TUBERCULOSIS DETECTION FROM CHEST X-RAYS USING IMAGE SEGMENTATION AND CLASSIFICATION.

BY

MD TUSHAR AHMED
ID: 201-15-3549

This Report Presented in Partial Fulfillment of the Requirements for the Degree of Bachelor of Science in Computer Science and Engineering

Supervised By

Israt Jahan
Lecturer (Senior Scale)
Department of CSE
Daffodil International University

Co-Supervised By

Md Rahmatul Kabir Rasel Sarker
Lecturer
Department of CSE
Daffodil International University

DAFFODIL INTERNATIONAL UNIVERSITY

DHAKA, BANGLADESH

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APPROVAL

This Project titled "**Tuberculosis Detection From Chest X-rays Using Image Segmentation and Classification**", submitted by Md Tushar Ahmed to the Department of Computer Science and Engineering, Daffodil International University, has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on 23rd January 2024.

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DECLARATION

We hereby declare that, this project has been done by us under the supervision of **Israt Jahan, Lecturer (Senior Scale), Department of CSE** Daffodil International University. We also declare that neither this project nor any part of this project has been submitted elsewhere for award of any degree or diploma.

Supervised by:

____

Israt Jahan
Lecturer (Senior Scale)
Department of CSE
Daffodil International University

Co-Supervised by:

____

Md Rahmatul Kabir Rasel Sarker
Lecturer
Department of CSE
Daffodil International University

Submitted by:

____

Md Tushar Ahmed
ID: 201-15-3549
Department of CSE
Daffodil International University

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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.

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

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LIST OF ABBREVIATION

Abbreviation	**Meaning**	**Page**
CXR	Chest X-ray	1
WHO	World Health Organization	1
TB	Tuberculosis	2
VGG	Visual Geometry Group	4
CAD	Computer Aided Design	4
CNN	Convolutional Neural Network	5
TL	Transition Layer	7
FC	Fully Connected	7
ROC	Receiver Operating Characteristic	15
Grad-CAM	Gradient-weighted Class Activation Mapping	25

CHAPTER 1

Introduction

1.1 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. It is mostly lung-related and is brought on by Mycobacterium tuberculosis. Coughing, fever, and weight loss are some of the symptoms. Regions of interest within the CXR are identified and highlighted using image segmentation, especially those displaying anomalies associated with TB. 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. 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.

Chest X-rays are one of the most accessible and affordable imaging modalities available for tuberculosis screening. However, in order to improve speed and dependability, the correct interpretation of these pictures requires sophisticated computational techniques. According to this study, combining picture segmentation and classification methods offers a viable way to increase the accuracy of TB identification from chest X-rays. The process of image segmentation is essential in identifying possible tuberculosis-related anomalies in chest X-ray images by separating and emphasizing certain regions of interest. Simultaneously, classification algorithms help in the proper classification of these divided areas, facilitating the distinction between healthy and unhealthy states. The combination of these two approaches provides a thorough strategy for detecting TB, utilizing computer vision to enhance the abilities of medical practitioners.

1.2 Motivation

The rising incidence of tuberculosis and the concomitant difficulties in prompt and precise diagnosis are the fundamental driving forces behind this study. The motivation part emphasizes how important it is to have cutting-edge technology, including picture segmentation and classification, in order to improve patient outcomes by increasing the effectiveness of diagnostics. The motivations for this study typically include a sense of duty to solve a serious global health crisis, a dedication to pushing the limits of medical science, and a sincere desire to significantly improve the lives of TB patients. By employing this multidisciplinary strategy, I want to significantly influence the early identification and treatment of tuberculosis (TB), ultimately working toward a day when precise diagnosis is a vital component of the worldwide effort to combat infectious illnesses. Finally, find out best accuracy of tuberculosis.

1.3 Rationale of the Study

This study on the segmentation and classification of images for the purpose of TB detection is based on a thorough analysis of the status of tuberculosis diagnostics today and the inherent shortcomings of present techniques. 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. More advanced diagnostic technologies are desperately needed since millions of people are impacted globally. The study's objective is to aid in the creation of these instruments in line with the more general objective of enhancing healthcare results.

1.4 Research Questions

The emphasis of the study is anchored by the elaboration of specific research questions. The usefulness of image segmentation and classification in TB detection. Some questions:

From where the dataset was collected?

What is the dimension of chest x-ray images?

How many models applied in the data and which is algorithm performance is the best?

1.5 Expected Output

The research aims to identify TB by segmenting and classifying images is expected to yield a variety of improvements and contributions to the medical imaging and diagnostics fields. 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. I applied several different methods like densenet121, ResNet50, VGG16, InceptionV3 and ConvNet.

1.6 Project Management and Finance

The effectiveness and sustainability of the study on TB diagnosis by image segmentation and classification depend heavily on the strategic coordination of project management and budgetary concerns. To encourage iterative changes, the timetable incorporates feedback integration and stringent quality assurance checks. Frequent checkpoints and feedback loops make it easier to modify techniques iteratively, keeping the study focused on its goals and flexible enough to respond to new possibilities and difficulties.

1.7 Report Layout

Introduction

Background

Research Methodology

Experimental Results and Discussion

Conclusion

Reference

CHAPTER 2

Background

2.1 Preliminaries/Terminologies

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 comprehensive 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. Important concepts, including image segmentation, convolutional neural networks (CNNs), and diagnostic tools specific to tuberculosis (TB) detection, will be methodically defined. The Dense Convolutional Network, or DenseNet, requires fewer parameters than a traditional CNN. A smaller number of new feature-maps are added by DenseNet's very thin layers. Four typical variations of DenseNet exist: DenseNet196, DenseNet201 and DenseNet121 etc. DenseNet lets each layer access gradients from the loss function as well as the original input picture directly. Without DenseNet we applied VGG16, InceptionV3, ResNet50 etc. This promotes a common understanding of the language used throughout the study and guarantees that readers, regardless of background, may navigate through the research with clarity and accuracy.

