Detection and Analysis of Tuberculosis Disease from Chest X-Ray (CXR) Images using Machine Learning and Deep Learning Techniques

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***Abstract*—Tuberculosis (TB), a significant global health concern, is a chronic lung disease resulting from bacterial infection and ranks among the top 10 leading causes of mortality worldwide. This research aims to propose a model to tackle Tuberculosis's early diagnosis problem. Two publicly available benchmarked datasets from Kaggle namely, Tuberculosis (TB) CXR Database and Shenzhen Hospital CXR Set were used in this work. In this pursuit, a hybrid framework for Tuberculosis classification is proposed. Initially, a deep CNN, DenseNet201 was employed for feature extraction. Following this, the robust eXtreme Gradient Boosting (XGBoost) classifier was used to classify images into TB and Normal classes. This ensemble approach aids in the automated detection of Tuberculosis from CXR images. A comprehensive set of metrics, including accuracy, precision, sensitivity, specificity and F1-scores are used to evaluate the results of the proposed model. DenseNet201-XGBoost performs exceptionally well on both datasets giving F1-scores of 99.83% and 80% respectively. Various other CNNs and Transformer based models such as ResNet101, VGG19, Inception and EfficientNet in combination with the XGBoost classifier were implemented for a comparative analysis. Thus, by amalgamating deep feature extraction models with advanced classification models, this study forges a path toward enhanced Tuberculosis detection.**

***Index Terms*—tuberculosis, CXR images, feature extraction, Xception, EfficientNet, ResNet101, VGG19, DenseNet201, XGBoost, data augmentation**

I. Introduction

Tuberculosis (TB), stemming from Mycobacterium tuberculosis [1], predominantly impacts the lungs and is airborne. According to the World Health Organization (WHO), TB is one of the top 10 causes of death worldwide. Despite its preventability and treatability, TB remains the leading infectious cause of death worldwide, claiming 1.5 million lives annually [2]. It poses a significant threat to those with HIV and plays a substantial role in antimicrobial resistance. While prevalent in low- and middle-income countries, TB is a global concern, with eight nations contributing to half of all reported cases. Roughly 25% of the world's population has encountered TB bacteria, underscoring the need to comprehend risk factors for effective prevention strategies.

The effective control of tuberculosis relies on precise and rapid diagnosis, but traditional TB tests often yield either inaccurate results or prolonged wait times for confirmation. There is a notable absence of a quick and reliable diagnostic approach capable of distinguishing between active and latent TB infections.

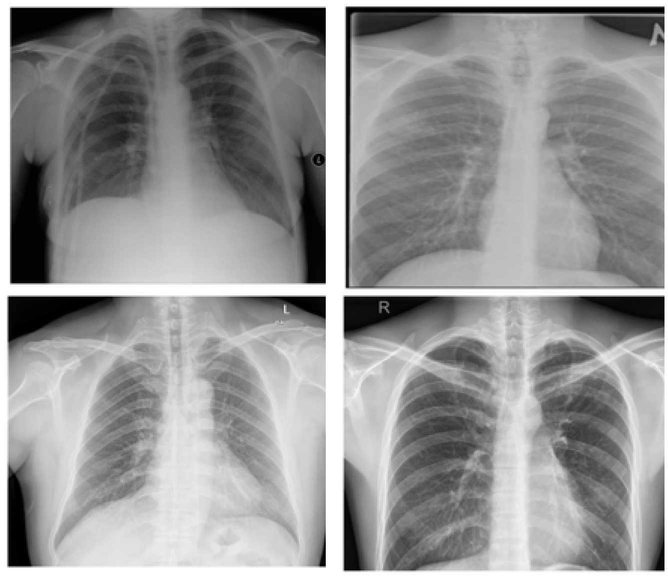

Fig. 1. A sample of Chest X-Ray Images (CXRs)

