© May 2025 | IJIRT | Volume 11 Issue 12 | ISSN: 2349-6002

X-Ray Segmentation Based Tuberculosis Detection Using Deep Learning

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Abstract: **Tuberculosis (TB) remains one of the most prevalent and life-threatening infectious diseases worldwide, particularly in low-resource regions. Chest X-ray imaging is a primary diagnostic tool for TB, but manual interpretation is often subject to variability and diagnostic delay. This research introduces an automated tuberculosis detection framework based on deep learning and X-ray image segmentation. The proposed system utilizes a U-Net-based architecture for lung region segmentation, followed by a convolutional neural network (CNN) for TB classification. By isolating the region of interest, the model improves detection accuracy and robustness. Experimental results on public chest X-ray datasets demonstrate the system's high sensitivity, specificity, and classification accuracy. This approach has the potential to assist radiologists and healthcare providers by offering fast, scalable, and consistent TB diagnosis from X-ray scans.**

Keywords: - **X-ray images, Deep Learning, Tuberculosis Detection, and Accuracy.**

1. INTRODUCTION

Tuberculosis is a major global health concern, causing over a million deaths annually. Despite advancements in medical imaging, TB diagnosis still heavily relies on manual evaluation of chest radiographs, which can be time-consuming, error-prone, and limited by radiologist availability. Automated diagnostic tools based on deep learning are emerging as valuable alternatives, offering rapid and consistent image interpretation.

However, general-purpose classification models may underperform when trained on raw chest X-rays due to noise and irrelevant anatomical regions. Therefore, segmenting the lung area before classification is critical for enhancing model focus and improving detection performance. This paper proposes an efficient TB detection pipeline combining X-ray segmentation (via U-Net) and deep learning classification (via CNNs or pretrained models). The framework is designed to be lightweight and adaptable for real-time or point-of-care diagnostic systems.

As a result of suffocation and other symptoms connected with lung disorders, patients frequently experience severe pain and suffering. This is because lung diseases make it difficult for patients to breathe normally. The lung infection known as tuberculosis (TB) is one example of a potentially harmful variety of lung infections that has had a terrible effect on human health. Tuberculosis is a disease that is caused by the bacteria known as Mycobacterium tuberculosis. The lungs are the primary target location of this disease, although it can also affect other sections of the body. In general, the lungs are the primary target area. When people who are sick with tuberculosis cough or sneeze, they spread the bacteria that cause the disease via the air. This is because tuberculosis is a contagious disease. A healthy individual can be efficiently infected with these germs with only a modest amount due to their low concentration.

Even though scientific discoveries and research have been contributing to the reduction of the expanding impact of tuberculosis (TB), the meager annual medical advancement rate in this sector has not been successful in bringing about a significant decrease in the number of patients who are affected by TB. There were roughly 10 million persons affected by tuberculosis worldwide in 2019, as stated in the Global Tuberculosis Report, 2020, produced by the World Health Organization [1]. In addition, HIV/AIDS and tuberculosis together constitute a lethal combo. In other words, HIV infection greatly reduces the strength of an individual's immune system, which creates a favorable environment for a patient who is HIV positive to become infected with tuberculosis. There were more than 200,000 individuals who tested positive for HIV among the 1.4 million people who passed away as a result of tuberculosis in 2019.

With the assistance of deep learning algorithms, systems have rapidly expanded. With the assistance of natural language processing, scientists can identify and improve the drug-drug interaction in medical literature. Predictive modeling and decision-making are important applications of artificial intelligence in primary care. In tuberculosis (TB), computer-aided detection (CAD) is the most widely used artificial intelligence tool. This tool analyzes the patient's chest X-rays and determines whether or not the patient is affected by TB. This process reduces the burden on radiologists to meticulously scan through each radiographic film, ultimately speeding up the screening process. This research's unique approach is to leverage the power of normalization-free networks to escalate X-ray image classification.

2. RELATED WORKS

Using chest radiographs, Rahman et al. [2] proposed a Transfer Learning (TL) using deep convolutional neural networks (CNN) for the automatic detection of tuberculosis (TB). As part of the tuberculosis classification process, the robustness of multiple CNN techniques was implemented. A superior performance was achieved by Chex Net compared to the other nine models. A comparison was made between the outcomes obtained with and without segmentation. In this study, it was demonstrated that the classifier that included segmentation produced superior results.

