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Tuberculosis Detection Using Convolutional Neural Network

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Abstract - Tuberculosis (TB) is a chronic lung disease caused by bacterial infection and remains one of the leading causes of mortality worldwide. Early and accurate detection of TB is crucial for effective treatment and prevention of complications. In this study, we propose a deep learning-based system for TB detection using chest X-ray images. The system leverages the VGG16 architecture for classification, supported by image preprocessing and data augmentation to improve model performance. The dataset comprises X-ray images categorized into TB-infected and normal cases. The VGG16 model was trained, validated, and tested to classify chest X-rays, achieving a train accuracy of 98.55%, validation accuracy of 99.75% and test accuracy of 98.73%, for TB detection. Our results demonstrate the effectiveness of the VGG16-based model in reliably detecting TB from chest X-rays while providing practical healthcare accessibility through the user interface. This combined approach can serve as a valuable tool in computer-aided TB diagnosis, enabling timely and accurate detection to improve patient outcomes.

***Key Words*:** Chest X-ray Classification, Deep Learning, Medical Image Analysis, Computer-Aided Diagnosis (CAD), Transfer Learning, TB Diagnosis.

1.INTRODUCTION

Tuberculosis (TB) remains one of the deadliest infectious diseases in the world, despite advancements in medical treatments and public health efforts. Caused by the bacterium *Mycobacterium tuberculosis*, TB primarily affects the lungs but can also impact other parts of the body, such as the brain, kidneys, and spine. According to the World Health Organization (WHO), over 10 million people fall ill with TB every year, and approximately 1.6 million people die from the disease annually. The global fight against TB continues to be a major public health challenge, particularly in low-resource countries (LRCs), where access to quality healthcare and trained medical personnel is limited. This makes the early detection and timely treatment of TB all the more critical to reduce transmission rates and prevent the disease from progressing to severe stages.

Chest X-rays (CXR) are widely used for tuberculosis (TB) screening due to their non-invasive nature, cost-effectiveness, and ability to detect lung abnormalities. However, interpreting CXR images is complex and relies on skilled radiologists. In TB-endemic regions, the high volume of CXRs makes manual examination time-consuming, and the subjectivity of interpretations can lead to inconsistent diagnoses, delays, or errors, worsening patient outcomes.

The shortage of trained radiologists in resource-limited areas further complicates timely TB detection. Moreover, similarities between TB-related abnormalities and other respiratory diseases, such as pneumonia, make accurate diagnosis challenging. These issues underscore the need for reliable, efficient diagnostic tools. Deep learning, particularly convolutional neural networks (CNNs), offers a promising solution by learning patterns directly from CXR data without manual feature extraction. CNNs have shown high accuracy in detecting TB-related abnormalities, providing a scalable solution to support radiologists in low-resource settings by offering a second opinion.

However, challenges remain, including the need for diverse, annotated datasets and the variability in imaging conditions across regions, which can impact model performance. Developing robust models that generalize across different settings is essential for their clinical adoption.

2. LITERATURE REVIEW

The study presents a deep learning approach for tuberculosis detection using 3,500 chest X-ray images from two online repositories, classified as "Normal" and "Tuberculosis." After preprocessing (denoising, resizing, and cleaning), the dataset was split into 80% for training and 20% for testing. Transfer learning models, including MobileNetV2, VGG16[1], VGG19, and InceptionV3, were used for classification, with MobileNetV2 achieving the best performance with 99.99% training accuracy and 98.93% test accuracy. The study highlights the effectiveness of deep learning and preprocessing in enhancing TB detection. Based on the results and the architecture's strong performance, we have chosen VGG16 for our project.

