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Convolutional Neural Network-Based Framework for the Detection of Tuberculosis

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ABSTRACT

Tuberculosis (TB) remains a significant public health issue worldwide, especially in low- and middle-income countries, where access to accurate and rapid diagnostic tools is limited. Early diagnosis and treatment are essential to control spread and improve patient outcomes. Traditional TB diagnosis methods, such as sputum microscopy and culture, are time consuming and require specialized laboratory facilities. In this study, we explored the application of machine learning techniques in automating and enhancing TB detection, focusing on the analysis of chest radiograph images (X-ray). Hence, a Convolutional Neural Network-based framework is presented. The framework used advanced image preprocessing and augmentation techniques to enhance feature learning and mitigate data set imbalance to support early screening and clinical decision making. The system demonstrated high precision, correctly identifying 97% of normal chest x-rays and achieving a perfect 100% precision for TB cases, which means no false positives were recorded. In terms of recall, the model correctly detected all normal X-rays but misclassified 5% of TB cases as normal, resulting in a 95% recall for TB detection. The F1-score, which balances precision and recall, was 98% for both normal and TB cases, indicating strong classification performance. Additionally, the macro and weighted averages were both 98%, reflecting consistent and reliable model performance across different case distributions. The results indicate that the proposed CNN-based framework provides a robust, scalable, and cost-effective solution for automated TB detection, offering potential integration into computer-aided diagnostic systems.

1. INTRODUCTION

Tuberculosis (TB) is one of the single infectious diseases that cause high death rates. [1] report that tuberculosis caused 1.7 million deaths in 2016, surpassing HIV/AIDS. [2] confirm that TB remains among the top 10 global causes of death, with an estimated 10 million new cases per year. [3] provides additional context, noting that approximately 1.5 million people die from TB each year. In fact, it is one of the top ten causes of death. The WHO (2017) reported the death of 1.3 million people annually from tuberculosis. The report attributed fresh incidences of TB in 5.8 million men, 3.2 million women and 1 million children, with India having 27% of them [4]. However, an estimated 10.8 million people fell ill with TB in 2023 and about 1.25 million people died, making TB once again the leading infectious-disease killer globally [5]. TB is chronic in nature and is caused by a d-shaped bacterium, Mycobacterium tuberculosis which affects the lungs but can also affect several other areas like bones, intestines, urinary tract and the skin [6]. The damaging effect of TB led the United Nations into deliberate moves to eradicate it by 2030.

Detection of tuberculosis early is crucial in order to ensure a suitable and effective treatment. In the literature, TB detection takes several methods, of which many seem to be cumbersome and time consuming, leading to subjective inconsistencies in its diagnosis [7], [8]. Chest X-ray (CXR) is generally seen in settings with limited access to molecular tests or expert radiologists because it uses low-cost screening tools [9]. Hence, it is seen as the most popular method of TB detection. TB can also be detected by Skin test, Sputum microscopy, and Interferon-gamma release assay (IGRA) [10]. Despite any method used, accurate detection is essential in eradicating the disease [11], [12]. This is because most of the time, CXR images of tuberculosis are often misclassified to other diseases of similar radiologic patterns [13], [14], which can lead to wrong medication for patients and thus worsen the carrier's health condition.

In this perspective, computer-aided diagnosis (CAD)

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systems can play an important role in the analysis of chest X-ray images. Most importantly, AI-based solutions would be the best fit for this purpose, considering their widespreadness in the contemporary world [15]. This points particularly to machine learning, where appropriate algorithms would help classifying images according to quality and type. Hence, convolutional neural networks (CNNs) can achieve successful image recognition from large-scale labeled datasets. CNNs allow data-driven, highly representative, hierarchical image features to be learned from adequate training data, but to obtain datasets in the medical imaging domain as comprehensively annotated [16], [17], [18]. This shows that CNNs are the most promising in image classification among other machine learning techniques (see Fig. 1). In this context, CNNs are widely adopted by the research community [19], [20].