2.2 Related Works

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 characteristics 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 performance 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 accuracy. 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 addresses 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.

2.3 Comparative Analysis and Summary

This section does a thorough comparison analysis to assess and compile current approaches for TB detection using image segmentation and classification. The aim is to condense knowledge about the advantages, disadvantages, and particular contributions of different methods in this specialized field. The related paper [1] applied VGG16 where the accuracy found out 99.7%. At [2] presented a transfer learning approach with CNN where accuracy is 87%. Furthermore, the study [3] applied densenet121 and accuracy was 96.67%. The proposed model EfficientNetB3 which achieved highest accuracy of 99.1%. They [7] achieved the best AUC is 0.925. The paper [8] deals with and utilized VGG16, VGG19 and achieved a score of 0.9992 which gained all matrices. The suggested conclusion provided [9] over 90% precision and accuracy in TB monitoring and identification. The total dataset 4200 and the accuracy of that was 97.00% [10]. They applied [11] more CNN based models and got among them ResNet50 which accuracy was 92.61%. The study [12] applied ResNet50 and ResNet152 both algorithms accuracy was 99.25%. So, different model gives different accuracy.

A more focused and knowledgeable study is made possible by the summary, which compiles the information gathered during the literature review. The densenet121 figure 2.3.1 given.

Densenet121

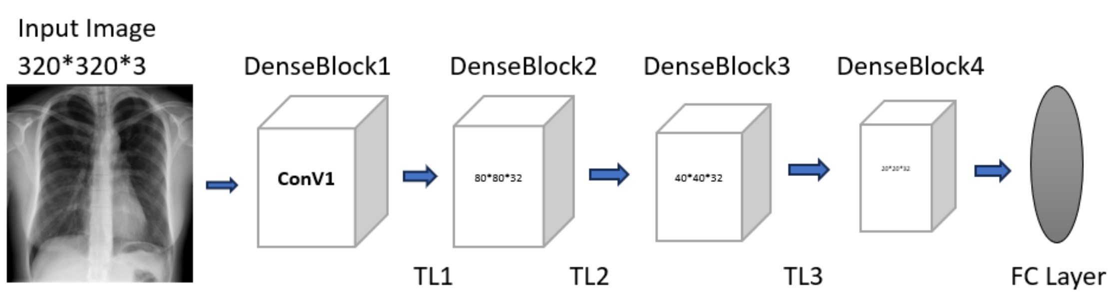


Figure 2.3.1: Densenet121 Architecture

By embracing dense connections, it sets itself apart in the field of deep learning architectures and addresses issues with information flow in deep networks. On the contrary, it is made up of several thick blocks, each of which is made up of a number of layers that are closely connected to one another. To help manage computational complexity, transition layers with pooling operations are positioned strategically between these dense blocks to adjust the channel depth and geographical scale.

VGG16:

Figure 2.3.2: VGG16 Architecture

The VGG16 architecture figure 2.3.2 has been shown to be effective in image classification tasks, so we purposefully used it in our TB detection methods. With its established track record in medical imaging and thorough training in pathology, VGG16 is a solid option for improving diagnosis accuracy in our study. The adaptability and flexibility of the design enhance the technical aspects of TB detection, highlighting its critical significance in our investigation procedures.

U-net: We used U-Net technique figure 2.3.3 for the x-ray images segmentation. Because of its specific design, which is excellent at catching particular features that are vital for differentiating TB patterns, it provides unmatched accuracy and improves diagnostic precision in medical imaging. U-Net's reliable performance positions it as a key component in our goal of a highly accurate and efficient TB detection system. U-Net, a semantic segmentation method, is the preferred method for TB identification due to its ability to process limited labeled data, adjust to changing patterns, and extract various attributes from chest X-ray images.

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 2.3.3: U-Net Model of my work

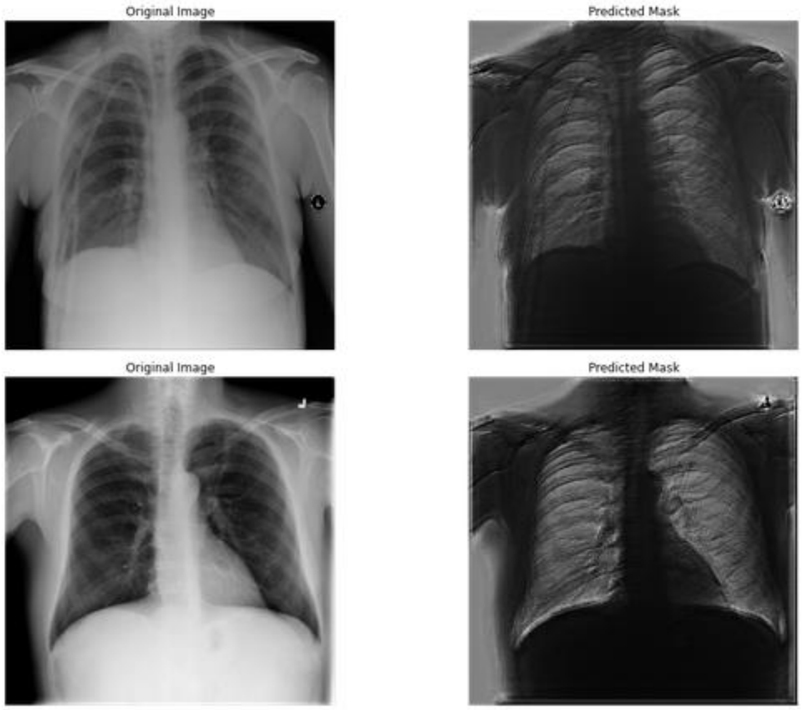


Figure 2.3.4: After applied U-Net model the original and predicted mask

2.4 Scope of the Problem

The scope is based on inclusion criteria and emphasizes datasets that include a variety of CXR images, including both normal and tuberculosis-affected patients. The study widens its scope to include a variety of image segmentation techniques, from advanced deep learning methods like U-Net and Mask R-CNN to more conventional approaches like thresholding and region-based segmentation. The goal is to have a thorough understanding of how well these methods isolate areas in chest X-ray images that are suggestive of TB pathology.