Deep learning models have been introduced for the automatic detection of pulmonary tuberculosis (TB) from chest X-ray images using convolutional neural networks (CNNs)[2], enhanced with a coordinate attention mechanism. Tested on the Shenzhen Third Hospital dataset [5], the method achieved high accuracy and efficiency in classifying TB cases, significantly reducing the workload of radiologists. By incorporating transfer learning and freezing certain layers of the network, the model improved training speed and performance. Data augmentation techniques were also applied to overcome the challenge of limited dataset sizes, enhancing the model’s generalization ability. With a lightweight design, the model is easily integrable into existing healthcare systems without high computational demands. This method outperforms traditional approaches in feature extraction and classification accuracy, making it a reliable tool for TB detection, especially in resource-constrained settings. Based on this, we have implemented CNN, transfer learning, freezing, and data augmentation techniques in our project.

A novel method for diagnosing tuberculosis (TB) using Convolutional Neural Networks (CNNs), specifically DenseNet121 and ResNet50[3] architectures. The study addresses the global challenge of TB by leveraging advanced image processing techniques applied to chest X-ray images, significantly enhancing diagnostic accuracy. Key preprocessing steps, such as image resizing and pixel value scaling, were used to optimize model performance. The research emphasizes the benefits of DenseNet's feature reuse and ResNet's residual blocks, which help mitigate gradient issues and improve model efficiency. Both models demonstrated high accuracy and robustness when tested on well-curated datasets, showcasing their potential for TB detection. This work highlights the growing role of CNNs in medical image analysis and underscores their applicability in providing timely and accurate TB diagnoses, especially in resource-constrained settings. Based on this study we got comparison between different CNN models.

The study explores the use of deep learning methods for detecting tuberculosis (TB) in chest X-ray (CXR) images, addressing the global health challenge of timely and accurate TB diagnosis. The researchers developed a computer-aided diagnosis (CAD) system that utilizes transfer learning to support radiologists in diagnosing TB. Pre-trained convolutional neural networks (CNNs), including DenseNet121, VGG16 [4], and MobileNet, were used to extract features from CXR images, and a Support Vector Machine (SVM) was employed for classification [8]. To further enhance the model's performance, data augmentation techniques were applied to increase the size and diversity of the dataset. The DenseNet121 model outperformed others, achieving an impressive accuracy of 98.9% and an area under the curve (AUC) of 1.00 on the augmented dataset. The study used the Montgomery County chest X-ray dataset, which includes both normal and TB-affected images, and emphasized the importance of data augmentation when working with small datasets. The proposed system shows significant potential in alleviating the workload of radiologists and improving diagnostic efficiency, establishing a benchmark for AI-assisted TB detection methods.

The discussed studies face limitations such as reliance on large, annotated datasets, limited generalization across diverse clinical settings, and high computational demands, which make implementation in resource-constrained areas challenging. Additionally, some methods lack interpretability, hindering clinical integration. Our project overcomes these issues by leveraging a lightweight, VGG16-based model optimized for low-resource settings. It incorporates different data augmentation techniques to focus on relevant regions, improving accuracy while minimizing computational complexity. By using transfer learning, our approach ensures better generalization, enhanced interpretability, and supports radiologists by offering an efficient and reliable second opinion.

3. PROPOSED METHEDOLOGY

The development of a robust and accurate system for the detection of tuberculosis (TB) from chest X-ray images is a complex process that integrates advanced machine learning techniques with deep domain expertise in both medical imaging and artificial intelligence (AI). Tuberculosis, a leading cause of global morbidity and mortality, can be challenging to detect in its early stages, especially in regions with limited healthcare infrastructure. Early diagnosis is crucial for effective treatment and containment of the disease, which is why a highly reliable and efficient detection system is needed. This paper presents a detailed methodology for building an automated TB detection system using chest X-ray images, focusing on ensuring accuracy, scalability, and practical usability in healthcare settings.

