Tuberculosis Detection From Chest X-Rays Using Image Segmentation and Classification

Abstract: The study focuses on improving detection accuracy of tuberculosis using advanced image segmentation and classification methodologies. Accurate TB recognition by chest X-ray analysis has become a significant goal with the integration of medical imaging due to the help of technologies. It used Densenet121, VGG16, ResNet50, InceptionV3, ConvNet algorithms and for segmentation applied U-Net technique. I implemented U-Net for segmentation since it has been shown to be effective in maintaining spatial features and catching complex structures in chest X-ray images. After that, I used Grad-CAM to evaluate the heatmaps that were created and discovered that they were not centered on the regions where the illness is truly present. The fundamental objective was to improve tuberculosis detection in chest X-ray images by utilizing the specific features of these architectures. The methodology effectively integrates algorithms for initial image classification, followed by the precision of U-Net for accurate segmentation. With excellent results, a number of deep learning algorithms such as Densenet121, VGG16, ResNet50, InceptionV3, ConvNet. Among them Densenet121 and ResNet50 given same accuracy which was 83.33%. InceptionV3 gives the accuracy of 75.00% and ConvNet gives the accuracy almost 77%. VGG16 gives the highest accuracy which was 99%. So, the highest accuracy of the paper found by the technique. Then DenseNet121 which was the second highest accuracy. The significance resides in its possibility to improve tuberculosis diagnostics, offering a technological improvement that can translate into earlier detection, improved patient outcomes, and more efficient healthcare practices. By using different types of normal and tuberculosis affected x-rays we had found effective accuracy of diagnosis which plays a significance role in the medical sector.

Keywords: Convolutional Neural Network(CNN), DenseNet121, ResNet50, VGG16, InceptionV3, ConvNet, Grad-CAM.

1 Introduction

Tuberculosis (TB) remains a global public health challenge, with millions of lives affected annually. A timely and precise diagnosis is essential for the disease's optimal therapy and control. One of the worst and most ancient infectious illnesses known to man is tuberculosis. Chest X-ray screening is crucial for early detection and effective treatment of tuberculosis infections. It is mostly lung-related and is brought on by Mycobacterium tuberculosis. Coughing, fever, and weight loss are some of the symptoms. A radiology professional can use chest x-ray imaging to diagnose or test for tuberculosis [1]. The World Health Organization advises frontal-anterior chest radiography due to the low sensitivity and significant intra- and inter-observer variability in chest X-rays (CXR) [2].

Regions of interest within the CXR are identified and highlighted using image segmentation, especially those displaying anomalies associated with TB. Additionally, a visualization approach is employed to verify that CNN primarily learns from the segmented lung areas, leading to increased detection accuracy [3]. Patients with active tuberculosis need to be treated effectively by doctors. Early diagnosis of tuberculosis implies an earlier beginning of treatments, a shorter time of spread, and better medical outcomes [4].

The World Health Organization (WHO) estimates that 10 million individuals contracted tuberculosis (TB) in 2020, and 1.5 million of those people, 214,000 of whom were HIV positive, died from the illness. HIV infection greatly reduces a person's ability to fight against infection, making it more likely for an HIV-positive patient to get tuberculosis [5]. Chest radiography is recommended by the World Health Organization (WHO) as a crucial modality for TB screening and detection. This inclination stems from its comparatively higher sensitivity when compared to alternative diagnostic techniques [6,7].
Although tuberculosis is a dangerous and common lung illness, not all cases are often identified [8]. Despite its limited specificity and challenging interpretation, posterior-anterior chest radiography remains one of the recommended modalities for TB screening [17].

The goal of research has been to create a computer-aided detection (CAD) system that uses medical imaging to make a preliminary diagnosis of disorders associated to tuberculosis [19]. The most accurate way to estimate the spread of tuberculosis (TB) in a community and track the effectiveness of TB control initiatives in places with inadequate routine observation systems is through presence investigations [20].

The rising Incidence of tuberculosis and the concomitant difficulties in prompt and precise diagnosis are the fundamental driving forces behind this study. The necessity to investigate this area stems from the realization that traditional diagnostic methods sometimes struggle to deliver precise and fast results for TB cases. Enhancement and improvement of TB diagnosis and increased model accuracy are the main anticipated outcomes. It wants to have a significant impact on the medical technology field at large. In this work, I want to find out the most accurate output using different algorithms. We experiment with different normalization-free architectures and prove their superiority by comparing them to the standard version. We applied several different methods like densenet121, ResNet50, VGG16, InceptionV3 and ConvNet.

