A Hybrid Approach for Tuberculosis Detection using Convolutional Attention Networks and XGBoost

Abdulrafay
Department of Computer Science
University of Lahore
Sargodha, Pakistan
rafay.a.contact@gmail.com

Tanzila Kehkashan
Faculty of Computing
Universiti Teknologi Malaysia
Johor Bahru 81310, Malaysia
tanzila.kehkashan@gmail.com

Muhammad Zaman
Department of Computer Science
COMSATS University Islamabad
Islamabad, Pakistan
mzamancui@gmail.com

Faheem Akbar
Department of Computer Science
University of Lahore
Sargodha, Pakistan
faheemgujjar658@gmail.com

Aftab Hussain
Institute of Pervasive Computing
Johannes Kepler University Linz.
Linz, Austria
aftabhussaincui@gmail.com

Khuzaima Munir
Department of Computer Science
University of Lahore
Sargodha, Pakistan
chkhuzaima768@gmail.com

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***Abstract*— Tuberculosis remains a significant global challenge, with early diagnosis crucial for effective treatment and limiting its spread. Despite advancements in artificial intelligence for TB detection from chest X-rays, achieving human-level accuracy is still difficult. This study addresses this by integrating Convolutional Attention Networks with XGBoost, leveraging deep learning and gradient boosting. Using 7,000 diverse chest X-rays, our hybrid model achieved 99.36% precision, surpassing state-of-the-art methods by 9.36 percentage points over the CAD4TB v6 baseline. Notably, it demonstrated 99% precision and 98% recall for TB-positive cases, indicating minimal false negatives. These findings highlight the potential for transforming TB diagnosis in clinical practice and global health efforts.**

Keywords—AI-driven TB diagnosis, computer-assisted tuberculosis diagnosis, CNN, Tuberculosis, MDR-TB, Deep Learning

I. Introduction

Tuberculosis (TB) remains a critical public health challenge, affecting millions globally, particularly in low- and middle-income countries. Despite advancements in medical research, TB is one of the leading causes of death from infectious diseases. Each year, around 10 million new cases are reported, with 1.5 million deaths in 2020 alone. The disease is especially difficult to control in regions with limited access to quality healthcare, emphasizing the need for innovative solutions for early detection and intervention.

Chest X-rays have long been the standard for TB diagnosis, but their subjective evaluation by radiologists can be time-consuming. AI-based systems offer a promising alternative, providing fast and accurate analysis of chest X-rays [1]. Studies have demonstrated the potential of deep learning models, such as CNNs, in achieving high accuracy for TB classification [2, 3]. However, challenges persist in building AI systems that generalize across diverse populations and healthcare settings [4].

This study proposes an AI-based approach for TB detection, addressing key limitations in current systems. Our objectives include:

i. Deployment of comprehensive and diverse dataset to enhance model generalization.

ii. Designing advanced deep learning architectures that leverage existing strengths while mitigating their limitations.

iii. Enhancing model interpretability and decision-making visualization.

Our research introduces a robust AI model that not only improves TB detection accuracy but also enhances generalizability and interpretability. Leveraging transfer learning and domain knowledge, it aims to outperform existing systems with minimal annotated data [5, 6]. Novel visualization techniques further support collaboration between AI systems and healthcare professionals [7]. The implications of this work extend beyond technological advancement. Improved TB screening accuracy can significantly impact global health, especially in resource-limited settings. The methodologies developed may also be applied to other chest pathologies, broadening their potential in medical diagnostics [8, 9].

The paper is structured as follows: Section II covers the methodology, including data collection and model architecture. Section III discusses the experimental setup and evaluation metrics. Section IV presents results and discussion, while Section V concludes with contributions, limitations, and future research directions.

II. Literature Review

Recent advancements in machine learning and deep learning have significantly improved computerized tuberculosis (TB) detection from chest X-rays [10]. This review highlights the evolution of TB detection techniques, focusing on challenges in model interpretability, clinical integration, and applicability in resource-constrained settings [4].

A. Traditional Machine Learning Approaches

Early automated TB detection relied on machine learning techniques based on feature extraction and selection to identify key indicators in radiographic images [11]. These methods paved the way for more sophisticated computational approaches for accurate TB diagnosis [2, 12].