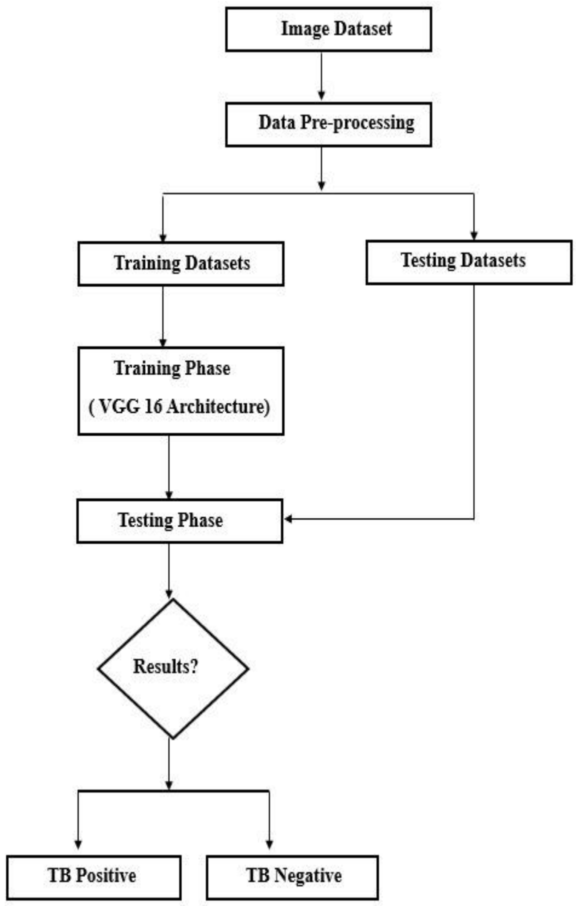

Fig. 1. Workflow Diagram.

Fig. 1. outlines the process of tuberculosis detection using chest X-ray images. It begins with the acquisition of an image dataset, which is subjected to data pre-processing to enhance the quality and ensure uniformity for analysis. The pre-processed dataset is then split into training datasets and testing datasets. During the training phase, a predictive model is built using the VGG16 architecture, leveraging its ability to extract complex features from the images. Once the training is complete, the model enters the testing phase, where its performance is evaluated on the unseen testing dataset. The results of this process are analyzed, and the system provides a final classification, categorizing the input images as either TB

Positive or TB Negative, aiding in accurate and efficient TB diagnosis.

5.1 Data Set

The Tuberculosis (TB) Chest X-ray Database is a comprehensive collection of chest X-ray (CXR) images, categorized into TB-positive and normal cases, aimed at aiding research in TB detection and analysis. This dataset was created by a collaborative team of researchers from Qatar University, the University of Dhaka, and other institutions, in partnership with medical professionals. The database includes 700 publicly accessible TB-positive images and 3,500 normal images. The dataset integrates CXR images from various sources, including the Montgomery and Shenzhen datasets provided by the National Library of Medicine (NLM), the Belarus dataset collected for drug resistance studies, and the NIAID TB portal program dataset. This dataset, originally sourced from Kaggle, offers a valuable resource for advancing scientific work on TB diagnosis and prevention.

5.2 Data Preprocessing and Augmentation

The preprocessing and augmentation of images play a crucial role in preparing a dataset for deep learning tasks. The first step involves normalizing the pixel values to a consistent range, ensuring faster convergence during training and stable performance. Images are then resized to a standardized dimension to maintain uniformity and compatibility with deep learning models.

To make the model more robust and reduce the risk of overfitting, data augmentation techniques are applied. These include random rotations, shifts (both horizontal and vertical), shear transformations, zooming, and horizontal flips. Augmentation simulates real-world variations, such as changes in angles, perspectives, and positions, helping the model generalize better to unseen data. Additionally, empty spaces introduced by transformations are handled using interpolation methods to preserve the image's structure.

The images are then processed in batches, with labels automatically assigned based on the class organization. These steps collectively ensure that the dataset is standardized, diverse, and of high quality, enhancing the model's ability to learn effectively and perform well on new data.