The focus is mostly on convolutional neural networks (CNNs) and other machine learning techniques, although the scope also includes categorization models. It examines several model architectures, hyperparameter setups, and training approaches to see how they affect the precision of the categorization of normal and tuberculosis-affected chest X-rays. The evaluation of performance indicators, such as accuracy, precision, recall, and F1-score, is essential to the scope. In order to give a thorough evaluation of the effectiveness of several picture segmentation and classification techniques in TB detection, the study methodically assesses the advantages and disadvantages of each approach.

2.5 Challenges

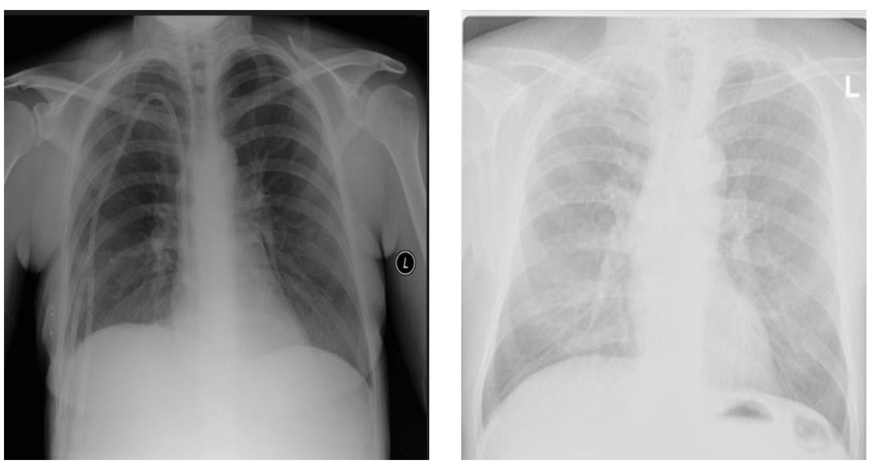
Transparency and well-informed research depend on the recognition of the difficulties that are inherent in the field of TB detection. Generally, it openly addresses difficulties that arise when using picture segmentation and classification including class imbalances, image variability, and interpretability problems. There are some challenges about it such as: data variability and biases, interdisciplinary collaboration, ethical considerations and scalability and development in real world settings etc. These features could be subtle and not detectable for a person that have the expertise. By the way, it is important to carefully assess the ethical implications of using automated diagnostic technologies. Building confidence in the use of cutting-edge technology in healthcare requires finding a balance between innovation and ethical responsibility.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Research Subject and Instrumentation

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.



Normal X-ray TB affected X-ray

Figure 3.1: Normal and Tuberculosis X-Ray

3.2 Data Collection Procedure/Dataset Utilized

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. 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.

Table 3.2: Dataset Description

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

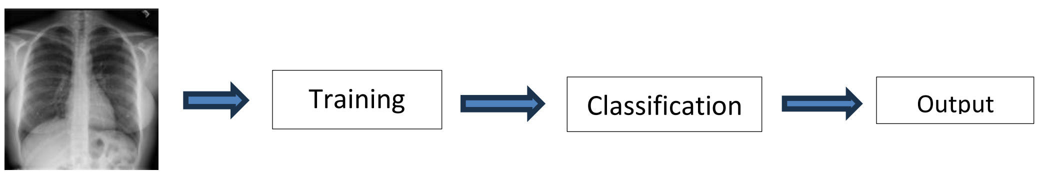


Figure 3.2: Procedure Diagram

Partition data equally split for both normal and tuberculosis which was train, test and validation respectively 80, 10, 10. I'm dealing with class disparity in this piece. Prejudiced feature representations may result from imbalanced datasets. After collecting the data, I applied pre-processing technique. Firstly, normalize the mean and standard deviation of each data and shuffle the input after each epoch. And set the image size to be 320px by 320 px. I apply some augmentation (Rotation, Zoom, width shift and height shift) based on the position deviation which could possibly be slightly changed when radiographers x-ray patients. According to the Figure 3.2 Procedure Diagram a chest x-ray train it and after classification find out the final accuracy or result.

3.3 Statistical Analysis

I'm use a strong statistical framework at this crucial stage of our research technique to interpret the subtleties of model performance. I am 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 are.

