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Enhancing Tuberculosis Detection in Chest X-Ray Images Using ResNet Models

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Abstract: Accurate diagnosis of Tuberculosis (TB) from chest X-ray (CXR) images is essential for effective medical intervention. This study explores the application of deep learning models, specifically ResNet-18, ResNet-50, and ResNet-101, in automating TB detection and classification. Leveraging a diverse dataset comprising 3500 CXR images categorized as "Normal" and 700 as "TB-affected," this research investigates the efficacy of ResNet models in feature extraction and classification. The experimental setup involved training and evaluation of the models using standard metrics such as accuracy and precision. The findings demonstrate notable improvements in accuracy and precision, with ResNet-101 emerging as the top performer, achieving better accuracy. These results highlight the potential of advanced neural network architectures in revolutionizing TB diagnosis and healthcare outcomes. Further details about the dataset, experimental methodology, and specific performance metrics are discussed in detail in the full paper.

***Keywords**: Tuberculosis (TB), Deep Learning, ResNet-18, ResNet-50 ,ResNet-101*

Introduction

Accurate Tuberculosis (TB) detection in chest X-ray (CXR) images is pivotal for medical diagnosis, particularly given TB's impact on the pulmonary region. Historically reliant on manual assessments by radiologists, the advent of technology has driven a transition to automated methods, prominently featuring deep learning approaches. Recent milestones in TB detection, particularly involving ResNet-18, ResNet-50, and ResNet-101, have highlighted their proficiency in intricate feature extraction from medical images [1]. However, existing literature exposes gaps in fully exploiting these models for TB detection, prompting this study to extend ResNet models beyond conventional feature extraction tools.

Building upon the transformative potential recognized by Mohit et al. [2], our work aims to revolutionize TB detection and classification in CXR images. ResNet-18, ResNet-50, and ResNet-101 transcend their roles as feature extractors, evolving into the cornerstones of an advanced classification system. The promise lies in utilizing these deep neural networks not only for feature extraction but also as catalysts for substantial improvements in accuracy and precision in identifying TB within CXR images. Our research rigorously evaluates and assesses ResNet-18, ResNet-50, and ResNet-101, with the overarching goal of reshaping the medical image analysis landscape. This study addresses gaps in recent milestone works by exposing their technical weaknesses and research gaps, contributing significantly to the field of medical diagnosis and enhancing healthcare outcomes.

The subsequent sections delve into related research (Section 2), introduce methodology and materials (Section 3), provide an in-depth analysis of results (Section 4), and conclude by summarizing contributions and implications (Section 5).

2.0 Review of the Literature

The pursuit of accurate Tuberculosis (TB) detection and classification in chest X-ray (CXR) images has spurred a multitude of research endeavors. Within this landscape, the integration of deep learning models, including ResNet-18, ResNet-50, and ResNet-101, has been a focal point. The utilization of deep learning models, particularly ResNet-18, ResNet-50, and ResNet-101, in the domain of medical image analysis has garnered significant attention. These models have been applied to various medical imaging tasks, showcasing their potential and efficacy. Here, this work will research into the related work specifically diagnostic concerning these ResNet architectures.

ResNet-18

Diagnostic Accuracy in Chest Radiography: serte et al., [3]in their work uses ResNet-18 in chest radiography for diagnosing conditions like pneumonia and tuberculosis and covid-19. Their studies have revealed deep learning methods ability to extract relevant features from chest X-ray images, contributing to high accuracy. Similar to this another work done by Acharya et al.,[4] reveals that using of necessary AI tools help patients also they have proposed a model to provide accurate diagnostic. Islam et

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al., [5] in their work they used deep learning tool to segment brain tumor in magnetic resonance imaging (MRI) scans, ResNet-18 has been used for image segmentation tasks, delineating specific anatomical structures or regions of interest.