The authors Pavani et al. [3] introduced a new automated approach for the rapid identification of tuberculosis-related lung disease. Before beginning the segmentation of the images, preprocessing was performed, and Chan-Vese active contour was utilized for the segmentation. Following the extraction of several features, the NB classifier was used to select the most relevant feature for utilization in classification.

A new tuberculosis detection model was utilized by Ayaz et al. [4], which incorporated hand-crafted features with CNN through the utilization of an ensemble model. Following the initial step of normalization, the images were then provided to the feature extractor. The extraction of hand-crafted and deep features was accomplished through the use of GF and pre-trained models. For the purpose of achieving superior ROC findings, two benchmark datasets were utilized.

CNN with AEO (Artificial Ecosystem Optimization) was used by Sahlol et al. [5] to detect tuberculosis. First, MobileNet was used to segment the input image, and then AEO was used to select features. Through this optimization, 50,000 features were reduced to 19 and 29 features, which were then classified as TB and non-TB images.

Win et al. [6] automatically screened for tuberculosis using a hybridized feature learning model. Lung segmentation was done using DeepLabv3. After that, features were chosen using the optimization PSO (Particle Swarm Optimization) and fed into the optimized SVM. Both TB and normal were classified using this classifier.

3. SYSTEM METHODOLOGY

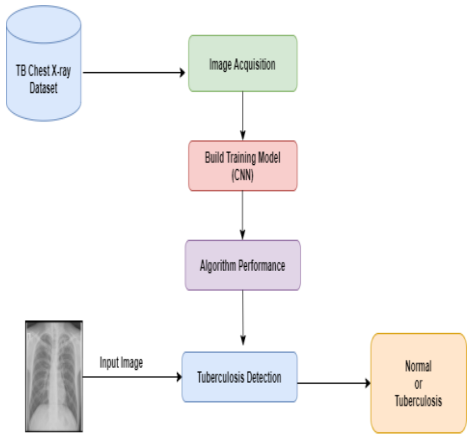

Figure.1 System Model

From figure.1, this system model was explained with various stages in the following:

3.1 Image Acquisition:

In this system, we have imported the Tuberculosis (TB) Chest X-ray dataset from the Kaggle repository https://www.kaggle.com/datasets/tawsifurrahman/tuberculosis-tb-chest-xray-dataset). This dataset contains 3500 Normal images and 700 Tuberculosis images.

3.2 Training CNN model:

In this paper, the Tuberculosis dataset was split into 70 percent training data and 30 percent testing data for training the CNN model. After image acquisition, the Tuberculosis images are collected from various folders and performed image processing and feature extraction. Based on these features, The CNN architecture will be prepared and generate the training model by passing the training and testing dataset samples.

3.3 Algorithm Performance:
Here the trained model will be predicted with the testing dataset and return predicted values. The algorithm accuracy was calculated based on predicted values for every epoch and plotted the line chart graph between accuracy and loss of the training and validations.

3.4 Tuberculosis Detection:
After the calculation of the algorithm's performance, the CNN model will be generated. The Chest X-ray image will be given as input to the CNN model for Tuberculosis detection. At the prediction, this system will return the prediction result as Normal or Tuberculosis.

4. DEEP LEARNING MODEL

AlexNet Architecture (CNN):
Classifying whether an X-ray image shows the presence of tuberculosis is the aim of TB detection. By modifying its fully connected layers, AlexNet can be adapted for this binary classification problem.
Input Layer: Images that have been scaled to 224x224 pixels with three color channels are often accepted by the AlexNet input layer. Single-channel (grayscale) images from chest X-rays can be handled as grayscale by altering the first convolutional layer, or they can be duplicated to three channels.
Convolutional Layers: AlexNet features five convolutional layers with different strides, padding, and filter sizes (e.g., 11x11, 5x5, and 3x3). These layers pick up important details in the pictures, like lung patterns or TB-related anomalies.
Pooling Layers: These are applied after some convolutional layers, and they help to capture bigger structures in lung images by reducing the spatial dimensions while maintaining the key features.

Fully Connected Layers: There were initially three layers of AlexNet that were fully connected. with TB detection, the output layer is often reduced to a single node (or two nodes with softmax activation for binary classification). This is also the case with binary classification.