The are many existing standard diagnostic tests for TB, including chest X-ray, tissue culture, tuberculin skin test (TST), and acid-fast staining, all with certain inherent limitations. Chest X-ray (CXR) imaging is crucial for tuberculosis (TB) detection, revealing primary lesions, cavities, fibrotic scarring, and miliary TB patterns [3]. A few sample images of CXRs for lung disease classification are reflected in Fig. 1. CXRs aid in diagnosing and monitoring TB, allowing for early treatment and reducing disease spread. Integration of deep learning techniques enhances diagnostic accuracy, promising improved efficiency in TB detection. Datasets commonly employed for tuberculosis (TB) detection and classification through chest X-ray (CXR) analysis include the Tuberculosis (TB) Chest X-ray Database, datasets featuring pulmonary CXR abnormalities, lung image segmentation datasets, the NIH Chest X-rays dataset, and the Shenzhen Hospital CXR Set. Hence, the chest radiography (CXR) screening has emerged as a valuable tool for early diagnosis not only of tuberculosis (TB) but also for other respiratory conditions such as pneumonia and Covid-19 [4].

Deep learning techniques stand out in handling extensive datasets and intricate medical image classification tasks, making it particularly adept for efficient tuberculosis (TB) classification [5]. DL models are increasingly employed for efficient TB classification, demonstrating their efficacy in detecting abnormalities in chest X-rays and contributing to the broader success seen in various medical conditions such as pneumonia, and, most recently, the COVID-19 epidemic. Wide range of Deep CNN models like DenseNet121, VGG19, ResNet50, Inception, EfficientNet, Xception and many more have been used in lung disease classification. The following are the major contributions of this research work:

- Creating a hybrid model for TB detection task using a combination of DenseNet201 for feature extraction and XGBoost for classification, producing effective TB diagnosis.
- Exploring wide range of Deep pre-trained CNNs and Transformer based models like ResNet101, VGG19, Xception and EfficientNet in combination with the XGBoost classifier for a comparative study.
- Handling class imbalance in datasets by performing Data Augmentation, oversampling the images in TB class.
- Comparing the results of the proposed model on two different benchmarked CXR datasets.

The paper is structured into six sections. Section I comprises of the Introduction. Section II covers a literature review of the previous research in this field. Section III provides information regarding the data origin. The proposed methodology is presented in Section IV. Experimental results and a comparative study of different models is presented in Section V. Section VI concludes the research work and outlines the plausible future work in this field.

II. Related Work

Computer Assisted Diagnosis (CAD) is crucial for identifying lung-related diseases from chest X-rays (CXRs). The challenge of Tuberculosis detection in CXRs has persisted due to limitations in conventional approaches, such as a shortage of training datasets and imprecise feature extraction. Recent progress underscores the potential of deep learning, especially Convolutional Neural Networks (CNNs), as a promising solution. Their automatic extraction of pertinent features from input images enhances efficiency, rendering them increasingly favored for image classification in disease identification.