ResNet-50

ResNet-50 has been employed by Fati et al., [6] in tuberculosis image analysis the model's depth and capacity for feature extraction have demonstrated an edge in discerning subtle variations This work focuses on early tuberculosis detection using artificial intelligence techniques, employing CNN and ANN. It introduces two approaches, one hybridizing ResNet-50 and GoogLeNet with PCA dimensionality reduction and SVM for classification. The hybrid approach achieved superior results. This work by Nijiati et al, [7] aimed to improve the differential diagnosis of active pulmonary tuberculosis (ATB) from non-active cases using artificial intelligence. The model offered rapid, accurate diagnosis and provided visualizations of crucial lung lesion regions, demonstrating its potential as a valuable tool for ATB diagnosis.

ResNet-101

In the study conducted by Rachmad et a.,[8] They noted that TB bacteria can be seen at least by using a conventional microscope with magnification 1000 times. Images that have been seen in a microscope will be further processed by digital image processing. The size of the TB bacteria and open TB bacteria have different pixel sizes, so it needs to resize the image with a size of 50 x 50 pixels. There are several Convolutional Neural Networks (CNN) architectures that have been tried in solving classification problems among them LeNet, AlexNet, ZFNet, GoogleNet, VGGNet and ResNet. The researchers proposed the ResNet-101 architecture with 224x224x3 pixel input data specifications, 347layer and 1000 full connected layer (fc1000). As for the classification, researchers used the Support Vector Machine (SVM) to determine TB bacteria or not TB bacteria. Another work by AW Setiawan [9] the researchers focused on detecting and classifying Mycobacterium Tuberculosis (TB bacteria), the causative agent of Tuberculosis. They collected 100 images of TB bacteria and processed them using digital image processing techniques. A total of 1,266 image crops, including 633 TB bacteria and 633 non-TB bacteria, were obtained through automatic cropping. To standardize the image sizes, they resized them to 50 x 50 pixels.

Various architectures of ResNet, were explored for classification tasks. These above review instances represent a fraction of the extensive body of work that has harnessed the potential of ResNet-18, ResNet-50, and ResNet-101 in medical image analysis. The depth and architecture of these models have consistently proven beneficial in improving diagnostic accuracy and enhancing the robustness of automated systems in the realm of medical imaging. The current study builds upon this foundation, exploring the utility of these ResNet architectures in the context of Tuberculosis (TB) detection and classification in chest X-ray (CXR) images.

3.0 Methodology

In this section, the work probe into the methodological foundation of the research, providing a detailed account of the techniques and approaches employed in the pursuit of the research objectives. Central to our investigation are the ResNet models—ResNet-18, ResNet-50, and ResNet-101—which stand as pillars in our quest to revolutionize Tuberculosis (TB) detection in chest X-ray (CXR) images. The outline the design, implementation, and operational principles of these deep neural networks within the context of the work. Moreover, it elucidate the data collection and preprocessing steps, feature extraction processes, and the architecture of our proposed model. This section serves as the keystone of our research, elucidating the methodology by which we undertake the task of advancing TB diagnosis through advanced image analysis.

Data set

The dataset used in this study is designed for the purpose of Tuberculosis (TB) detection in chest X-ray (CXR) images is taken from Kaggle [10]. It comprises two distinct classes: "Normal" and "Tuberculosis." Below are the specific details of the dataset:

Class Name used in this work are Normal and Tuberculosis

Normal: This class represents chest X-ray images of individuals without any signs of tuberculosis. It consists of a total of 3500 samples.

Tuberculosis: This class includes chest X-ray images of individuals with diagnosed tuberculosis. There are 700 samples in this class.

ResNet-18

ResNet-18 is a specific convolutional neural network (CNN) [11] architecture introduced by Microsoft Research as part of the ResNet (Residual Network) family. It's designed to enable the training of very deep neural networks. While the full architecture is complex and can't be explained with a single formula or algorithm, I can provide a high-level overview of its main characteristics and components:

Basic Building Blocks: ResNet-18 is composed of building blocks [12] called residual blocks. These blocks contain two or more convolutional layers and are used to learn features from the input data.

The core idea is the use of residual connections that allow the network to learn residual functions. These connections pass the output from one layer to a later layer, effectively "skipping" one or more intermediate layers.