2 Literature Review

Traditionally, feature extraction and pattern recognition technologies have been the backbone of the CAD system for illness diagnosis. An effective use of gray-scale invariant char- acteristics to identify tumors from breast ultrasound images was given by Yang. (2013). The research addresses the critical need for accurate TB diagnosis, as errors can impact treatment outcomes.

The proposed [1] system achieved an accuracy of 99.76% in classifying TB and normal lungs, offering a potential tool to assist radiologists in TB detection. They were introduced
[2] a transfer learning methodology utilizing deep convolutional neural networks (CNNs) to autonomously differentiate between tuberculosis (TB) and normal cases based on chest radiographs which assessed the effectiveness of six distinct CNN models in identifying TB in chest X-ray images. Notably, the Exception, ResNet50, and VGG16 models demonstrated superior performance compared to other deep CNN models, particularly when coupled with image augmentation techniques.

It [3] highlights scholars have delved into innovative strategies, such as lung segmentation techniques employing U-Net models, which enable precise delineation of lung regions. Presents a robust deep learning-based approach and the proposed method [4] demonstrates potential for effective early detection of TB from chest X-rays, contributing to improved patient outcomes and reducing mortality associated with delayed diagnosis.
The presented study [5] conducts a comprehensive analysis and the paper

encompasses performance comparison, transfer learning, data augmentation, and disease localization, shedding light on the evolution of the field since 2016.

A pioneering study [7] leveraging this approach, showcased impressive accuracy in multi-label classification of diverse TB- related abnormalities [6]. In the realm of medical imaging, tuberculosis (TB) diagnosis using deep learning techniques has garnered significant attention. [8] By combining the strengths of pre-trained VGG16 and VGG19 models and incorporating attention mechanisms for spatial information extraction, the proposed approach demonstrates robust performance.

FPGA technology [9] is harnessed to expedite deep learning inference, enabling real-time TB classification with heightened efficiency. The paper proposed [10] CBAMWDnet model, a specialized convolutional neural network tailored for tuberculosis classification.

Its deep architecture, containing over 8 million parameters, emphasizes feature extraction from input images. The study evaluates CBAMWDNet's perfor- mance through various metrics, including accuracy, sensitivity, specificity, precision, negative predictive value, and F1 score. Compared to other CNNs, CBAMWDNet showcases superior diagnostic accuracy and efficiency, particularly in distinguishing tuberculosis cases.

The authors [11] systematically explore various techniques including normalization-free networks, progressive resizing, and Score-CAM visualization. Moreover, the comparison with other state-of-the-art models underscores the superiority of the proposed approach. [12] By conducting comprehensive experiments and comparisons, the authors demonstrate that their proposed methodology significantly enhances the accu- racy. The paper provides a systematic literature review of lung segmentation and tuberculosis (TB) detection in chest radiography using deep learning. It examines the transition from traditional methods to deep learning architectures such as GoogleNet, VGGNet, ResNet, DenseNet, and EfficientNet.
It [13] highlights the effectiveness of deep learning in automating feature extraction, enabling accurate TB detection.

[14] Image augmentation is used to expose the model to a broader range of training cases. Segmentation helps save time by evaluating selected portions of images. Deep learning systems that are able to accurately identify these irregularities reliable and comprehensible information has to be created.

This study [15] presents a unique strategy to collect low-level features and suggests an improved method for TB identification in medical imaging using transfer learning, highlighting the drawbacks of utilizing ImageNet weights. The paper ad- dresses the difficulties in data-constrained healthcare settings and highlights the significance of establishing strong medical imaging tools for TB screening.

It highlights [16] the challenges of defining soft tissue anatomical structure and suggests machine learning for identifying anomalies in chest X-ray pictures using hierarchical feature ex- traction. [17] The global impact of tuberculosis, its prevalence in resource-limited settings, and the growing interest in auto- mated algorithms, particularly deep convolutional networks, for diagnosing the disease.

[18] X-ray pictures and Canny edge-detected images, showing enhanced precision, efficacy, and efficiency above current techniques. [19,20] Both paper deals with detection of tuberculosis with help of CAD depends on specific algorithms to choose and collect useful infectious characteristics within images.