This section presents a thorough literature review conducted from 2019 to 2023, in the field of tuberculosis detection. The analysis included a meticulous examination of various research works, enabling advancements and innovations within the field over the recent years. A study focuses on precise tuberculosis recognition from chest X-ray images using advanced techniques [6]. The dataset, created through image preprocessing and segmentation, utilizes nine CNN models, including DenseNet20, achieving remarkable accuracy (98.6%) and sensitivity (98.56%). Visualizing segmented lung regions underscores their importance. The method has significant potential for rapid computer-aided tuberculosis diagnosis. A similar work in the domain of tuberculosis detection involves the construction of a Convolutional Neural Network (CNN), a deep learning model, utilizing a publicly available TB dataset [7]. The effective identification of tuberculosis in chest X-rays (CXR) is realized through the incorporation of data augmentation, image preprocessing, and deep learning techniques. Transfer learning is employed to train four distinct CNNs—InceptionResNetV2, InceptionV3, MobileNetV2, and Xception—resulting in noteworthy outcomes. Notably, InceptionResNetV2 achieves a remarkable 99% F1-score, surpassing previous studies in terms of accuracy and reliability. A hybrid model combining Mask RCNN and BiDLSTM architectures, utilizing three datasets for training and testing has been employed in [8]. Optimization with the Crystal algorithm enhances precision in lung disease segmentation. The model demonstrates high accuracy and reduced loss, validated through cross-validation. However, challenges include heterogeneous training data, complexities in multiclass classification, and accurate image labeling, which may impact reliability across diverse disease categories and data sources. Another study employs U-Net for CXR image segmentation and applies pre-processing steps like Histogram Equalization and Rescaling [9]. Transfer learning involves multiple pre-trained models, enhancing TB detection accuracy. The model is robust across diverse populations and achieves a notable 98.38% accuracy in classifying normal and TB cases. Challenges include the potential for improved performance with larger datasets, exploration of new augmentation techniques to prevent overfitting, and consideration of unsupervised learning to efficiently handle unlabeled medical data, addressing the resource-intensive nature of manual labeling. The study in paper [10] proposes a comprehensive methodology for tuberculosis (TB) detection in chest X-rays, incorporating data preprocessing, lung segmentation using a modified U-Net, and TB lesion detection with Faster RCNN. Customizations to the Feature Pyramid Network enhance accuracy for various lesion sizes, and a false-positive reduction module improves overall performance. The approach successfully handles multicategory lesion detection, reduces false positive rates, and enhances lung segmentation. However, the paper does not explicitly address or highlight open challenges in the TB detection domain. Another related work in [11] proposes a robust methodology for tuberculosis (TB) classification using a two-class dataset, involving preprocessing, dataset splitting, and feature extraction from pre-trained networks VGG19, ResNet101, DenseNet201. XGBoost classifiers tailored to each network variant demonstrate outstanding diagnostic reliability, achieving a remarkable 99.92% accuracy and a 99.93% AUC. The model excels in accurately identifying TB cases while minimizing false positives, outperforming VGG19-XGBoost and ResNet101-XGBoost. The study proposes CBAMWDNet [12], a novel architecture for tuberculosis classification in medical images, combining wide architecture, dense blocks, and CBAM attention mechanisms. Despite achieving high diagnostic accuracy on Tuberculosis CXR dataset with efficient training (50 epochs), the model's computational intensity, indicated by a significant parameter count (8,159,134), poses challenges for wider adoption, particularly for researchers with limited computing resources. Addressing this limitation is essential for enhancing the model's accessibility and applicability in the field of tuberculosis classification.

Another TB detection research employs deep learning models, including DenseNet-169, MobileNet, Xception, and Inception-V3 [13]. It addresses the limitations of traditional TB diagnosis methods and emphasizes early detection through medical image analysis. The study utilizes two datasets, incorporating data preprocessing and augmentation techniques to enhance classifier performance. Results reveal DenseNet-169 as the top-performing model with a validation accuracy of 91.6%, showcasing its potential for improving TB identification. A study assesses the effectiveness of a lightweight CNN, alongside established models, for early detection of lung infectious diseases like COVID-19, pneumonia, and tuberculosis using chest X-ray images from various datasets [14]. Achieving state-of-the-art results, the proposed CNN demonstrates comparable precision of 99.15%, 98.89%, and 97.79% across diverse datasets, highlighting its efficiency. The lightweight CNN's potential for quick and accurate diagnoses makes it suitable for widespread screening in resource-limited areas, offering valuable insights for young scientists in creating highly efficient CNN models for early disease identification with medical images. A study addresses the challenge of tuberculosis (TB) detection using computer-aided diagnostic (CAD) systems and compares transfer learning models with a proposed simple deep neural network (DNN) architecture [15]. Existing models, Inception-v3, ResNet50, VGG16, VGG19, and DenseNet, pretrained on ImageNet, show unexpected and overfitted behavior when applied to TB detection from chest X-ray (CXR) images. The proposed DNN, designed for TB datasets, outperforms transfer learning models, showcasing competitive training and validation accuracies. The research highlights the limitations of using generic pre-trained models in medical image analysis and advocates for tailored, simpler models for TB detection. Another research focuses on tuberculosis detection using deep learning, specifically the Inception-V3 CNN, on a dataset of 7,000 chest X-ray images [16]. The Inception-V3 model achieves an impressive 99% accuracy in classifying tuberculosis and normal cases. The study emphasizes the importance of data augmentation and batch normalization in model preparation, presenting results through training and validation graphs and a confusion matrix. Overall, the research demonstrates the effectiveness of deep learning, particularly the Inception-V3 model, in accurate tuberculosis identification from chest X-ray images. Another research study introduces an AI-driven tuberculosis diagnostic system using chest X-ray images [17]. The system comprises a tuberculosis data generator, U-Net-based lung field cropping, and a multiple-model ensemble for classification. It aims to enhance recognition rates, expedite interpretation, and provide interpretability through Grad-CAM. Evaluation metrics encompass sensitivity, specificity, accuracy, and AUROC. The results indicate high performance across models, achieving an accuracy of 99.6% and sensitivity, specificity, and AUROC scores above 99%. The specific gap lies in the limited exploration of effective strategies to handle class imbalances in tuberculosis datasets and the comparative analysis of multiple models in this domain. In the context of tuberculosis detection, our dataset reveals a notable class imbalance with 3500 images categorized as normal and only 700 as tuberculosis. To address this imbalance during training, data augmentation techniques have been implemented. Moreover, our research extends beyond existing literature by introducing two additional models, namely Xception and EfficientNet, alongside the model mentioned in the existing papers. Filling this gap is essential for enhancing the robustness and generalizability of tuberculosis detection models, especially in scenarios with imbalanced class distributions.

