitute for the expertise of a trained radiologist and should always be used in conjunction with clinical evaluation and other diagnostic tests as appropriate.



7. Conclusion

TensorFlow is a valuable tool for tuberculosis detection with X-ray images. By using deep learning models built with TensorFlow, it is possible to accurately analyze large sets of X-ray images and detect the presence of tuberculosis with high accuracy.

Tuberculosis is a serious and potentially life-threatening disease that can be difficult to diagnose in its early stages. By using TensorFlow to analyze X-ray images, healthcare providers can quickly and accurately identify patients with tuberculosis and begin treatment to prevent the spread of the disease.

Overall, the cost of implementing CAD with Tensorflow and CNN for tuberculosis detection can vary widely depending on factors such as the size and complexity of the dataset, the number of GPUs and software licenses required, and the amount of time and resources needed for model development and maintenance. However, it is likely to be a significant investment in terms of both time and money, and would require careful consideration of the potential benefits and limitations of the approach.

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