Softmax or Sigmoid Activation: A final sigmoid activation layer, which is used for binary output, provides an indication of the likelihood that tuberculosis is present in the X-ray.

Pretraining on ImageNet: Transfer learning is a frequent method for dealing with tuberculosis detection. This is due to the fact that AlexNet was initially trained on ImageNet. The network is able to generalize faster with a smaller number of tagged X-ray images for tuberculosis because it makes use of pre-trained weights.

Fine-tuning: Training the model further on datasets that are particular to tuberculosis (TB) allows it to be fine-tuned to recognize traits that are associated with TB.

5. MODEL EVALUATIONS

Table 1: Details of training and validation set for the tuberculosis classification.

Epochs	Training Loss	Training Accuracy	Validation Loss	Validation Accuracy
1	0.4401	0.8777	0.2679	0.9417
2	0.2685	0.9143	0.3141	0.9274
3	0.1907	0.9429	0.1117	0.9714
4	0.1628	0.9500	0.1103	0.9643
5	0.1560	0.9473	0.1206	0.9583
6	0.1709	0.9443	1.5393	0.4940
7	0.1139	0.9607	1.2065	0.4905
8	0.1253	0.9577	0.1606	0.9500

Table 1 describes the training of the deep learning model CNN using the Tuberculosis (TB) Chest X-ray dataset with several epochs.

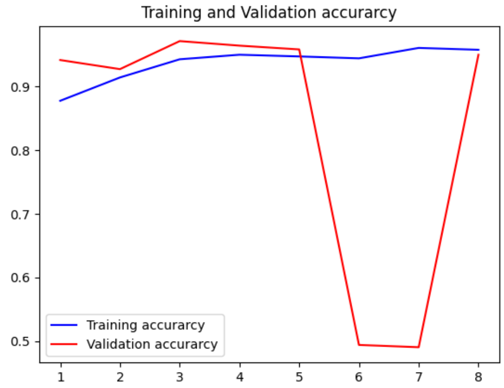

Figure 2: (a) Training and validation accuracy versus Epoch

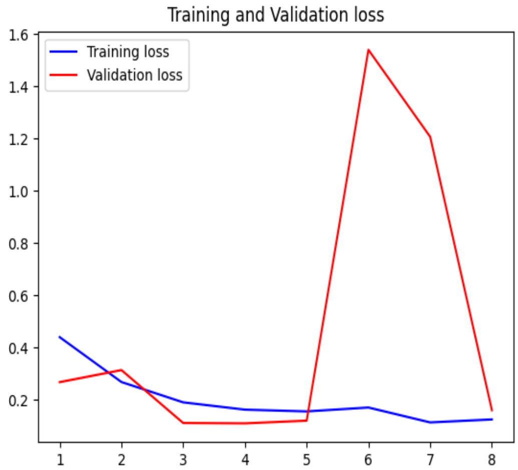

Figure 2: (b) Training and validation loss versus Epoch

Figure 2(a) and Figure 2(b) describe the losses and accuracies obtained during training and validation for the Tuberculosis (TB) Chest X-ray dataset.

6. CONCLUSION

This paper presents a robust and efficient system for tuberculosis detection using chest X-ray segmentation and deep learning. By isolating lung regions using a U-Net segmentation model before classification, the system significantly improves diagnostic accuracy and reduces noise from irrelevant features. The combination of segmentation and transfer learning yields strong performance even on limited data, making it suitable for deployment in real-world clinical and rural healthcare environments. Future work will focus on multi-disease detection, real-time processing, and integration with hospital management systems (HMS) or telemedicine platforms to further enhance accessibility and impact. With the assistance of deep learning algorithms, systems have rapidly increased their capabilities. Scientists can recognize and improve the drug-drug interaction in medical literature with the assistance of natural language processing (NLP). Among the most important applications of artificial intelligence in primary care are predictive modeling and decision-making. The artificial intelligence tool that is utilized the most frequently in tuberculosis is known as computer-aided detection (CAD). By analyzing the chest X-rays of the patient, the instrument can detect whether or not the patient is suffering from tuberculosis. The screening process is ultimately sped up as a result of this method, which results in a reduction in the workload of the radiologists who are responsible for meticulously scanning through each radiographic film. To enhance X-ray image categorization, this research takes a novel technique by utilizing the potential of normalization-free networks.

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