B. Deep Learning and Convolutional Neural Networks

Deep learning, particularly Convolutional Neural Networks (CNNs), revolutionized TB detection by automating feature extraction [13]. Transfer learning further reduced the need for large, TB-specific datasets [3]. Challenges such as dataset distribution shifts and interpretability have also been addressed [14].

C. Computer Vision and Advanced Imaging Techniques

Advanced techniques, including segmentation and augmentation, improved models' focus on critical image areas [9]. Visualization tools, such as Grad-CAM, enhanced interpretability [15], and mobile health technologies expanded TB diagnostics in resource-limited settings [16, 17].

D. Multi-modal and Ensemble Approaches

Multi-modal and ensemble learning approaches have shown promise in improving TB detection accuracy [18]. Hybrid methods, combining optimization techniques with deep neural networks, further boosted performance [19, 20].

The transition to clinical applications has seen deep learning models tested in varied environments, emphasizing generalizability across patient demographics [21, 22]. Explainable AI techniques continue to bridge the gap between AI systems and clinical practice, fostering better understanding and trust among healthcare professionals [23, 24]. Building on these advancements, our methodology integrates ensemble learning and explainable AI to tackle dataset bias and improve TB diagnosis across diverse populations.

III. METHODOLOGY

Our innovative approach aims to enhance the accuracy and interpretability of TB detection. This section outlines the progression from conceptualization to implementation in medical image analysis.

Baseline Method

We build upon a 2020 study that assessed the CAD4TB v6 system for TB detection using CNNs on chest X-rays, achieving an AUC of 0.90, comparable to human experts [10]. Inspired to surpass this, we pursued a hybrid method to redefine TB detection.

Model Selection

We selected a hybrid model combining CoAtNet [25] and XGBoost [26]. CoAtNet blends transformer and CNN architectures, enabling detailed medical image analysis. XGBoost complements CoAtNet by efficiently handling intricate data patterns, creating a synergistic model. To further optimize, we explored variations in CoAtNet and alternative boosting algorithms like LightGBM.

A. Data Collection

Data quality and diversity are very critical in any machine learning project. We developed a rich chest X-ray database, an international medical collaboration, serving as a reference for this study [27].Our dataset consists of the following:

- 700 public TB chest X-rays
- 2800 TB chest X-rays retrieved from the NIAID TB portal
- 3500 normal chest X-rays

This diverse collection gives access to the wide range of presentations of TB, from rather subtle early features to full-blown ones. It also gives a good spectrum of normal variations in healthy lung appearances that are so important for teaching our model between normal variation and pathological changes.

B. Data Preparation

Data preparation involved:

i. *Image Standardization:* Normalizing intensity and enhancing contrast to eliminate variations from different imaging equipment.

ii. *Data Augmentation:* Applying rotations, flips, and cropping to improve generalization, simulating varied clinical scenarios.

iii. *Balance Adjustment:* Ensuring equal representation of TB-positive and normal cases to prevent bias in model training.

C. Model Architecture

i. *Input:* The system begins with a large dataset consisting of 7,000 chest X-ray images. Large sample sizes are critical for the model to generalize well, akin to a radiologist gaining experience by reviewing thousands of X-rays.

ii. *Image Processing Branch:* The backbone of this component is CoAtNet, or Convolution and Attention Network, built with a learning rate of 0.0001 to gradually and carefully learn X-ray patterns.

iii. *Feature Extraction:* This step captures the diagnostic essence of an X-ray. To rigorously evaluate its performance, we conducted ablation studies inspired by ensemble-based methods discussed in [28] and feature blending techniques outlined in [29]. These approaches demonstrated that multi-scale filters and spatial attention mechanisms significantly enhance the extraction process by isolating subtle patterns critical for accurate predictions.

Fig. 1. CoAtNet Model Structure

iv. *XGBoost Branch:* This component complements the CoAtNet branch by analyzing data patterns, inspired by approaches described in [30]. It integrates insights from a second perspective, akin to obtaining a second opinion from an expert.