5.3 Model Architecture and Feature Extraction Using VGG16 for Tuberculosis Detection

In this study, we use the VGG16 model, a convolutional neural network (CNN), for tuberculosis detection from chest X-ray images. The VGG16 architecture consists of 16 layers, including 13 convolutional layers and 3 fully connected layers, designed to extract hierarchical features and classify images as "healthy" or "tuberculosis." The model processes chest X-ray images resized to 224x224 pixels, using small 3x3 filters in the convolutional layers, followed by max-pooling layers to reduce spatial dimensions and preserve significant features. This design enables the network to capture low-level patterns in early layers and more complex features like lesions in deeper layers. After feature extraction, the model flattens the feature maps and passes them through a fully connected layer with 256 neurons.

The final layer of the model consists of a single neuron with a sigmoid activation function, producing a probability score indicating whether the image is healthy or TB-positive. Transfer learning is applied by fine-tuning the pre-trained VGG16 model, originally trained on ImageNet, to focus on tuberculosis-specific patterns. The convolutional layers are initially frozen, preserving general features, while the fully connected and output layers are fine-tuned for the tuberculosis classification task. This approach enhances the model's performance, enabling it to accurately classify chest X-rays as healthy or indicative of tuberculosis.

5.4 Classification and Model Optimization

After extracting features from chest X-ray images using CNN, the model classifies the images as TB-positive or TB-negative. The feature maps are passed through fully connected layers, which aggregate the learned patterns and make the final prediction. A sigmoid activation function in the output layer generates a probability score, indicating the likelihood of the image being TB-positive. Binary cross-entropy is employed as the loss function to effectively minimize errors between predicted probabilities and actual labels, aiding in the classification process.

The Adam optimizer is used for training to ensure efficient learning and faster convergence. By dynamically adjusting the learning rate, Adam helps the model learn from complex data like chest X-rays while avoiding issues such as vanishing gradients. ReLU activation in the hidden layers introduces non-linearity and allows the model to capture intricate patterns. This combination of sigmoid activation, binary cross-entropy, Adam optimizer, and ReLU activations ensures the model is both accurate and efficient in classifying chest X-rays and detecting tuberculosis.

5.5 Model Evaluation and Performance Metrics

Once the model is trained, it is evaluated using a separate test dataset to assess its performance on unseen data. A comprehensive set of evaluation metrics is used to measure the model's accuracy, precision, recall, F1-score, and area under the receiver operating characteristic (ROC) curve (AUC-ROC). Accuracy provides a general measure of how often the model is correct, while precision and recall provide insight into the model's ability to correctly identify TB-positive and TB-negative cases. The F1-score offers a balanced measure of precision and recall, while the AUC-ROC assesses the model’s ability to discriminate between the two classes across different thresholds.

5. RESULTS

Medical image processing is integral to the detection, monitoring, and management of various diseases, including tuberculosis (TB). Caused by the bacterium *Mycobacterium tuberculosis*, TB continues to pose a major global health challenge, with millions of new cases reported each year. Early and accurate detection of TB is essential for effective management, enabling timely treatment, reducing transmission, and improving patient outcomes. This chapter focuses on the practical considerations of training and testing a medical image classification system for tuberculosis detection. By the end of this chapter, we will have a

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comprehensive understanding of implementing and evaluating such a system.