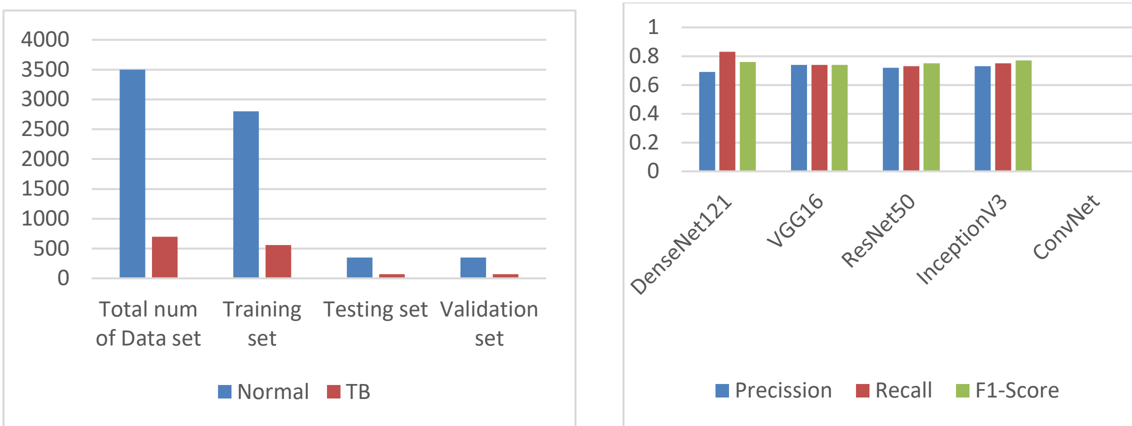


Figure 3.3.1: Dataset visualization

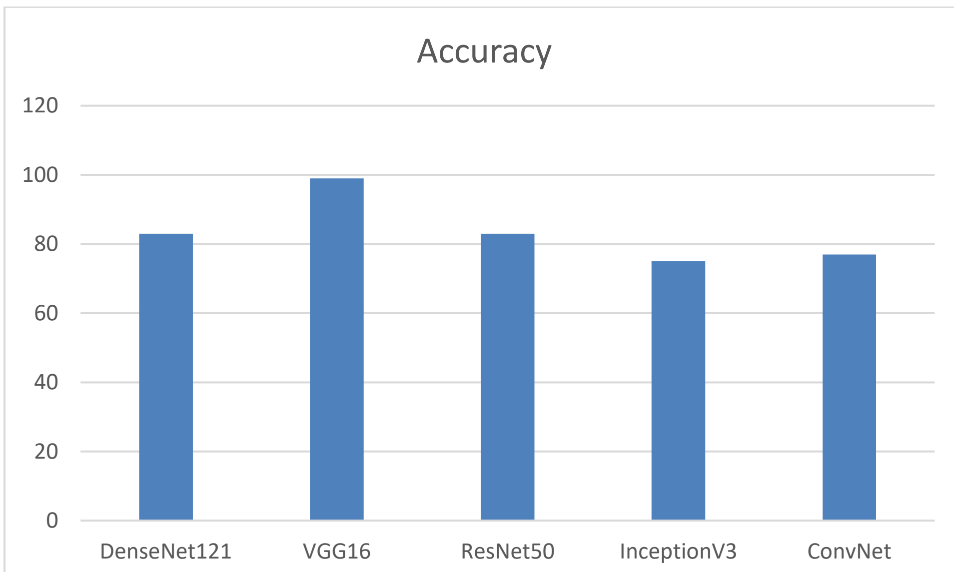


Figure 3.3.2: Accuracy of Different Models

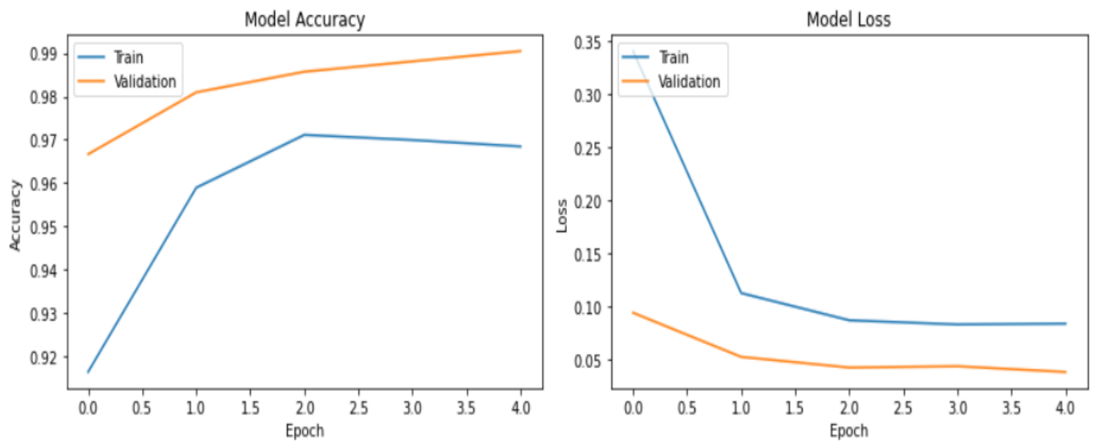
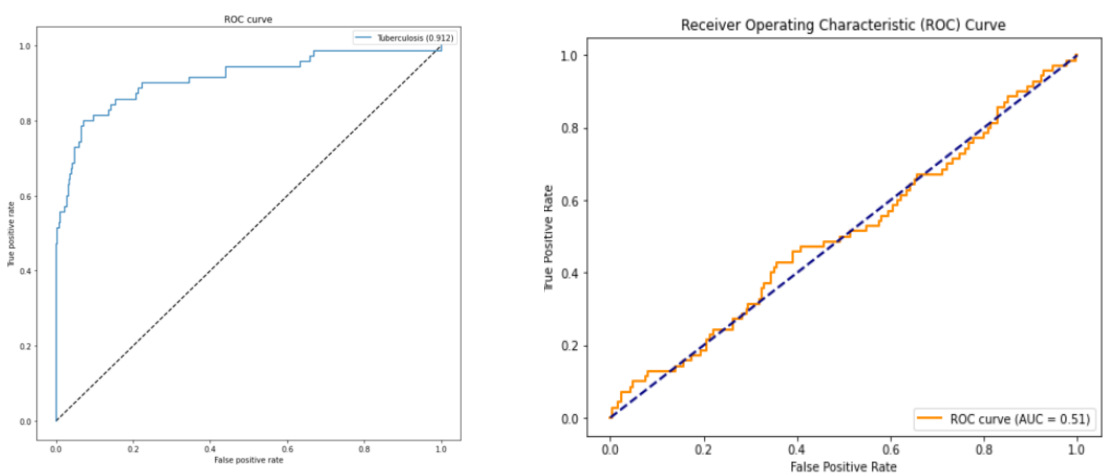


Figure 3.3.3: VGG16 accuracy and loss curve



Densenet121 ROC | ResNet50 ROC

Figure 3.3.4: ROC Curve Comparison of DenseNet121 and ResNet50

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, in my work I found out best accuracy by applied VGG16 and the test accuracy was 99.76% and test loss was 0.0201.