1.1. Global Burden and Challenges in Tuberculosis Detection

TB continues to impose a substantial global health and economic burden, disproportionately affecting low- and middle-income countries where diagnostic resources remain scarce [21]. Although international health initiatives aim to reduce both TB incidence and mortality, the disease remains one of the deadliest infectious diseases in the world [22]. Conventional diagnostic methods—including sputum smear microscopy and culture testing—are often slow, resource intensive, and dependent on laboratory infrastructure that may not exist in rural or under-resourced settings. These constraints delay early detection, increase the risk of transmission, and adversely affect the prognosis of the patient [23]. Addressing these challenges requires more scalable, cost-efficient and accurate diagnostic approaches capable of functioning effectively in diverse healthcare settings.

1.2. Limitations of Conventional Chest X-ray Interpretation

Chest X-ray imaging is commonly used as an initial screening tool for tuberculosis due to its affordability and availability; however, its effectiveness is largely limited by the need for expert radiological interpretation [24], [25]. CXRs often exhibit overlapping visual patterns between TB, pneumonia, and other respiratory diseases, leading to diagnostic ambiguity even for highly trained specialists [26]. Variations in radiological expertise, differences in image acquisition quality, and subjective interpretation further contribute to inconsistencies in diagnosis [27]. In resource-limited regions, where radiologists are scarce, these challenges become more pronounced. Consequently, there is a critical need for automated and objective methods that can support or improve radiology decision-making, particularly for large-scale TB screening.

1.3. Emergence of Machine Learning and CNN-Based Diagnostic Systems

Advances in machine learning—and particularly deep learning—have paved the way for more reliable and automated analysis of medical images [28]. Convolutional Neural Networks (CNNs) have gained prominence because of their ability to learn hierarchical discriminative features directly from raw images, minimizing the dependence on manual feature engineering [29]. Their success in various medical imaging tasks, such as tumor detection, organ segmentation, and disease classification, demonstrates their ability to capture subtle variations in image patterns. When coupled with data preprocessing, augmentation, and class rebalancing strategies, CNNs become even more effective in handling the challenges inherent in unbalanced medical datasets [30], [31], [32]. Consequently, CNN-based CAD systems offer a promising solution for TB detection, providing rapid, scalable, and accurate diagnostic support, especially in regions lacking adequate radiological expertise.

In medicine, generally, CNNs have transformed computer vision and medical-image analysis by learning hierarchical image features directly from data without manual feature engineering. Architectures such as ResNet have enabled training of very deep models that generalize well across visual tasks, and transfer learning from such networks is now a common strategy in medical imaging where labelled data are limited. These convolutional neural network advances have been adopted for CXR-based TB detection, producing promising accuracy and sensitivity in retrospective evaluations [18]. However, CNN-based TB detection still faces challenges particularly in deployment to clinical workflows due to limited cross-domain generalization and device variability [9].

Figure 1 illustrates the proposed Convolutional Neural Network (CNN)-based framework for tuberculosis (TB) detection from chest X-ray images. The process begins with image acquisition, where raw chest X-ray images are collected and provided as input. These undergo preprocessing and augmentation, including noise removal, resizing, and normalization. Next, CNN layers perform feature extraction to identify distinguishing image features, which are then used in model training with architectures such as MobileNet or U-Net. The trained model classifies each image as TB-positive or normal, and the output provides a final diagnostic result for clinical decision making.

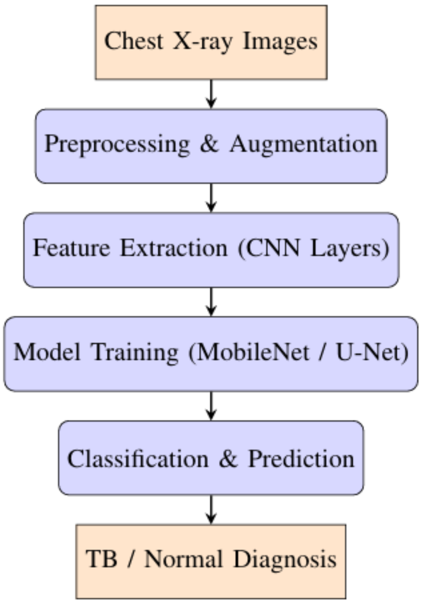

Figure 1. Convolutional Neural Network-based Framework for Tuberculosis Detection