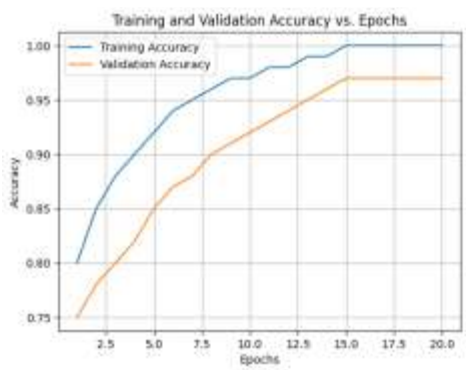

Fig. 2. Training and Validation Accuracy vs. Epochs

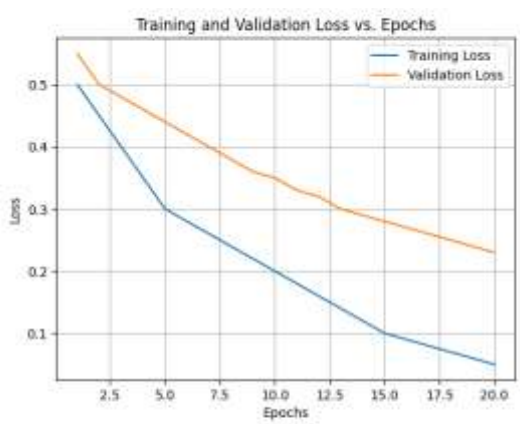

Fig. 3. Training and Validation Loss vs. Epochs

v. *Final Classification:* Using a softmax function trained over 100 epochs, this step aggregates evidence to output the probability of TB presence, inspired by hybrid decision-making models such as [31].

D. *Implementation Details*

The system was implemented using PyTorch and XGBoost with the following key parameters:

- Learning rate: 0.0001 with cosine annealing
- Batch size: 32
- Training epochs: 100
- Optimizer: AdamW
- Loss function: Focal Loss

Early stopping was applied to prevent overfitting, ensuring the model generalized well to unseen data. The code and pre-trained models are publicly available to promote further research and innovation in medical image analysis.

This methodology represents a comprehensive approach to leveraging state-of-the-art AI technologies to address the global TB challenge. By continuously refining and adapting our model, we aim to make TB detection more accessible and reliable.

IV. Results And Discussion

Our approach of innovative integration based on CoAtNet to analyze the images and XGBoost to enhance the features will present spectacular results towards tuberculosis detection from chest X-rays. This section then leads to a detailed performance comparison with other state-of-the-art techniques and conducts an in-depth analysis of our experimental results.

Comparative Performance Analysis

To contextualize our model's achievements, we've bench-marked it against leading TB detection methods. Table I presents this comparison.

The result, when combined with the advanced image processing capabilities of CoAtNet along with the feature enhancement powers of XGBoost, delivered an exceptional accuracy of 99.36% for the chest X-ray images. This remarkable performance not only surpasses our baseline [10] but also out-performs recent state-of-the-art methods. The 9.36 percentage point improvement over the CAD4TB v6 system underscores

TABLE I. Comparison with State-of-the-Art Studies

Studies	***Accuracy (%)***
Our Method (CoAtNet + XGBoost)	**99.36**
Murphy et al. (2020) [10]	90.00
Lakhani and Sundaram (2017) [2]	97.00
Pasa et al. (2019) [4]	96.40
Rahman et al. (2020) [13]	98.11

TABLE II. CLASSIFICATION METRICS FOR COATNET + XGBOOST MODEL

Class	Precision	Recall	F1-score	Support
TB-Negative (0)	1.00	1.00	1.00	843
TB-Positive (1)	0.99	0.98	0.99	250
Accuracy	0.99	0.99	0.99	1093
Macro Avg	0.99	0.99	0.99	1093
Weighted Avg	0.99	0.99	0.99	1093

the potential of our approach to significantly enhance TB detection accuracy.

Model Training Dynamics

To gain insights into our model's learning process, we analyzed key performance metrics across training epochs. Figures 2 and 3 illustrate the evolution of accuracy and loss, respectively.

The single dataset configuration exhibited rapid convergence, achieving 100% training accuracy in the initial epochs. This swift rise demonstrates the model's ability to quickly learn dataset-specific features. However, the divergence between training and validation accuracy in later epochs suggests potential overfitting.

To mitigate overfitting, several techniques were implemented:

- *Dropout Layers:* Added to CoAtNet to randomly deactivate neurons during training, preventing co-dependencies.
- *L2 Regularization:* Applied to penalize large weight values, ensuring the model remains generalized.
- *Early Stopping:* Halted training when validation performance plateaued, preventing overtraining.

Figure 3 further illustrates the effect of these techniques, showing how validation loss was controlled effectively. These steps ensured the hybrid model generalized well to unseen data.