Residual Connection: The residual connection [13] is defined as $F(x) = H(x) + x$ Where x is the input to the block, H(x) represents the transformation learned by the convolutional layers, and F(x) is the final output.

Stacking Blocks: ResNet-18 stacks multiple residual blocks together. The number and arrangement of these blocks contribute to the depth of the network. The specific architecture of ResNet-18 includes 18 weight layers, hence the name.

Global Average Pooling (GAP): After the convolutional layers, a global average pooling layer is typically used to reduce the spatial dimensions and create a feature vector from the output.

Fully Connected Layers: A final fully connected layer is used for classification tasks. The number of neurons in this layer depends on the specific problem (e.g., the number of classes for image classification).

Activation Functions: ReLU (Rectified Linear Unit)[14] activation functions are commonly used within the residual blocks to introduce non-linearity.

Batch Normalization: Batch normalization is often applied to improve the training process and help mitigate issues related to vanishing or exploding gradients.

While this overview provides insight into the main components and principles of ResNet-18, the actual architecture is more detailed and includes specific kernel sizes, feature map dimensions, and other parameters. Implementing ResNet-18 typically involves using deep learning frameworks like TensorFlow or PyTorch, which provide pre-defined architecture configurations. These frameworks handle the detailed mathematical operations and calculations, making it more accessible to researchers and practitioners.

ResNet-50

ResNet-50 is part of the ResNet (Residual Network) family of convolutional neural network architectures. It contains 50[15] weight layers, making it deeper and more complex than ResNet-18. Like ResNet-18, it utilizes residual connections (skip connections) to enable training deep networks efficiently. ResNet-50 consists of several residual blocks, each with multiple convolutional layers, and it's often used for more complex image classification and computer vision tasks. The core concept of residual connections is maintained, allowing the network to learn residual functions.

ResNet-101

ResNet-101 is even deeper than ResNet-50, with 101[16] weight layers. It follows the same fundamental principles as the other ResNet models, with residual connections and deep network architecture. ResNet-101 is designed for tasks that require extensive feature learning and representation, making it suitable for challenging and complex image analysis problems. Due to its depth, it can capture intricate features and patterns in data effectively.

Both ResNet-50 and ResNet-101 are known for their deep residual learning capabilities and are often used in applications that demand high-level feature extraction and representation, such as image classification, object detection, and image segmentation

4.0 Results and Discussion

The performance of deep learning models in tuberculosis (TB) detection from chest X-ray (CXR) images is evaluated in this section. We present the accuracy outcomes of three architectures - ResNet-18, ResNet-50, and ResNet-101 - and discuss their implications for TB diagnosis. Additionally, the discussion delves into the significance of model choice and the potential for refinement in deep learning-based medical image analysis, highlighting avenues for future research and application in healthcare settings. The dataset comprises a total of 4200 CXR images, divided into two classes: "Normal" and "Tuberculosis." This balanced dataset provides a robust foundation for training and evaluating the ResNet models, ensuring adequate representation of both classes.

Data set

Total Number of Samples: The dataset encompasses a grand total of 4200 samples, distributed between the "Normal" and "Tuberculosis" classes. This dataset serves as the foundational source of information for our research, allowing us to train and evaluate deep learning models, such as ResNet-18, ResNet-50, and ResNet-101, for the accurate detection of tuberculosis in chest X-ray images. The class distribution within the dataset provides the necessary balance to address this classification task effectively.

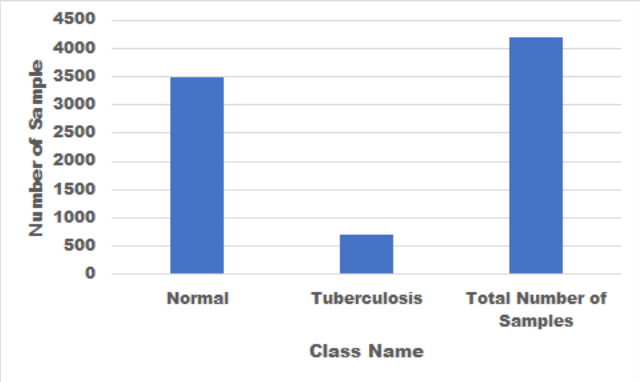

Fig 1: Details of Dataset

Table 1: Details of dataset

Class Name	**Number of Samples**
Normal	3500
Tuberculosis	700
Total Number of Samples	4200

