Detection Of Tuberculosis Using Deep Learning

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Abstract

Tuberculosis (TB) remains a main global health problem, requiring early and accurate diagnosis to reduce its impact [1][2]. Although CXR imaging is broadly used for screening, interpretation challenges can affect reliability [3].

This education presents a DL based framework for automated TB detection from CXR images, comparing traditional ML models with CNNs [4]. Model performance is improved using ensemble techniques and evaluated through metrics such as accuracy, precision, recall, specificity, and F1-score [5].

The system also includes performance analysis tools to support clinical decision-making [6]. Overall, the proposed approach provides an efficient and reliable solution for TB screening.

Keywords-Tuberculosis ,Deep Learning , CNN ,Chest X-ray , Medical Imaging

1. Introduction

Tuberculosis (TB) continues to be a main global health concern, effecting millions of deaths annually, particularly in developing countries [1]. Despite being curable and preventable, Initial detection remains challenging due to limited diagnostic resources and human error in radiographic interpretation [2].

CXR are commonly selected for TB screening due to their affordability and accessibility. However, manual interpretation by radiologists can be slow and subject to variability [3]. Recent advancements in AI and DL have opened other possibilities for automated disease detection using medical pictures [4].

Among these techniques, CNN have shown extraordinary performance in feature mining and patterns recognition, making them extremely suitable for identifying abnormalities in CXR images [5]. This research aims to develop a DL based model for accurate TB detection, assisting health care professionals in faster and more reliable diagnosis.

2. Related Work

Recent advancements in DL have significantly enhanced the detection of TB from CXR images. Early approaches relied on traditional ML techniques such as Support SVM and RF, which required manual feature taking out and often produced limited accuracy in complex medical datasets [3][4].

With the emergence of DL, CNNs have become the leading approach for clinical image analysis due to their ability to automatically learn ordered features. Studies such as Lakhani and Sundaram demonstrated that CNN-based models can accomplish performance comparable to expert radiologists in TB detection [3]. Similarly, Hwang et al. introduced DeepTB, which showed strong classification performance using deep architectures [6].

Further research has focused on improving accuracy through advanced architectures and hybrid techniques. Ensemble learning methods combining multiple CNN models have been given away to enhance robustness and reduce misclassification [9]. In addition, segmentation-based approaches, such as those using U-Net variants, help isolate lung regions and improve detection precision [11].

Visualization techniques like Grad-CAM have additionally beenwidely adopted to improve the modelinterpretability by highlighting important regions influencing predictions [9]. In spite of these improvements, challenges such as dataset imbalance, limited annotated data, and generalization across diverse populations remain significant concerns in real-world deployment [5].

3. Materials and Methods

A. Dataset

This study utilizes the TBX11K dataset, which contains approximately 11,200 CXR images collected from multiple healthcare sources [1]. The dataset includes TB-positive, normal, and other lung disease cases, along with annotations that assist in identifying infected regions.

Fig 1:Normal CXR

Fig 2:Infected CXR

B. Data Preprocessing

To ensure consistency and progress model performance, numerouspreprocessing steps are applied. Images are resized to anunchanging dimension and normalized to standardize pixel intensity values. Noise lessening techniques are used to enhance image quality. Moreover, data augmentation methods for example rotation, flipping, and scaling are used to increase dataset diversity and reduce overfitting [5].

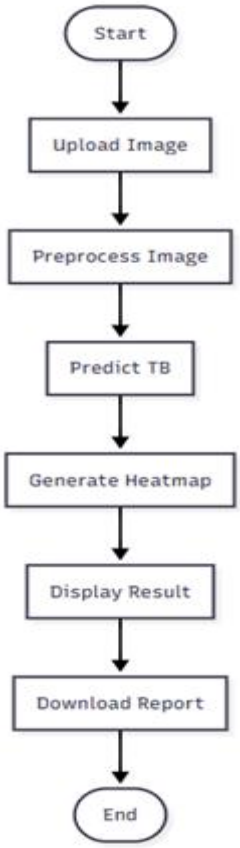

Fig 3: Data Flow Diagram

C. Model Architecture

The proposed system employs DL models based on CNN architectures. Transfer learning is applied using pretrained networks for exampleResNet and DenseNet to leverage previously learned features and reduce training time [4]. These models are fine-tuned on the TB dataset for classification into TB-positive and TB-negative categories.

D. Training and Evaluation

The dataset is divided into training and testing sets. Models are trained using optimization strategiessuch as Adam optimizer and estimated using performance metrics including accuracy, precision, recall, specificity, and F1-score [14].

E. Explainability

Grad-CAM is combined into the system to deliver visual explanations by highlighting regions in the X-ray images that pay to model predictions, improving transparency and clinical trust [9].

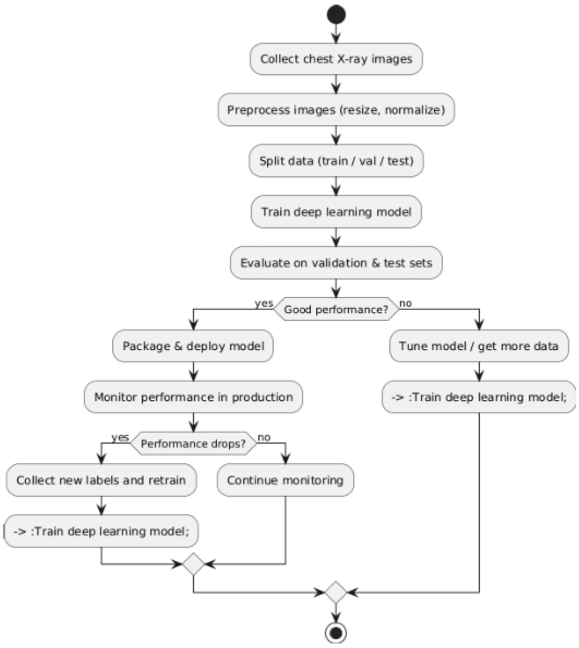

Fig 4: Activity Flow Diagram

4. Results and Discussion

The experimental results demonstrate that DL models, particularly CNN-based architectures, outperform traditional machine learning methods in TB detection from CXR images. Transfer learning models such as ResNet and DenseNet achieved high classification accuracy due to their ability to extract complex features from medical images.

The use of data augmentation and preprocessing techniques significantly improved model generalization and reduced overfitting. Ensemble approaches further enhanced prediction stability and minimized classification errors.

Performance evaluation using metrics such as accuracy, precision, recall, specificity, and F1-score indicates that the proposed system achieves reliable and consistent results in identifying TB cases. The confusion matrix studydiscloses that most misclassifications occur in cases with overlapping features between TB and other lung diseases.

Grad-CAM visualizations provided meaningful understandings into the decision-making method of the model by highlighting infected regions in the lungs, thereby improving interpretability and supporting clinical validation.

Complete, the projected framework demonstrates solid potential for automated TB screening. However, challenges such as dataset variability and real-world deployment constraints remain. Future improvements may include incorporating larger datasets, integrating medical metadata, and optimizing models for real-time applications.

5. Conclusion

This work presents a DL-based approach for TB detection using CXR images.The proposed system demonstrates that DL models outperform traditional ML methods in accuracy and robustness. Preprocessing and augmentation techniques further improve model performance and generalization. The framework enables reliable and automated TB screening to support clinical decision-making. Overall, the approach provides an efficient solution for early TB detection.

Upcoming work will focus on larger datasets and real-time deployment.

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