3.4 Proposed Methodology/Applied Mechanism

The methodology of proposed system is presented in Figure 3.4.1. Combining the techniques with segmentation capabilities, the methodological collaboration redefines the field of TB detection and creates a paradigm shift in diagnostic accuracy.

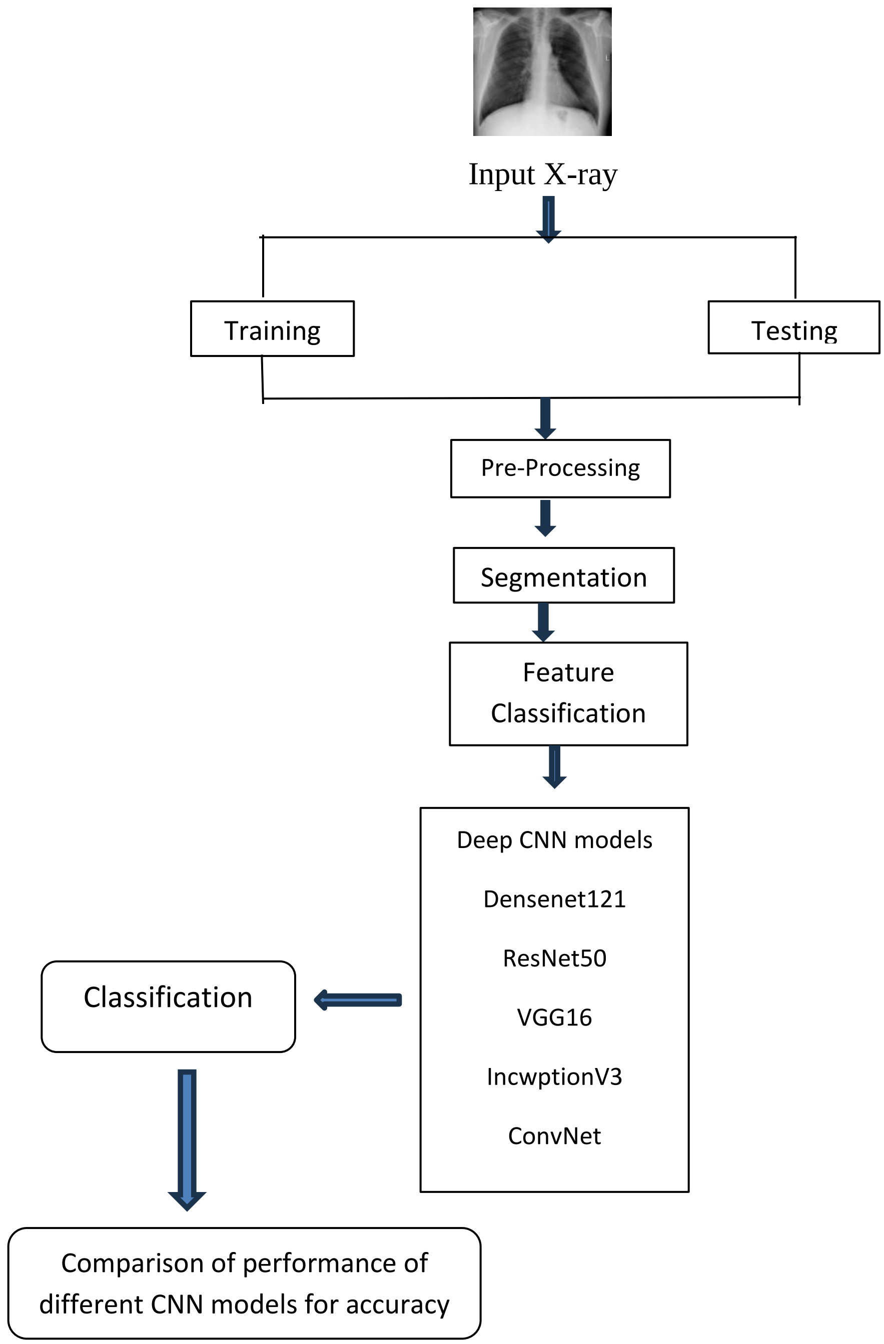


Figure 3.4.1: Diagram of proposed model

The implemented method coordinates the strategic weaving of U-Net Architecture Figure 3.4.2 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.