III. Data Description

A. Tuberculosis CXR Database

A collaborative effort between Researchers from Qatar University, collaborated with counterparts from the University of Dhaka, together with their partners in Malaysia, has resulted in the development of a chest X-ray image database [ ]. This database includes images of individuals diagnosed with Tuberculosis (TB) as well as images of individuals with normal lung conditions. In its current version, the publicly available dataset consists of 700 TB images, while an additional 2,800 TB images can be obtained by signing an agreement through the NIAID TB portal. Furthermore, there are 3,500 images of individuals with normal lung conditions included in this database.

B. Shenzhen Hospital CXR Set

The chest X-ray (CXR) images within this dataset have been gathered and generously conducted by Shenzhen No.3 Hospital, located in China [ ]. These images are formatted in PNG. The dataset comprises a total of 326 CXRs categorized as normal and 336 as abnormal. These abnormal CXRs showcase a range of manifestations consistent with Tuberculosis (TB). Additionally, the dataset includes consensus annotations provided by two radiologists for a subset of 68 images resized to 1024×1024 pixels, along with their corresponding radiology readings.

IV. Proposed Methodology

This section presents the methodology employed in the study, illustrated in Figure 2.

A. Data Pre-processing

Pre-processing steps were applied to the images in the dataset, which involved resizing and normalization. The original images in the TB CXR dataset had dimensions of 512×512 pixels, while those in the Shenzhen dataset were 1024×1024 pixels. Each chest X-ray image was resized to $224 \times 224 \times 3$ dimensions. Additionally, pixel values were normalized by dividing both the training and testing sets by 255, ensuring that

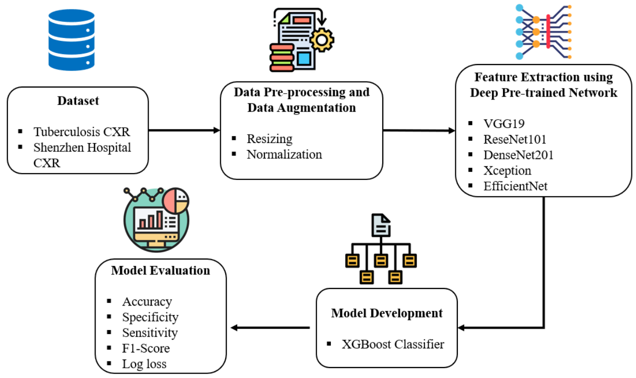

Fig. 2. Proposed High-Level Architecture for Tuberculosis Classification

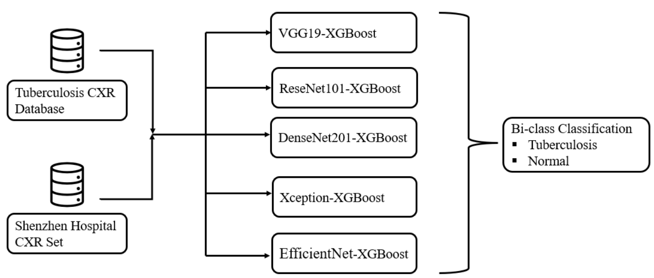

Fig. 3. Proposed Model Working Diagram

the pixel values ranged between 0 and 1.
Data augmentation is a frequently employed method in pre-processing when dealing with a small datasets. This pre-processing strategy encompasses a range of techniques such as data wrapping and oversampling, artificially enhancing the size of the training dataset. Class imbalance in the Tuberculosis CXR Database was handled by oversampling, wherein the existing 700 TB images were doubled to 1400 TB images.