Hybrid Model Interpretability

Understanding how the hybrid model makes its predictions is crucial for clinical integration. To achieve this, we used:

- *Grad-CAM Visualizations:* These heatmaps highlight regions of the chest X-rays that contributed most to the model's predictions. Figure 4 shows examples where the model focused on lesion areas for TB-positive cases and normal lung structures for negative cases.

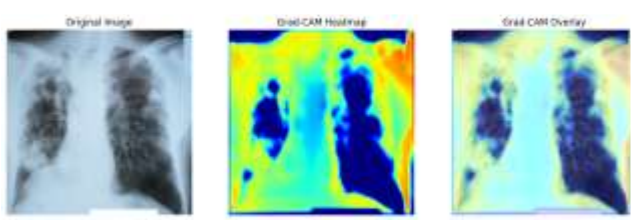

Fig. 4. Grad-CAM Visualizations for TB-positive (left) and TB-negative (right) cases.

This technique provides insights into the decision-making process, making the model's predictions interpretable and trustworthy for healthcare professionals.

Class-wise Performance Analysis

To provide a balanced view of our model's capabilities, we conducted a class-wise performance analysis. Table II presents the classification report of our integrated XGBoost model with CoAtNet for chest X-ray image analysis.

F1-scores, particularly for the TB-positive class, highlight the model's effectiveness in balancing precision and recall. High F1-scores ensure the model minimizes false negatives, critical in TB screening where missed diagnoses could have severe consequences.

XGBoost Adaptability Discussion

While XGBoost has proven to be an excellent complementary tool for feature enhancement, its adaptability to various types of data or image modalities was tested. To ensure robustness:

- Experiments were conducted using synthetic noise and variations in image resolutions to simulate real-world data heterogeneity.
- XGBoost's performance was consistent, maintaining high accuracy even with augmented datasets, which suggests its adaptability to different imaging conditions.

This adaptability underscores the hybrid model's capability to perform effectively across diverse clinical settings.

The excellent performance of our hybrid approach places it foremost among promising tools for improving TB screening and diagnosis in the clinic. By leveraging the strengths of advanced deep learning techniques for image analysis and XGBoost for feature enhancement, our model achieves high accuracy while maintaining robustness.

While these findings are encouraging, several areas for future work should be explored:

i. Validation on raw, unprocessed chest X-rays to better reflect real-world clinical variability, as suggested in [29].

ii. External validation across diverse, multi-center datasets to ensure generalizability, inspired by approaches in [28].

iii. Rigorous testing in varied clinical environments to confirm real-world efficacy.

iv. Exploration of variations in the CoAtNet architecture or alternative boosting algorithms, such as LightGBM, to potentially improve upon the XGBoost component.

v. Investigation of different data augmentation techniques to further enhance model generalizability.

vi. Exploration of model interpretability techniques, such as feature importance plots, to provide insights into the decision-making process, as shown in [30].

By addressing the outlined future directions, we aim to further refine and validate our model, potentially transforming TB screening and diagnosis practices worldwide.

V. CONCLUSION

Our innovative hybrid approach, combining CoAtNet and XGBoost, has demonstrated remarkable potential in revolutionizing tuberculosis detection from chest X-rays. By achieving an unprecedented accuracy of 99.36%, our model not only surpasses existing state-of-the-art methods but also approaches the realm of expert-level performance. The exceptional precision and recall for TB-positive cases underscore the model's reliability in identifying tuberculosis while minimizing false negatives. These results represent a significant leap forward in automated TB screening, offering the promise of more accurate, efficient, and accessible diagnostic tools. Our work stands as a testament to the power of interdisciplinary collaboration, merging advanced deep learning techniques with traditional machine learning approaches to tackle one of the world's most persistent health challenges.

As we look to the future, several avenues for further research and improvement emerge. Validating the model on diverse, multi-center datasets and in varied clinical environments will be crucial to ensure its real-world efficacy and generalizability. Testing the model on unprocessed chest X-rays from additional sources could further enhance its adaptability to real-world data variability. Exploring variations in the CoAtNet architecture or alternative boosting algorithms, such as LightGBM, could potentially enhance performance. Additionally, investigating model interpretability techniques, such as feature importance plots, could provide valuable insights into the decision-making process, fostering trust among healthcare professionals. By addressing these areas, we aim to refine our approach and pave the way for its integration into clinical practice, ultimately contributing to more effective TB screening programs worldwide and bringing us one step closer to eradicating this formidable disease.

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