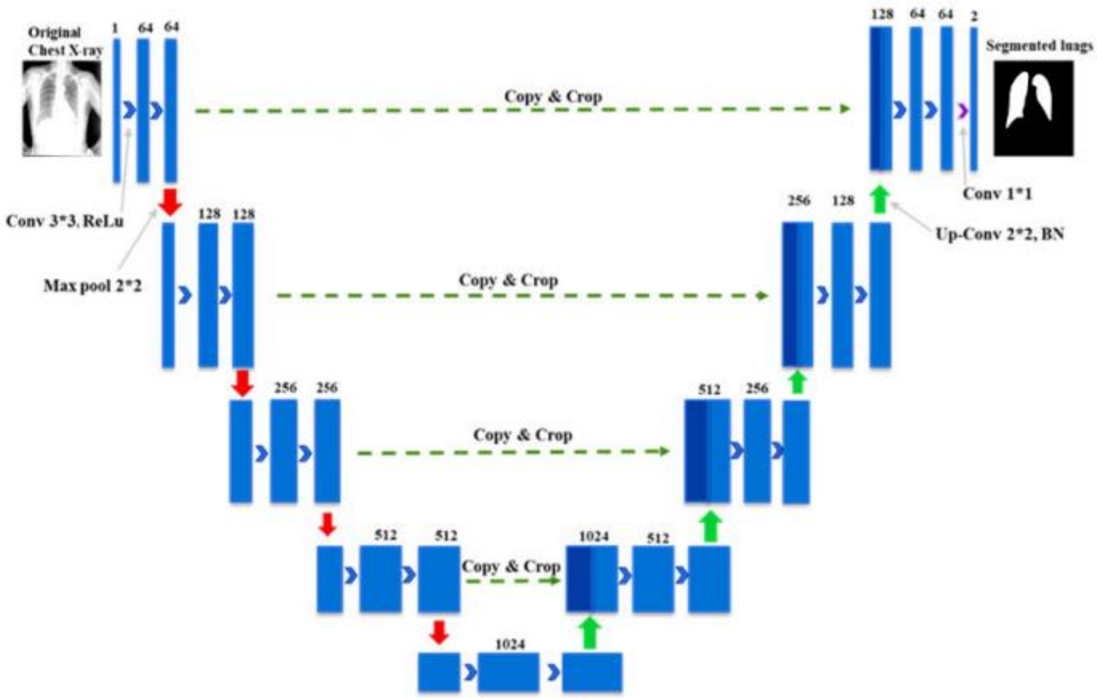


Figure 3.4.2: [3] U-Net Architecture

3.5 Implementation Requirements

To ensure repeatability, scalability, and practical utilization, our proposed methodology's execution requires careful analysis of many essential features. Computational infrastructure, software dependencies, data integration, model training protocol, 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. In order to guarantee the validity and generalizability of the TB detection model, model validation goes beyond conventional practices and includes cross-validation techniques and external validation metrics. After implementing the classification, various models have been given various levels of accuracy. Only depending on the test data set, the highest accuracy was given at VGG16, which is 99%, but the model isn’t suitable for this. Then the densenet121 model was given the second highest accuracy. In this research, the dataset has two categories: normal and tuberculosis.