B. *Feature Extraction using DenseNet201*

Feature extraction was automated through the utilization of deep learning models. In the proposed work, pre-trained DenseNet201 was employed to extract valuable image features from both the datasets independently, which were subsequently employed for training a classifier. DenseNet201 is employed for feature extraction by leveraging its pre-trained weights on the ImageNet dataset. DenseNet201 consists of 201 layers, where each layer is densely connected to every other layer. This connectivity pattern encourages feature reuse and enhances gradient flow, handles the vanishing gradient problem, enabling more effective learning of intricate patterns within CXR images. The model takes input CXR images of size 224 X 224 X 3 based on the standard ImageNet input size. It uses Softmax activation function in the final layer for classification.

C. *Classification using XGBoost Classifier*

After deep feature extraction, classification was carried out to distinguish between TB and normal cases based on their attributes. The Extreme Gradient Boosting(XGBoost) classifier was used for this purpose. XGBoost stands out as a versatile and powerful model compared to other boosting models for CXR image classification tasks. The algorithm's optimized implementation and ability to handle large datasets make it a preferred choice, ensuring reliable and accurate results in CXR classification tasks. For experimental purposes, the entire dataset is split into two subsets: the training set (80%) and the testing set (10%). The proposed model is the combination of DenseNet201 and XGBoost for Tuberculosis classification task.

D. *Model Evaluation*

To prove the efficacy of the proposed Densenet201-XGBoost model, four other recent deep pre-trained models have been used for feature extraction and classification in combination with XGBoost. The following combinations were thus implemented for comparison purpose: ResNet101-XGBoost, VGG19-XGBoost, Xception-XGBoost and EfficientNet-XGBoost.
A comprehensive experimental analysis was conducted to evaluate the performance of the proposed hybrid model. Various metrics, including accuracy, specificity, sensitivity, F1-score, and log loss were used for assessment. These results of the proposed model were compared to a reference base paper, serving as a benchmark for the implementation.

$$Accuracy = \frac{TP + TN}{TP + FN + TN + FP} \tag{1}$$

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

$$F1 - score = \frac{2 * Precision * Recall}{Precision + Recall} \tag{4}$$

$$Specificity = \frac{TN}{TN + FP} \tag{5}$$

V. Experimental Results and Comparison

This section presents the results and a comparative study on the performances of the different models on the two datasets: Tuberculosis CXR Database and Shenzen Hospital CXR Set. It's important to note that the Tuberculosis dataset underwent data augmentation to address class imbalance, doubling the number of TB images from 700 to 1400 before training. Table I shows the evaluated models on the Tuberculosis dataset before data augmentation. DenseNet201-XGBoost emerged as the top performer with the highest accuracy of 99.29%, precision 99.24%, recall 96.30%, F1-score 97.74%, and specificity 99.86%. VGG19-XGBoost also demonstrated strong performance, particularly in sensitivity 95.56% and F1-score 95.91%. ResNet101-XGBoost and Xception-XGBoost exhibited competitive results, while EfficientNet displayed a

TABLE I
RESULTS FOR TUBERCULOSIS CXR DATABASE BEFORE DATA AUGMENTATION

Architecture	Accuracy	Precision	Sensitivity	F1-score	Specificity
ResNet101-XGBoost	96.92	96.58	83.70	89.68	99.44
VGG19-XGBoost	98.70	96.27	95.56	95.91	99.29
Xception-XGBoost	98.58	98.43	92.59	95.42	99.72
EfficientNet-XGBoost	97.16	94.40	87.41	90.77	99.01
DenseNet201-XGBoost	**99.29**	**99.24**	**96.30**	**97.74**	**99.86**

slightly lower performance across all metrics.

