DEEP LEARNING FOR TB DETECTION IN CHEST X-RAYS

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***Abstract*— Pulmonary Tuberculosis (TB) remains a major global health challenge, recognised by the WHO as a leading cause of death. Automated computer-aided detection (CAD) systems using deep learning are critical for accurate TB detection, especially in resource-limited areas. Chest X-rays, a cost-effective tool, are essential for identifying TB-related abnormalities, and deep learning enhances the accuracy and efficiency of this process.**

This study proposes a hybrid deep learning approach using a pre-trained DenseNet-121 model for feature extraction, followed by CNN and BiLSTM networks for classification. The results highlight the potential of AI-driven tools in improving TB diagnosis and suggest that such models could be adapted to other medical conditions and imaging modalities, contributing to better global healthcare outcomes.

***Keywords*—Tuberculosis(TB), Chest X-rays, Deep Learning Model, Computer-aided detection (CAD), DenseNet121, CNN, BiLSTM**

1. INTRODUCTION

Tuberculosis (TB), caused by the bacterium Mycobacterium tuberculosis (MTB), remains a critical global health challenge, particularly in low- and middle-income countries. Each year, TB affects millions, with around 10 million new cases and approximately 1.5 million deaths reported annually. The disease primarily targets the lungs but can spread to other parts of the body, including the brain, bones, and kidneys. TB’s slow-growing nature enables it to evade the immune system, often resulting in chronic infections. Traditional diagnostic methods, such as sputum smear microscopy and chest X-rays, require skilled technicians and are often insufficient for early detection, leading to delays in diagnosis and treatment.

In response to these challenges, there is an urgent need for more accurate and accessible diagnostic tools, particularly in resource-limited settings. Artificial intelligence (AI) has shown significant promise in enhancing the diagnosis of TB by analyzing medical images, such as chest X-rays, with high precision. This project aims to develop an AI-based diagnostic system using Convolutional Neural Networks (CNNs) and Bidirectional Long Short-Term Memory (BiLSTM) networks. These models will be trained to accurately detect TB in chest radiographs, addressing issues related to imbalanced datasets through data augmentation. By comparing the performance of different AI models, the project seeks to identify the most effective approach for TB detection, ultimately enhancing diagnostic accuracy and supporting global health initiatives, including the WHO’s End TB Strategy.

2. LITERATURE SURVEY

Tuberculosis (TB), caused by Mycobacterium tuberculosis (MTB), affects over 10 million people annually and can be fatal if untreated. The World Health Organization (WHO) states that 85% of TB cases can be cured with a 4 to 6-month course of anti-TB medication, though treatment duration may vary.

Rahman et al. [2] present a deep-learning approach for TB detection using chest X-rays, integrating image segmentation and CNNs to accurately identify lung regions and detect TB. The model's high accuracy and robustness highlight its potential as an automated TB screening tool, especially in resource-limited settings. The study underscores the role of AI in enhancing TB diagnostics.

Kim et al. [3] aim to improve automated TB screening by refining dataset curation methods, and addressing biases and imbalances to enhance model reliability. The study proposes techniques for balancing class distributions and improving annotation quality, emphasizing the critical role of careful dataset curation in developing robust AI systems for accurate TB detection in clinical settings.

Van Engelen and Hoos [4] survey semi-supervised learning (SSL) techniques, categorizing approaches like self-training, co-training, and graph-based methods, and discussing their strengths and challenges. They highlight SSL's applications in natural language processing and computer vision, emphasizing its value in improving model performance when labelled data is limited. The survey underscores SSL's role in enhancing learning efficiency and accuracy.

The study by Orjuela-Cañón et al. [5] explores a decision support system using machine learning to aid TB diagnosis in resource-limited settings. The system enhances diagnostic accuracy despite incomplete or inconsistent data, demonstrating potential to improve patient outcomes. The research underscores the need for tailored tools in fragile healthcare environments.

Karmani et al. [6]: This study provides a taxonomy of machine learning methods for TB diagnosis, categorizing techniques like supervised, unsupervised, and hybrid methods. It discusses their strengths, limitations, and relevance in various clinical settings, highlighting machine learning's potential to enhance diagnostic accuracy, speed, and efficiency, especially in resource-constrained environments.

Meier et al. [7]: The study explores using machine learning to analyze immune responses to Mycobacterium tuberculosis antigens for TB diagnosis. By identifying specific immune markers, the approach aims to improve diagnostic accuracy, differentiating between TB-infected and non-infected individuals. The research underscores the potential of combining machine learning with immunological data for better TB detection.

Ayaz et al. [8]: This paper presents an ensemble learning approach to detect TB in chest X-rays, using hybrid feature descriptors to enhance accuracy. By integrating multiple machine learning models, the study captures diverse image characteristics, improving diagnostic performance. The approach shows promise for reliable TB detection in clinical settings.

Gao and Qian et al. [9]: The study focuses on predicting multidrug-resistant TB (MDR-TB) from CT pulmonary images using deep learning, particularly CNNs. The models effectively differentiate between resistant and non-resistant strains, enhancing diagnostic accuracy. This approach supports clinical decision-making and aims to improve patient outcomes in MDR-TB cases.