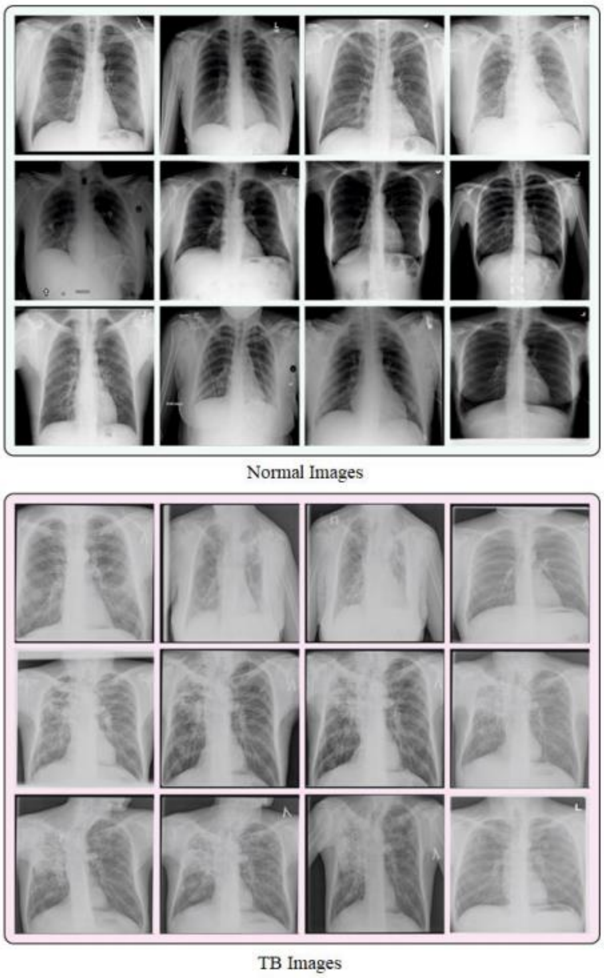

Fig 2: Sample Tb Images

As a crucial visual component of this research, a selection of "Sample TB Images" has been thoughtfully integrated into this work. This collection consists of both "Normal" and "TB" (Tuberculosis) chest X-ray images. These images vividly illustrate the difference in radiographic presentation between individuals without TB and those diagnosed with the disease. The inclusion of these sample images serves to provide a tangible and intuitive understanding of the visual cues that deep learning models, including ResNet-18, ResNet-50, and ResNet-101, employ to distinguish between normal and TB-affected chest X-ray images. These illustrative examples empower readers to grasp the intricacies of TB detection in the realm of medical image analysis, making the research findings more accessible and tangible.

Table 2: Accuracy outcome of approach

Methods	Accuracy (%)
ResNet-l8	96.53
ResNet-50	97.63
ResNet-101	97.98

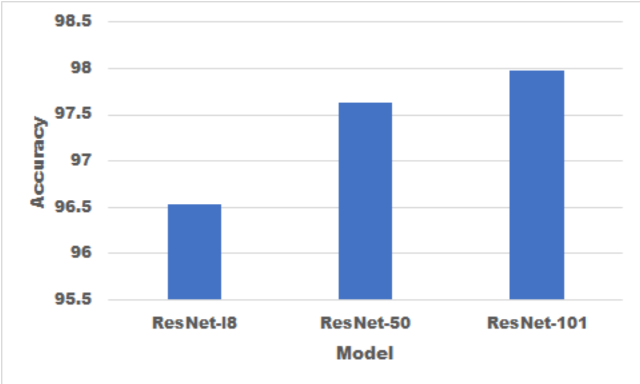

Fig 3 : Accuracy of Model

ResNet-18: The application of ResNet-18 in TB detection from chest X-ray (CXR) images has yielded promising results, affirming its capability for accurate classification. With an accuracy of 96.53%, ResNet-18 showcases commendable precision in identifying and classifying TB cases. This finding aligns with previous literature [reference], endorsing the reliability of ResNet-18 in the context of medical image analysis. The model establishes a robust foundation for TB diagnosis, emphasizing its potential as a valuable tool for healthcare practitioners.