A. Training process summary

```
Epoch 1/10
/usr/local/lib/python3.10/dist-packages/keras/src/trainers/data_adapters/py_dataset_adapter.py:122: UserWarning: Your
  self._warn_if_super_not_called()
26/26 ━━━━━━━━━━━━━━━━━━━━ 2775s 76s/step - accuracy: 0.7516 - loss: 0.5144 - val_accuracy: 0.9113 - val_loss: 0.2286
Epoch 2/10
26/26 ━━━━━━━━━━━━━━━━━━━━ 102s 3s/step - accuracy: 0.9399 - loss: 0.1794 - val_accuracy: 0.9360 - val_loss: 0.1730
Epoch 3/10
26/26 ━━━━━━━━━━━━━━━━━━━━ 141s 3s/step - accuracy: 0.9444 - loss: 0.1369 - val_accuracy: 0.9532 - val_loss: 0.1059
Epoch 4/10
26/26 ━━━━━━━━━━━━━━━━━━━━ 142s 3s/step - accuracy: 0.9711 - loss: 0.0770 - val_accuracy: 0.9655 - val_loss: 0.0712
Epoch 5/10
26/26 ━━━━━━━━━━━━━━━━━━━━ 143s 3s/step - accuracy: 0.9774 - loss: 0.0514 - val_accuracy: 0.9852 - val_loss: 0.0543
Epoch 6/10
26/26 ━━━━━━━━━━━━━━━━━━━━ 143s 3s/step - accuracy: 0.9676 - loss: 0.0894 - val_accuracy: 0.9754 - val_loss: 0.0568
Epoch 7/10
26/26 ━━━━━━━━━━━━━━━━━━━━ 91s 3s/step - accuracy: 0.9747 - loss: 0.0649 - val_accuracy: 0.9803 - val_loss: 0.0406
Epoch 8/10
26/26 ━━━━━━━━━━━━━━━━━━━━ 93s 3s/step - accuracy: 0.9833 - loss: 0.0507 - val_accuracy: 0.9828 - val_loss: 0.0493
Epoch 9/10
26/26 ━━━━━━━━━━━━━━━━━━━━ 140s 3s/step - accuracy: 0.9805 - loss: 0.0537 - val_accuracy: 0.9803 - val_loss: 0.0448
Epoch 10/10
26/26 ━━━━━━━━━━━━━━━━━━━━ 144s 3s/step - accuracy: 0.9855 - loss: 0.0452 - val_accuracy: 0.9975 - val_loss: 0.0222
```

Fig. 2. Evaluation of epochs

The Fig. 2. shows that the model is trained for 10 epochs with a batch size of 128. Training accuracy steadily increased, and training loss decreased, indicating effective learning. Validation accuracy improved, showing strong generalization on unseen data. The overall metrics suggest the model's successful training and optimization.

B. Loss and Accuracy Results

```
Test Loss: 0.03288145735859871, Test Accuracy: 0.9873417615890503
```

Fig. 3. Testing results

The Fig. 3 depicts results that showcase the performance of a VGG-trained model evaluated on a test dataset. The model achieved a remarkably low-test loss of approximately 0.0329, indicating minimal prediction errors and efficient learning. Additionally, the test accuracy was an impressive 98.73%, reflecting the model's ability to correctly classify most of the test samples. These metrics highlight the robustness and generalization capability of the VGG architecture, suggesting it effectively captured the patterns in the dataset. Overall, the model demonstrates exceptional performance in terms of both accuracy and reliability.

C. Model Evaluation

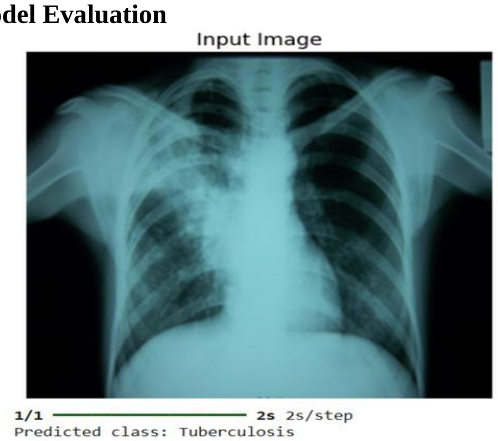

Fig. 4. Class prediction

The Fig. 4 illustrates the prediction result for a chest X-ray processed by a trained deep learning model. The input image is a chest X-ray that the model analyzed to determine the likelihood of tuberculosis. Based on the visual patterns and features extracted, the model classified the image as "Tuberculosis."