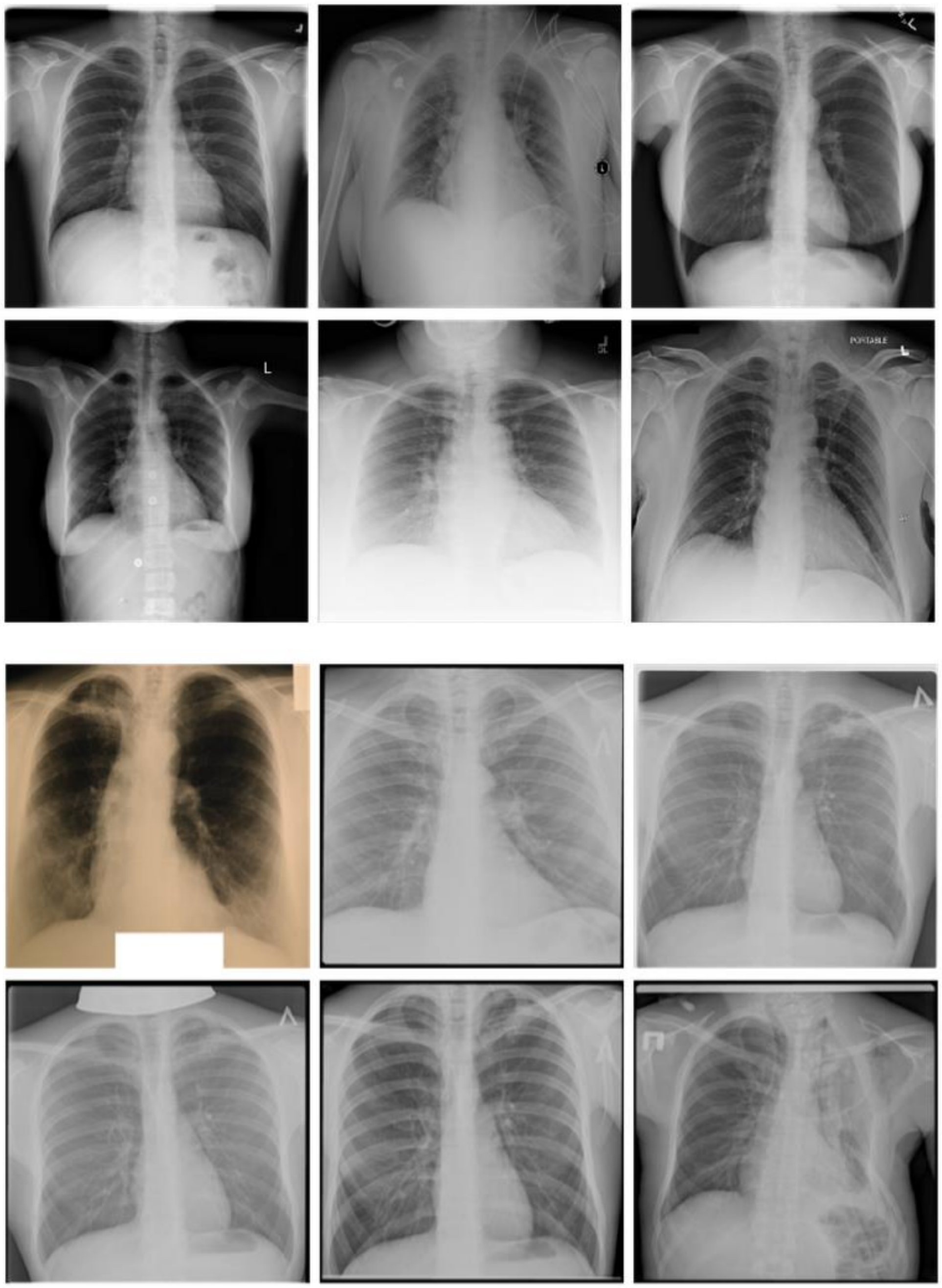


Figure 3.5.1: Normal and TB X-rays of data

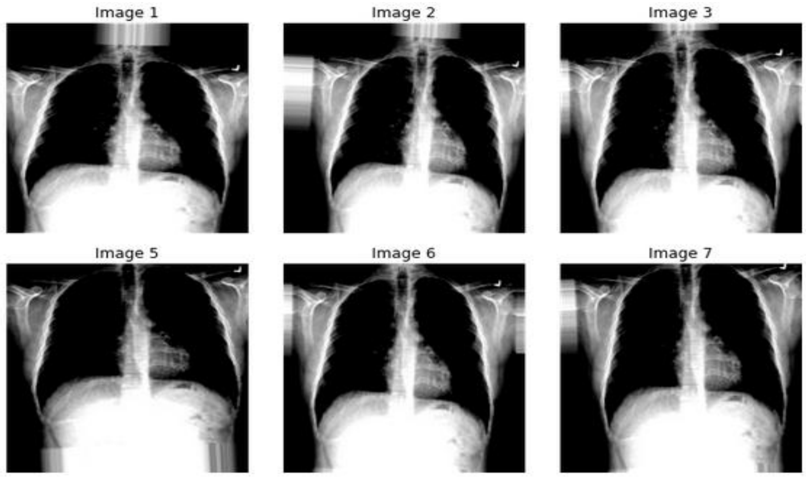


Figure 3.5.2 Normalization Images

Grad-cam Heatmap Tuberculosis Grad-cam overlay

Figure 3.5.3: Score-CAM visualization of properly identified TB infected chest x-ray

CHATER 4

Experimental Results and Discussion

4.1 Experimental Setup

When establishing the experimental framework, the dataset used for training and evaluation consisted of cases classified as “Normal” and “Tuberculosis. To understand potential bias, we looked at the distribution of classes within the dataset. Image preprocessing included standardization and normalization techniques to ensure consistency across the dataset. The models considered for experiments included DenseNet121, VGG16, ResNet50, InceptionV3, ConvNet. The dataset was split into training and validation sets, and a systematic training and validation loop was run to optimize the performance of each model. Figure 4.1 a simple individual steps of experimental setup process given.

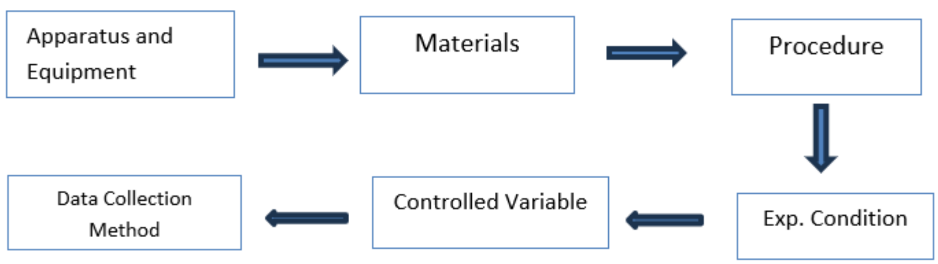


Figure 4.1: Steps of Experimental setup process

The dataset, model, model conversion, inference, and hardware computing devices are covered in this section. According to based on different devices has different capacity and run time complexity in it. So, it’s great impact on the project to run or initial setup.

4.2 Experimental Results and Analysis

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 in accurately classifying Tuberculosis instances. ResNet50 mirrored DenseNet121`s performance, emphasizing the consistent struggle in Tuberculosis detection. InceptionV3 achieved a balanced 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 metrics were carefully analyzed, revealing the persistent struggle across models in identifying Tuberculosis cases.

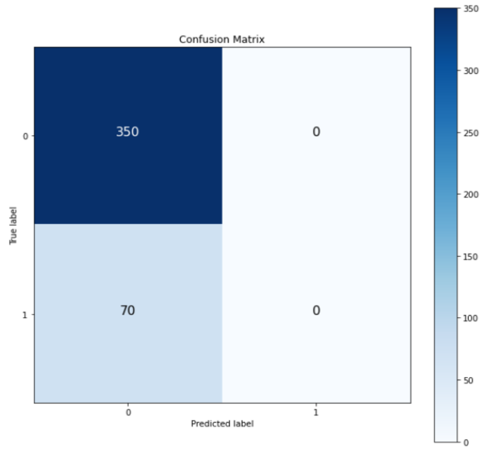
Accuracy = $\frac{(TP+TN)}{(TP+FP+TN+FN)}$

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

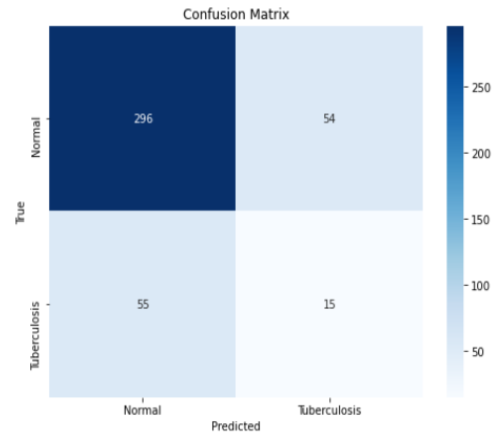
Precision = $\frac{(TP)}{(TP+FP)}$

F1-score = 2 x $\frac{(Precision \times Recall)}{(Precision+Recall)}$

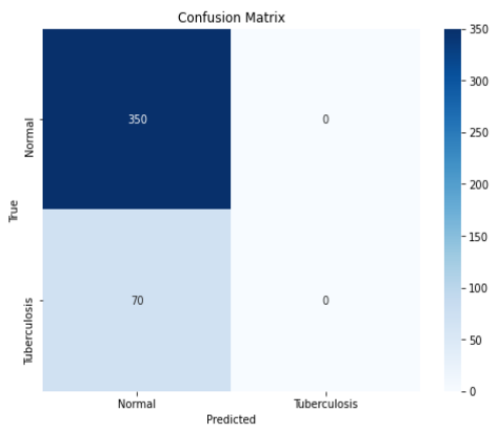
Figure 4.2 where confusion matrix for non-segmented CXR images of applied algorithms which are given below.