2. RELATED WORK

In an effort to detect TB, several machine learning approaches have been used in the previous literature [33]. However, CNN-based methods remain the most common owing to their ability to effectively perform image recognition within any dataset size. [34] compared SVM, kNN, RF, and a neural network (NN) on CXR data and reported that the NN outperformed others with approximately 80.45% accuracy. In other works, SVMs and ensemble classifiers have achieved accuracies in the 90–95% range on curated datasets [35], [36]. [36] also conducted a systematic literature review and found that among 47 relevant studies, 34 used deep learning and 7 used conventional ML in CXR-based TB detection. The most frequently used CNN architectures included ResNet-50, VGG-16, VGG-19, and AlexNet. [37] discovered through a review that CNN and transfer learning dominate works published after 2018. [38] combined AlexNet and GoogLeNet in an ensemble to detect TB and achieved high accuracy (approximately 98.7%). [39] used an ensemble of AlexNet, GoogLeNet, and ResNet across multiple datasets, reporting approximately 88.24% accuracy. [40] applied a segmentation step (U-Net) before classification by deep CNNs and reported accuracy up to 99.9%. The TSSG-CNN model integrates segmentation and classification in an end to-end approach, showing approximately 98.75% accuracy. [41] proposed LightTBNet, a lightweight CNN architecture attaining approximately 90.6% accuracy and AUC of approximately 0.961. Other explainable or self-supervised CNNs have achieved between 95–98% accuracy while improving interpretability [42], [43].

2.1. Traditional Machine Learning Approaches for TB Detection

Early research in TB detection relied primarily on traditional machine learning methods such as SVMs, Random Forests, kNN, and handcrafted feature extraction techniques. These approaches typically involved preprocessing steps like texture analysis, histogram features, or edge detection before feeding data into classifiers. While these methods demonstrated moderate effectiveness, their performance was heavily dependent on feature engineering and lacked generalizability across diverse datasets. Studies report accuracies ranging from 70% to 90%, but performance deteriorated when tested on heterogeneous or real-world clinical images. This limitation motivated a shift toward more robust, data-driven deep learning models capable of automatic feature extraction.

2.2. Deep Learning and Transfer Learning in CXR-Based TB Detection

With the rise of deep learning, CNN-based architectures quickly became the dominant approach in TB detection research. Pretrained models such as VGG, ResNet, DenseNet, and Inception have been widely adopted due to their ability to extract high-level representations from CXR images, even with limited datasets through transfer learning. Many works achieved high accuracy and AUC values by fine-tuning these pretrained networks on TB datasets. However, these models often require extensive computational resources and may over fit when datasets are small or imbalanced. Recent studies have explored lightweight CNNs and hybrid approaches to achieve comparable performance with reduced complexity, addressing deployment constraints in low-resource environments.

2.3. Emerging Trends: Explainability, Segmentation, and Lightweight Architectures

Recent research has begun to emphasize interpretability and clinical reliability through methods such as Grad-CAM, attention mechanisms, and explainable AI (XAI) frameworks. These approaches aim to enhance clinician trust by highlighting lesion regions relevant to TB classification. Additionally, segmentation-based pipelines using U-Net or similar architectures have gained traction for isolating lung regions prior to classification, improving feature focus and reducing background noise. Lightweight architectures – such as LightTBNet and MobileNet-based models – are increasingly explored for real-time TB screening in portable or mobile applications. Despite advancements, challenges remain regarding dataset imbalance, variation in imaging conditions, and generalization across populations, motivating ongoing research into more robust, scalable CNN-based solutions.

3. METHODOLOGY

The TB detection model in this study followed the Agile software development methodology, which supports iterative and modular improvement. Object-Oriented Analysis and Design (OOAD) was used to visualize system structure and behaviour through various software artefacts including use-case, activity, and flow diagrams. The framework consists of five phases: data collection, preprocessing, feature extraction, model training, and evaluation. These artefacts gave rise to a detailed architecture that captures the entire workflow within the TB detection system as shown in figure 2.