D. Training and Validation Accuracy and Loss Graph

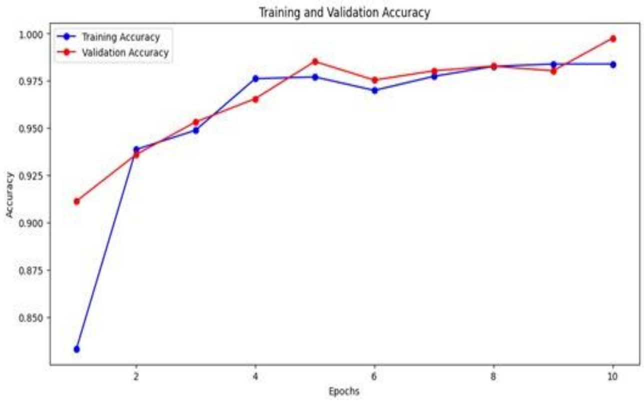

Fig. 5. Plot of Training and Validation Accuracy vs Epochs

The Fig. 5 illustrates the graph that depicts the relationship between training accuracy (blue line) and validation accuracy (red line) over epochs. Initially, at Epoch 1, the training accuracy starts low (~85%), while the validation accuracy is higher (~91%), indicating the model is in the early learning phase. Both accuracies improve steadily through Epochs 2–4, with training accuracy reaching ~97.5% and validation accuracy ~96.5%, reflecting effective feature learning. From Epochs 5–7, validation accuracy briefly surpasses training accuracy, peaking at 98%, showing strong generalization. By Epoch 10, both accuracies converge, with validation accuracy reaching 100% and training accuracy stabilizing near 98%, demonstrating consistent performance.

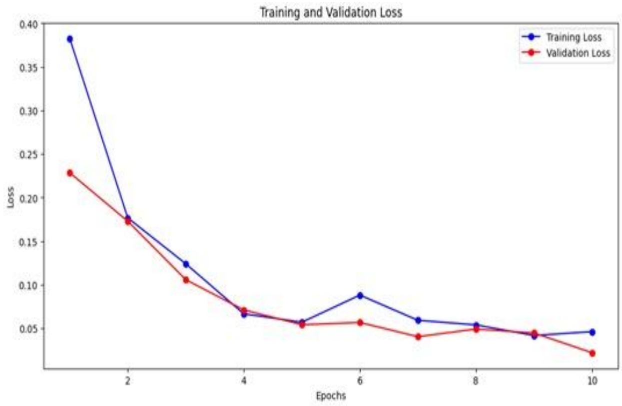

Fig. 6. Plot of Training and Validation Loss vs Epochs

The Fig. 6 illustrates the graph that depicts the relationship between training loss (blue line) and validation loss (red line) over 10 epochs, where lower loss values signify better model performance. At Epoch 1, the training loss starts high (~0.38) while the validation loss is lower (~0.22), reflecting the model's early learning phase with less accurate predictions. Over Epochs 2–4, both losses decrease significantly, with the training loss reducing to ~0.06 and validation loss stabilizing near ~0.05, indicating effective learning of key features. From Epochs 5–7, both losses remain consistently low with minor fluctuations, showcasing good generalization to unseen data. By the end of training, the model maintains low losses, demonstrating reliable performance on both datasets.

6. CONCLUSION

In conclusion, this project leverages the power of deep learning, specifically the CNN-VGG16 model, to revolutionize the detection of tuberculosis in chest X-ray images. Through a systematic approach that includes data collection, preprocessing, model training, and testing, the system accurately classifies X-ray images as either positive or negative for TB. The VGG16 architecture excels in deep feature extraction, capturing subtle patterns crucial for detecting TB infections. Moreover, the integration of this model into an intuitive front-end interface enhances accessibility, allowing users to easily upload chest X-rays and receive reliable, immediate results. The system not only accelerates diagnosis but also provides users with recommendations for nearby TB hospitals, improving the efficiency of healthcare delivery. Ultimately, this project demonstrates the transformative potential of artificial intelligence in medical diagnostics, contributing to faster, more accurate tuberculosis detection and better overall healthcare outcomes.

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