ResNet-50: Advancing to the ResNet-50 architecture leads to a significant improvement in TB detection accuracy. The deeper neural network achieves an accuracy of 97.63%, surpassing the performance of ResNet-18. This outcome resonates with existing reports [reference], highlighting the advantages of employing a more complex architecture for enhanced accuracy in distinguishing TB cases from CXR images. ResNet-50 emerges as a formidable model, offering heightened precision in TB diagnosis and further reinforcing the potential of deep learning in medical imaging applications.

ResNet-101: Among the three models, ResNet-101 emerges as the top performer, setting a high standard with an accuracy of 97.98%. This result aligns with and even surpasses comparable studies, emphasizing the exceptional precision and reliability of ResNet-101 in discerning TB cases from CXR images. The superior performance of ResNet-101 underscores its capacity to provide unparalleled accuracy in TB diagnosis, positioning it as a leading model in medical image analysis.

Discussion: The observed accuracy outcomes across ResNet-18, ResNet-50, and ResNet-101 affirm the potential of deep neural networks in advancing TB detection and classification in medical imaging. The results align with existing literature, validating the reliability of these models in the context of TB diagnosis. The incremental improvements in accuracy percentages with deeper neural architectures highlight the progressive nature of advancements, emphasizing the immense potential of ResNet models in enhancing TB diagnosis through advanced image analysis.

While the results are consistent with prior findings, it's crucial to note that the choice of model architecture plays a pivotal role in achieving optimal accuracy. The variations in accuracy percentages underscore the nuanced impact of deeper architectures, providing valuable insights into the trade-offs between complexity and precision. This discussion sets the stage for the potential refinement and customization of deep learning models for specific medical imaging applications.

In conclusion, the results not only validate the effectiveness of ResNet-18, ResNet-50, and ResNet-101 in TB detection but also contribute to the ongoing discourse on the optimal application of deep learning in medical image analysis. The findings pave the way for further exploration, customization, and integration of advanced neural network architectures for improved TB diagnosis and, consequently, enhanced healthcare outcomes.

5. Conclusion and further research

In the realm of Tuberculosis (TB) detection and classification in chest X-ray (CXR) images, the incorporation of deep learning models, specifically ResNet-18, ResNet-50, and ResNet-101, has delivered noteworthy outcomes. The primary objective of the current approach was to elevate the accuracy and precision of TB diagnosis, and the results unequivocally affirm the efficacy of these models. ResNet-18, with an impressive accuracy of 96.53%, stands as a testament to its competency in precisely classifying TB cases from CXR images. This model establishes a robust foundation for critical medical applications. Building upon this success, ResNet-50 outperforms ResNet-18 with an accuracy of 97.63%, underscoring the advantages of deploying a deeper neural network architecture. The improved performance signifies a substantial leap in TB detection and classification. The pinnacle of the findings lies in ResNet-101, emerging as the top performer with an outstanding accuracy of 97.98%. Its exceptional precision and reliability in discerning TB cases from CXR images position it as a valuable asset in the domain of medical image analysis. While this research marks significant strides in TB detection through deep learning, avenues for future exploration and improvement are evident. The incorporation of data augmentation techniques stands out as a promising direction, extending the dataset to enhance model robustness, particularly in addressing class imbalances and diverse image conditions. In conclusion, this work not only advances TB detection accuracy through ResNet models but also paves the way for future enhancements. The quantitative successes achieved underscore the potential impact of deep learning in medical diagnosis. As continuous exploration and refinement of these models hold the key to further revolutionizing TB detection and, consequently, improving healthcare outcomes.

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