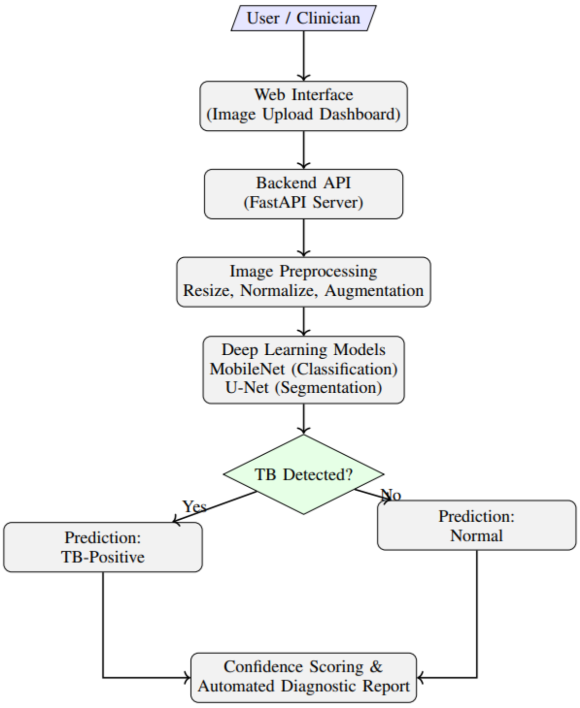

Figure 2. Consolidated System Architecture and Workflow of The Proposed TB Detection Framework

In figure 2, the various components of the TB detection system are integrated comprising user interaction, image upload, backend processing, preprocessing and augmentation, CNN-based segmentation and classification (U-Net and MobileNet v2), decision logic, confidence scoring, and automated report generation. The diagram presents a consolidated view of the end-to-end architecture and operational workflow of the proposed tuberculosis (TB) detection framework. It further illustrates how user interaction, backend processing, deep learning inference, and diagnostic output are seamlessly integrated into a unified system.

The workflow begins with the user or clinician, who interacts with the system through a web-based interface designed for uploading chest X-ray images. This frontend component serves as the primary access point, enabling secure and user-friendly image submission. Once an image is uploaded, it is transmitted to the backend application programming interface (API) implemented using FastAPI, which manages request handling, data validation, and communication with the processing modules.

Upon receipt by the backend, the image undergoes preprocessing operations, including resizing, normalization, and data augmentation. These steps ensure that all images conform to the input requirements of the deep learning models and help improve robustness against variations in image quality and acquisition conditions. The preprocessed image is then forwarded to the deep learning model layer, which consists of two complementary architectures: U-Net for lung region segmentation and MobileNet v2 for TB classification. U-Net focuses on isolating clinically relevant lung areas, while MobileNet v2 extracts discriminative features to determine the presence or absence of tuberculosis.

The output of the model inference stage is evaluated at a decision node, where the system determines whether TBrelated abnormalities are detected. Based on this decision, the image is classified as either TB-positive or normal. Regardless of the classification outcome, both paths converge at the final stage, where the system computes a confidence score and generates an automated diagnostic report.

3.1. Data Collection

Chest X-ray data were obtained from the National Institutes of Health (NIH) Chest X-ray Dataset on Kaggle, comprising over 1000 frontal-view images labelled as TB-positive or TB-negative. The division of the dataset is summarized in Table 1.

Table 1. Dataset Division

S/N	Class	No. of Images
1.	Healthy	4,649
2.	TB-Diseased	3,155

Table 1 shows the dataset division used in this study. Chest X-ray images were separated into healthy and TB-diseased classes to ensure a balanced training process. This helps to differentiate TB among healthy patients and other lung disorders using images. The final number of images included in the study was determined after applying predefined inclusion and exclusion criteria. Initially, all collected images were screened for relevance and quality. Images that were duplicated, incomplete, low quality, or did not meet the study's eligibility criteria were excluded. The remaining images that satisfied all criteria constituted the final dataset used for analysis.

3.2. Data Preprocessing and Augmentation

The NIH dataset was further split into 80% for training, 10% for validation, and 10% for testing to provide reliable performance evaluation. All images were resized to 255 × 255 pixels and normalized using z-score standardization. Augmentation techniques (rotation 5°–15°, scaling ±10%, and translation ±20%) were applied using TensorFlow to address class imbalance.