3 Methodology

My work focuses on the challenging field of Tuberculosis detection using chest x-ray image segmentation and classification. Specialized convolutional neural networks (CNNs) are among the methods that we have selected, such as DenseNet121, ResNet50, VGG16, InceptionV3 and ConvNet. Convolutional neural networks (CNNs) and high-performance image processing tools are well-known for their ability to precisely analyze and extract complex information from chest X-ray pictures in order to identify TB. The technical foundation required to identify the complex patterns present in TB pathology in medical imaging datasets is described in more detail in this article.

3.1 Data Collection Procedure

Generally, data collection methods are divided in two ways. There are two types of data collection: primary data collection and secondary data collection. A thorough description of the preprocessing method is provided, including the rigorous procedures of image standardization, quality control, normalization, and augmentation. This comprehensive dataset ensures its validity, broadness, and relevance by reflecting the complexities of real-world medical circumstances. I collected secondary data, which contains normal and affected chest x- ray images. In my paper, collected data from different files which is one of the contribution of my work. After collecting the data, preprocess the dataset using the DL classification technique. For applying the techniques, I split the data into three types, for example, training, testing, and validation. After doing that, I saved different images into these folders. Here's dataset description table:

TABLE I

DATASET DESCRIPTION

Category	Train	Test	Validation
Normal	2800	350	350
Tuberculosis	560	70	70

Prejudiced feature representations may result from imbalanced datasets. According to the Figure 3.1 Procedure Diagram a chest x-ray train it and after classification find out the final accuracy or result. Procedure diagram given below:

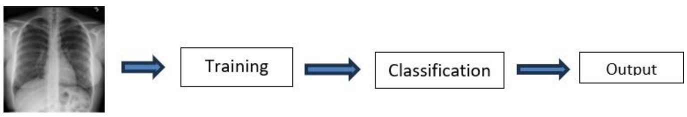


Figure 3.1: Procedure Diagram

3.2 Proposed Methodology

The methodology of proposed system is presented in combining the techniques with segmentation capabilities, the methodological collaboration redefines the field of TB detection and creates a paradigm shift in diagnostic accuracy. My methodology workflow-

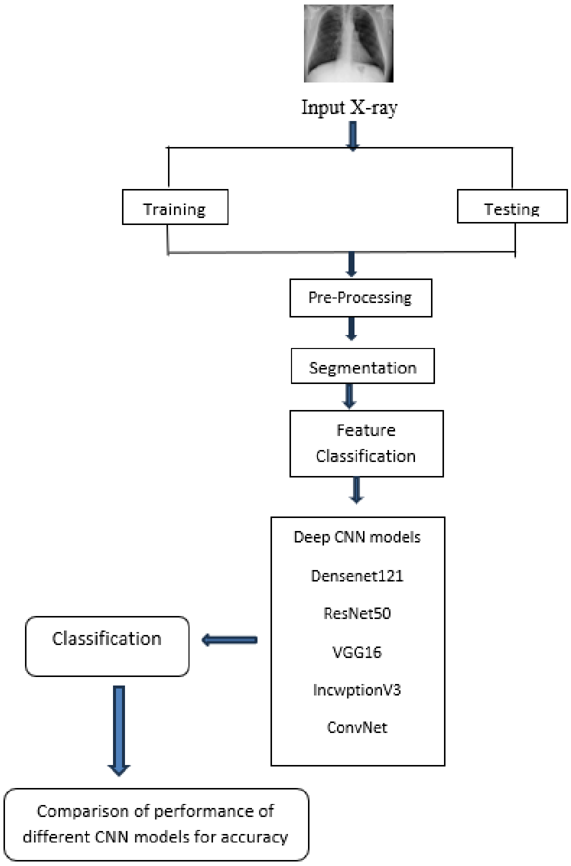


Figure 3.2 Diagram of Methodology

The implemented method coordinates the strategic weaving of U-Net Architecture into our diagnostic process. This structural decision is a ground-breaking one in the field of medical image processing, improving our ability to identify patterns that are essential for TB identification. Here U-Net model which I applied in my paper work given bellow:

Layer (type)	Output Shape	Param #	Connected to
input_2 (InputLayer)	[(None, 320, 320, 3)]	0	[]
conv2d (Conv2D)	(None, 320, 320, 64)	1792	['input_2[0][0]']
conv2d_1 (Conv2D)	(None, 320, 320, 64)	36928	['conv2d[0][0]']
max_pooling2d (MaxPooling2D)	(None, 160, 160, 64)	0	['conv2d_1[0][0]']
conv2d_2 (Conv2D)	(None, 160, 160, 128)	73856	['max_pooling2d[0][0]']
conv2d_3 (Conv2D)	(None, 160, 160, 128)	147584	['conv2d_2[0][0]']
max_pooling2d_1 (MaxPooling2D)	(None, 80, 80, 128)	0	['conv2d_3[0][0]']
conv2d_4 (Conv2D)	(None, 80, 80, 256)	295168	['max_pooling2d_1[0][0]']
conv2d_5 (Conv2D)	(None, 80, 80, 256)	590080	['conv2d_4[0][0]']
max_pooling2d_2 (MaxPooling2D)	(None, 40, 40, 256)	0	['conv2d_5[0][0]']
conv2d_6 (Conv2D)	(None, 40, 40, 512)	1180160	['max_pooling2d_2[0][0]']
conv2d_7 (Conv2D)	(None, 40, 40, 512)	2359808	['conv2d_6[0][0]']
up_sampling2d (UpSampling2D)	(None, 80, 80, 512)	0	['conv2d_7[0][0]']
concatenate (Concatenate)	(None, 80, 80, 768)	0	['up_sampling2d[0][0]', 'conv2d_5[0][0]']
conv2d_8 (Conv2D)	(None, 80, 80, 256)	1769728	['concatenate[0][0]']
conv2d_9 (Conv2D)	(None, 80, 80, 256)	590080	['conv2d_8[0][0]']
up_sampling2d_1 (UpSampling2D)	(None, 160, 160, 256)	0	['conv2d_9[0][0]']
concatenate_1 (Concatenate)	(None, 160, 160, 384)	0	['up_sampling2d_1[0][0]', 'conv2d_3[0][0]']
conv2d_10 (Conv2D)	(None, 160, 160, 128)	442496	['concatenate_1[0][0]']
conv2d_11 (Conv2D)	(None, 160, 160, 128)	147584	['conv2d_10[0][0]']
up_sampling2d_2 (UpSampling2D)	(None, 320, 320, 128)	0	['conv2d_11[0][0]']
concatenate_2 (Concatenate)	(None, 320, 320, 192)	0	['up_sampling2d_2[0][0]', 'conv2d_1[0][0]']
conv2d_12 (Conv2D)	(None, 320, 320, 64)	110656	['concatenate_2[0][0]']
conv2d_13 (Conv2D)	(None, 320, 320, 64)	36928	['conv2d_12[0][0]']
conv2d_14 (Conv2D)	(None, 320, 320, 1)	65	['conv2d_13[0][0]']

Figure 3.2.1 U-net Model

To ensure repeatability, scalability, and practical utilization, our proposed methodology's execution requires careful anal- ysis of many essential features. Computational infrastructure, software dependencies, data integration, model training pro- tocol, ethical considerations, validation and testing etc. are requirements of implication. Mainly, I measure the efficacy of our methods with rigorous assessment measures, such as F1-score, accuracy, and recall.

Within the field of TB detection using image segmentation and classification, the Preliminaries/Terminologies part serves as an important basis, guaranteeing that readers possess a comprehension of fundamental ideas that are vital to the study. A summary of medical imaging concepts that highlights the importance of chest X-rays in the diagnosis of TB may be included. To provide readers with a foundational analysis, the important procedural stages involved in picture segmentation and classification are also clarified. It typically aims to give readers a solid foundation by providing pertinent prior knowledge and vocabulary necessary to understand the nuances of TB diagnosis through image segmentation and classification.

A. *DenseNet121*

A convolutional neural network design called DenseNet- 121 uses densely linked blocks to enable feature reuse across layers. It delivers state-of-the-art performance in image classification applications by promoting high feature propagation and parameter efficiency.

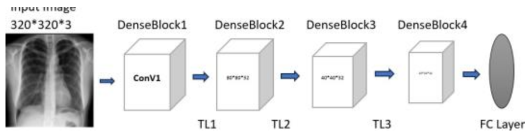


Figure 3.2.2: Densenet121 Architecture

B. VGG16

With 16 weight layers—13 convolutional and 3 fully connected—the Visual Geometry Group's VGG16 is a well- known convolutional neural network architecture. The VGG16 architecture has been shown to be effective in image classification tasks, so we purposefully used it in our TB detection methods.