Following the application of data augmentation techniques to address class imbalance, the Tuberculosis dataset exhibited enhanced model performance as illustrated in Table II . Among the various models with XGBoost, DenseNet201-XGBoost emerged as the standout performer, achieving unparalleled results. Specifically, DenseNet201-XGBoost attained a perfect precision of 100%, reflecting its precision in correctly identifying positive cases without any false positives. Furthermore, it demonstrated exceptional accuracy 99.90%, sensitivity 99.67%, F1-score 99.83%, and specificity 100%, showcasing its superior ability to comprehensively discriminate between tuberculosis and non-tuberculosis instances. Data augmentation had a significant positive impact on DenseNet201-XGBoost in the Tuberculosis dataset, while other models showed more modest gains. The consistently high performance of DenseNet201-XGBoost reinforces its efficacy and substantiates its position as the optimal method for tuberculosis detection within our dataset, affirming its suitability for subsequent stages of our research.

In evaluating the performance of various architectures on the Shenzen dataset, Table III shows the results obtained. Among the considered models, DenseNet201-XGBoost emerged as the top performer, achieving an accuracy of 81.20%, precision of 73.53%, sensitivity of 87.72%, F1-score of 80%, and specificity of 76.32%. While other models, such as ResNet101-XGBoost, VGG19-XGBoost, and Xception, also displayed competitive results, DenseNet201-XGBoost exhibited the most robust and balanced performance across the various evaluation metrics.

Finally, comparing the results on both the datasets, it is evident that Shenzhen dataset shows slighlty lower performance compared to the Tuberculosis dataset, which may be attributed to the differences in the dataset characteristics. The Shenzen dataset includes additional anatomy in the images like hands and lower rib cage, making the task more challenging. Models trained on TB dataset might not generalize well to Shenzen due to these differences. Nevertheless, DenseNet201-XGBoost consistently performs exceptionally well on both datasets, suggesting its suitability for TB detection in CXR images. This suggests that DenseNet201-XGBoost is well-suited for the complexity introduced by the inclusion of additional anatomy in the Shenzen dataset.

TABLE II
RESULTS FOR TUBERCULOSIS CXR DATABASE AFTER DATA AUGMENTATION

Architecture	Accuracy	Precision	Sensitivity	F1-score	Specificity
ResNet101-XGBoost	98.17	98.63	95.35	96.96	99.41
VGG19-XGBoost	97.76	97.94	94.68	96.28	99.12
Xception-XGBoost	98.76	98.88	93.64	96.19	99.79
EfficientNet-XGBoost	97.93	96.27	91.17	93.65	99.29
DenseNet201-XGBoost	**99.90**	**100**	**99.67**	**99.83**	**100**

TABLE III
RESULTS FOR SHENZHEN HOSPITAL CXR SET

Architecture	Accuracy	Precision	Sensitivity	F1-score	Specificity
ResNet101-XGBoost	80.45	71.23	91.23	80	72.37
VGG19-XGBoost	78.95	70.42	87.72	78.12	72.37
EfficientNet-XGBoost	78.20	70.00	85.96	77.17	72.37
Xception-XGBoost	**81.95**	**73.91**	**89.47**	**80.95**	**76.32**
DenseNet201-XGBoost	**81.20**	**73.53**	**87.72**	**80**	**76.32**

VI. CONCLUSION AND FUTURE SCOPE

This study demonstrates a comprehensive evaluation of multiple pre-trained deep learning models, coupled with XGBoost, for the detection of tuberculosis in chest X-ray (CXR) images. Results on TB dataset revel that DenseNet201-XGBoost consistently outperformed other models, showcasing superior accuracy, precision, sensitivity, F1-score, and specificity. Data augmentation techniques significantly enhanced the performance of DenseNet201-XGBoost, on the TB dataset. Subsequent evaluation on the Shenzen dataset, characterized by the inclusion of additional anatomy in images, revealed that DenseNet201-XGBoost continued to excel. These findings underscore the adaptability and robustness of DenseNet201-XGBoost across diverse dataset characteristics. The future research can focus on identifying and developing architectures specifically tailored for handling diverse anatomical features in chest X-ray images. Additionally, there is a scope for the deployment of DenseNet201-XGBoost in real-world clinical settings, emphasizing scalability and interpretability for practical applications in tuberculosis diagnosis.

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