3.3. Model Training and Validation

The dataset was split (80% train, 10% validation, 10% test). MobileNet v2 was used for classification and U-Net for segmentation. The Adam optimizer minimized binary cross entropy loss. Training was performed with a batch size of 32 over 30 epochs. To prevent overfitting, early stopping was implemented, halting the training process if the validation loss did not improve after five consecutive epochs. U-Net model generated segmented leaf masks serving as inputs for subsequent classification. Evaluation metrics included precision, Recall, F1-Score, and AUC-ROC.

4. RESULTS AND DISCUSSION

The developed TB detection system allows users to upload chest X-ray images through a web interface and receive immediate classification output. The system leverages a CNN model trained on a curated dataset to provide accurate predictions for TB-positive and TB-negative cases. Table 2 summarizes the classification performance metrics.

Table 2. Initial Results

Class	Precision	Recall	F1-Score
Healthy chest X-rays	0.97	1.00	0.98
TB-diseased chest X-rays	1.00	0.95	0.98
Overall Accuracy	0.98	-	-
Macro Average	0.98	0.98	0.98
Weighted Average	0.98	0.98	0.98

The table presents classification performance metrics of the proposed CNN framework. The model achieved 98% overall accuracy, perfect precision for TB-positive cases, and high recall for healthy images. Both macro and weighted averages confirm consistent performance across classes. The high performance is largely related to the system functionality which is primarily driven by the structure of datasets used for training and validation, such that users can successfully upload medical images, receive accurate TB classifications, and view results.

4.1. Model Prediction and Output Generation

After the image is uploaded, the CNN model performs feature extraction and classification. The system provides confidence scores and generates structured reports for clinician review. The confidence score allows clinicians to gauge the model's certainty, which is particularly useful when interpreting borderline or low-quality images. Automated report generation standardizes output presentation, facilitating integration into existing clinical workflows. This also enhances record keeping, auditability, and the ability to track patient progress over time.

4.2. Performance Interpretation and Clinical Implications

The CNN model demonstrated robust classification performance, achieving 98% overall accuracy and strong F1 scores across both classes. All healthy images were correctly identified (100% recall), while TB-positive cases achieved 95% recall. The slight decrease in TB recall highlights the challenge of detecting subtle pathological changes in early stage or low-quality X-rays, consistent with previous studies [9].

The high precision for TB-positive cases (1.00) ensures minimal false positives, which is crucial in clinical screening to avoid unnecessary treatment or patient anxiety. The balanced macro and weighted averages (98%) indicate consistent performance across heterogeneous datasets, suggesting the model is generalizable to diverse patient populations.

Overall, the system demonstrates the potential for integration into computer-aided diagnostic pipelines, offering rapid, reliable, and scalable TB screening, hence providing suitable support for clinical decisions. Future deployment should focus on evaluating real-world performance across multiple clinical sites, addressing data variability, and improving recall for difficult TB cases through ensemble methods or further data augmentation.

5. CONCLUSION

This work successfully demonstrated the use of CNNs for classifying chest X-ray images into TB-positive and TB negative categories. Developed with Agile and OOAD principles, the model achieved 98% accuracy and 98% F1-score, showing its reliability for clinical integration. The F1-score of 98% was recorded for both categories of labels, striking a balance at the model's ability to distinguish the two classes of images. The model provides a practical and efficient solution for the early detection of TB via distinguishing healthy chest X-ray images from TB-diseased chest X-ray images.

Declaration of Ethical Standards

Some parts of the text were refined using a large language model (ChatGPT) for grammar and clarity. All technical content, experimental design, analysis, and conclusions were produced and verified by the authors.

Credit Authorship Contribution Statement

The first author designed the model with respect to the objectives of the study. The second author conducted the review of related works while the first and third authors jointly developed the model and finally involved the second author in the analysis and discussions.

Declaration of Competing Interest

This is to declare that there are no conflicts of interest in any form among the authors of this research article.

Author's Note

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