Figure 3.2.4: VGG16 Architecture

4 Experiments and Result

The results obtained from the experimental phase showed different performances of the considered models. DenseNet121 demonstrated an accuracy of 83.33%, excelling in identifying "Normal" cases but encountering challenges in Tuberculosis detection. VGG16 exhibited an impressive accuracy of 99.76% of test cases, yet faced difficulties inaccurately classifying Tuberculosis instances. ResNet50 mirrored DenseNet121's performance, emphasizing the consistent struggle in Tuberculosis detection. InceptionV3 achieved abalanced accuracy of 75.00%, providing moderate precision, recall, and F1-score for both classes. The ConvNet model,with an accuracy of 76.67%, showcased similar challenges in Tuberculosis detection. Precision, recall, and F1-score met- rics were carefully analyzed, revealing the persistent struggle across models in identifying Tuberculosis cases.

Formula for Confusion matrix:

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + TN + FN} \quad (1)$$

$$\text{Recall} = \frac{TP}{TP+FN} \quad (2)$$

$$\text{Precision} = \frac{TP}{TP+FP} \quad (3)$$

$$\text{F1-Score} = 2 \text{ X } \frac{Precision\ X\ Recall}{Precision+Recall} \quad (4)$$

A. Confusion Matrix

A table used to describe how well a classification algorithm performs is called a confusion matrix. A confusion matrix visualizes and summarizes the performance of a classification algorithm. In bellow given confusion matrix for non segmented CXR images:

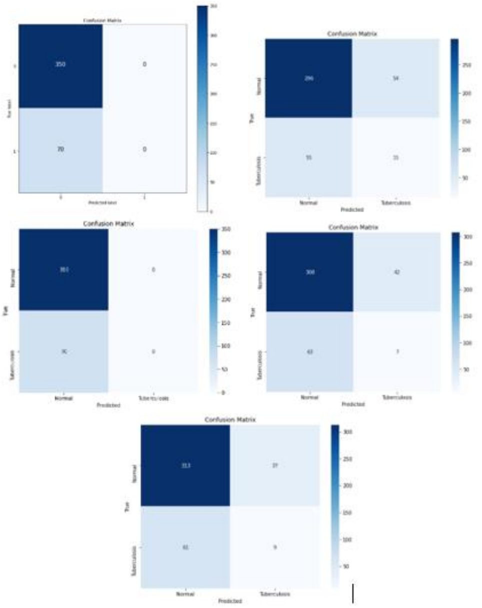


Figure 4.1: Confusion Matrix

B. Result

For the final implementation of my paper, I used total five algorithms such as DenseNet121, VGG16, ResNet50, InceptionV3 and ConvNet. Different algorithms give different accuracy and the accuracy of each model given here.

TABLE II

MODEL PERFORMANCE OF APPLIED ALGORITHMS

Models	Precision	Recall	F1-Score	Accuracy
DenseNet121	0.83	1.0	0.91	0.83
VGG16	0.84	0.85	0.84	0.99
ResNet50	0.83	1.0	0.91	0.83
InceptionV3	0.83	0.88	0.85	0.75
ConvNet	0.84	0.89	0.86	0.77

C. Statistical Analysis

We use a strong statistical framework at this crucial stage of our research technique to interpret the subtleties of model performance. We are able to evaluate the importance of our results using inferential statistics, which makes it easier to draw relevant comparisons across various experimental configurations. By utilizing statistical metrics like accuracy, recall, and F1-score, we are able to assess how successful our TB detection algorithms.

Here, first figure shows the ROC of densenet121 and the other side, figure shows ResNet50 model’s ROC. At ResNet50 means that it’s not ideal because the curve is closer to the diagonal line which indicates a poor performance. So, according to the applied algorithms of my work VGG16 gives highest accuracy.