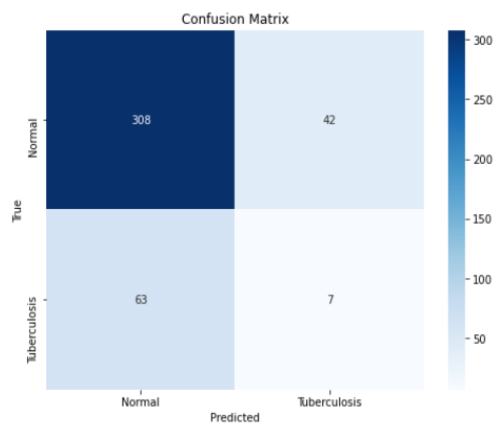
DenseNet121



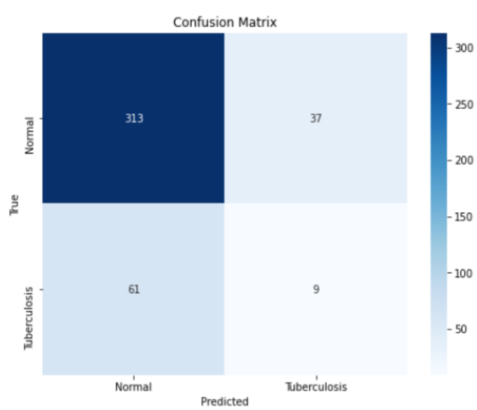
VGG16



ResNet50



InceptionV3



ConvNet

Figure 4.2: Confusion Matrix of applied Models

Table 4.2: Model Performance of Applied Model

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

4.3 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. Recognition that class imbalances contribute to indicator skew has led to consideration of strategies to address such imbalances. Differentiated comparisons between models and their strengths and limitations are highlighted, especially in the context of real diagnostic applications. 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.

CHAPTER 5

Impact on Society, Environment and Sustainability

5.1 Impact on Society

The realization of tuberculosis detection using advanced image processing technology will have a major impact on society. This technology provides an efficient and automated method for diagnosing tuberculosis using chest X-rays, contributing to early detection and timely intervention.

The societal impact extends to the optimization of resources within the health system, allowing for better resource allocation and increased efficiency in the treatment of tuberculosis cases. So, it'll have a great impact on our society.

5.2 Impact on Environment

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. Early detection and treatment of tuberculosis contribute to reducing the overall burden on healthcare systems. This could lead to a reduction in the carbon footprint of medical facilities and practices.

Moreover, the transition towards automated diagnostics may contribute to the reduction of physical film usage and the adoption of digital imaging technologies, aligning with eco-friendly practices in the healthcare sector. According to the describe, we can also say that, it’ll also have an impact on environment.

5.3 Ethical Aspects

Technology usage for medical diagnostics is heavily influenced by ethical issues. Informed permission, patient privacy, and openness are all crucial when using chest radiographs for diagnosis. An important ethical aspect is ensuring that people in different socioeconomic categories and geographical areas have equal access to technology. The advantages of tuberculosis detection will accrue to every segment of society, provided that technological innovation and ethical norms are harmonized. The pursuit of tuberculosis detection through image segmentation and classification raises important ethical considerations, including protecting patient confidentiality, reducing algorithmic biases, fostering transparent collaboration, validating models for clinical use, securing sensitive data, and promoting global health equity.

5.4 Sustainability Plan

Planning for sustainability is necessary to guarantee the viability and long-term efficacy of imaging-based TB detection. This calls for constant model monitoring and upgrading in order to accommodate changing diagnostic standards and medical procedures.

Establishing standards for the moral and responsible use of technology requires cooperation with regulatory bodies, healthcare organizations, and other pertinent parties.

Technology sustainability is aided by research and development spending, particularly when it comes to mitigating model biases and limits. Here, I used CAD for analysis, creation and optimization of design. In fact, it optimizes computing resources, promotes ongoing model improvement, and synchronizes research outputs with long-term social and environmental implications in TB detection.

CHAPTER 6

Summary, Conclusion, Recommendation and Implication for Future Research

6.1 Summary of the Study

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. 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. The research carefully assesses each model's performance, taking into account criteria including F1-score, accuracy, precision, and recall.

6.2 Conclusions

As a result of our study, we found that the dataset has an impact on a supervised learning model's diagnostic performance. This is due to the distribution of illness severity in various groups as well as the differing technical specifications of CXR images. I also implemented Grad-CAM for identified the tuberculosis affected area at chest x-ray. 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%, 99.76%, 83.33%, 75.00%, and 76.67%.

6.3 Implication for Further Study

The suggestions for further study provide a way for scholars to use image segmentation and classification to investigate more intricate aspects of tuberculosis detection. Segmentation and classification still have a lot of scope for development. I want to provide a thorough, integrated evaluation of the state of our knowledge about lung segmentation and disease classification in chest X-rays with this study. The gathered data shows that the recommended preparation methods are generally acknowledged and simple to use. I do improve with time, even if I don't need a lot of computational work or a lengthy preparation period. I would want to attempt producing heatmaps using the u-net network. Compared to other networks, I hope that these heatmaps will gather more pertinent data. I'll try it real time implementation and collaboration with healthcare professionals and continuous model monitoring and updating.

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