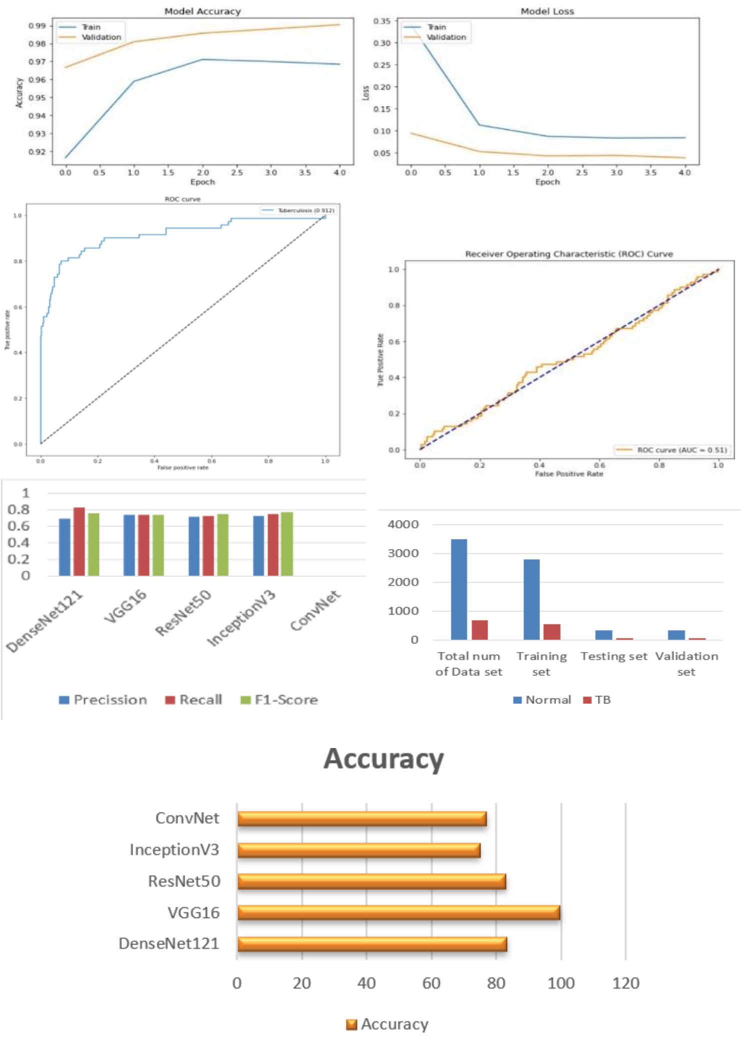
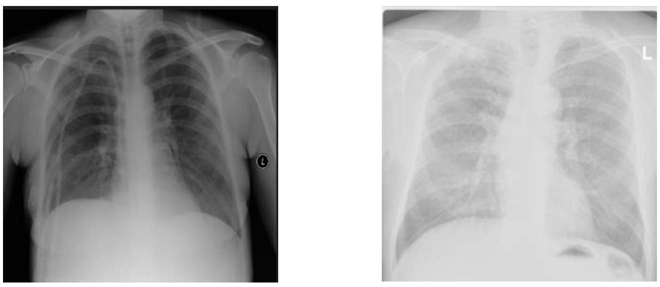


Figure 4.2: Statistical Analysis



Normal and TB affected Chest X-Rays

Figure 4.3: Score-CAM Visualization of properly indentified TB infected chestx-ray

5 Discussion

The discussion revolves around interpreting the meaning of the results obtained. The always-difficult nature of tuberculosis detection represents a focus and warrants further investigation into potential model improvements. We'll discuss insights into potential areas of improvement, including fine-tuning the model, tuning hyperparameters, and even considering advanced techniques such as transfer learning. We conclude this discussion with the broad implications of our results for the field of medical image classification and avenues for future research to improve the reliability of automated diagnostic systems. In fact, It'll help us to find out best accuracy of tuberculosis affected x-rays and identified also.

6 Conclusion

The study focuses on using cutting-edge image processing methods to improve the precision of diagnosing TB from chest X-ray images. The study starts by using image segmentation techniques to extract elements that are important for TB identification from the chest X-rays by identifying crucial regions of interest. The dataset has an impact on a supervised learning model's diagnostic performance. Then, to distinguish between healthy and tuberculosis-affected cases, a classification framework utilizing cutting-edge convolutional neural networks (CNNs) like DenseNet121, VGG16, and ResNet50 is put into practice. I also implemented Grad-CAM for identified the tuberculosis affected area at chest x-ray. While the direct impact on the environment may be limited in the context of tuberculosis detection from chest X-rays, the indirect effects through improved healthcare practices can be substantial. A harmful bacterial illness that affects the lungs in humans is called tuberculosis. The shortcomings of popular CNN designs imply that greater advancements are required, whether in the form of architectural modifications, hyperparameter tweaking, or deeper learning techniques. Early diagnosis of this infection is crucial in order to give the right treatment. Here we used Grad-CAM for identified the tuberculosis affected area in the chest of the x-ray. The different models have different accuracy, such as densenet121, VGG16, ResNet50, InceptionV3, and ConvNet, which have respectively 83.33%, 99.00%, 83.33%, 75.00%, and 76.67%.

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