Gupta and Kakkar et al. [10]: This review covers recent advancements in TB diagnostics, including molecular, biochemical, and imaging techniques. It highlights improvements in detection sensitivity, specificity, and speed, and discusses challenges and limitations. The paper offers insights into emerging technologies and future research directions in TB diagnostics.

WHO 2019 Policy Guidance [11]: The WHO recommends using molecular line probe assays (LPA) to detect resistance to second-line anti-TB drugs, particularly for diagnosing multidrug-resistant and extensively drug-resistant TB. The guidance emphasizes rapid, accurate detection and the integration of LPAs into existing frameworks, alongside proper training and quality control.

Ojha et al. [12]: This review highlights the advantages of LED-based fluorescence microscopy for TB detection, emphasizing its cost-effectiveness and portability. The paper discusses how LED microscopy improves TB bacteria visualization, enhancing detection sensitivity and specificity, particularly in resource-limited settings.

Mbuagbaw et al. [13]: The study evaluates bedaquiline treatment outcomes for MDR-TB patients, focusing on effectiveness and safety. It presents data on success rates and adverse effects, comparing bedaquiline with other treatments. The findings highlight its potential benefits and challenges in managing drug-resistant TB in clinical practice.

Subbaraman et al. [14]: This paper introduces care cascades for active TB, a framework to monitor programs and identify care quality gaps. By mapping the TB care process from diagnosis to treatment, the study emphasizes using care cascades to track patient progression and improve program performance and outcomes.

Sathitratanacheewin et al. [15]: The study investigates deep learning for automated TB classification in chest X-rays, focusing on dataset distribution shift challenges. It evaluates how variations in training and test datasets affect model accuracy, highlighting the limitations of current deep-learning approaches in adapting to diverse data distributions.

3. PROPOSED SYSTEM

The proposed system enhances TB diagnosis using chest radiographs through AI, integrating Convolutional Neural Networks (CNNs) and Bidirectional Long Short-Term Memory (BiLSTM) networks. It utilizes DenseNet121, a pre-trained CNN model, for feature extraction, capturing both spatial and temporal features from X-rays. The system starts with data preparation, resizing images to 128x128 pixels and balancing the dataset using augmentation techniques. A dual-pathway approach is employed: the CNN pathway focuses on spatial relationships, while the BiLSTM pathway captures temporal dependencies. Both models are trained with early stopping and model checkpointing to ensure optimal performance. The final system selects the model with the highest validation accuracy for deployment. Designed for scalability, it can be adapted for future applications, including integration with electronic health records (EHR) and additional imaging modalities, offering a robust and flexible solution for TB detection, particularly in high-burden areas.

4. IMPLEMENTATION

Implementation Steps for Tuberculosis Detection Models:

Data Collection:

- Input Data: Collect chest radiograph images categorized into "Normal" and "Tuberculosis" classes.

Pre-processing:

- The dataset used comprises chest radiography images categorized into "Normal" and "Tuberculosis" classes, sourced from the TB Chest Radiography Database. Images were resized to 128x128 pixels and preprocessed using the preprocess_input function from DenseNet121.

- Balancing the Dataset: To address the class imbalance, the majority class was downsampled to match the minority class size, preventing bias. The balanced dataset was converted into numpy arrays for further processing.

- Data Normalization and Encoding: Images were normalized to the float32 data type, ensuring pixel values were within a standardized range. Class labels were one-hot encoded into a binary matrix format for model training.

- Train-Test Split: The dataset was divided into training and testing sets with a 70-30 split ratio using scikit-learn's train_test_split function, providing a diverse training set and a separate validation set.

- Data Augmentation: To improve model generalizability, data augmentation techniques such as random rotations, shifts, horizontal flipping, and zooming were applied using Keras' Image Data Generator. These augmentations increase the robustness of the model by simulating various image orientations and variations.

Feature Extraction DenseNet121:

- Utilize a pre-trained DenseNet121 model to extract feature maps from the preprocessed images.

- Feed the extracted feature maps into two separate models: CNN and BiLSTM.

CNN Model Implementation:

- Input Layer: Process 4x4x1024 feature maps.

- Global Average Pooling: Reduce the dimensionality of feature maps.

- Dense Layer: Use 64 units with ReLU activation.

- Dropout Layer: Apply 50% dropout to prevent overfitting.

- Output Layer: Use Softmax activation for classification into "Normal" or "Tuberculosis".

- Apply early stopping and model checkpointing based on validation loss.

BiLSTM Model Implementation:

- Input Layer: Process the reshaped feature sequences.

- First BiLSTM Layer: 32 units, bidirectional, with return sequences enabled.

- Dropout Layer: Apply 50% dropout to prevent overfitting.

- Second BiLSTM Layer: 32 units, bidirectional.

- Output Layer: Use Softmax activation for classification.

- Apply early stopping and model checkpointing based on validation loss.

Model Comparison and Selection:

- Compare the CNN and BiLSTM models based on their performance.

- Select the model with the best performance for final deployment.

Model Output and Deployment:

- Final Model: Save the selected BiLSTM model in ".keras" format for deployment.

- Outputs: Generate confusion matrix, precision, recall, and F1-Score for evaluation.

- Visualizations: Generate accuracy plots for training and validation, along with ROC curve and image visualization showing actual vs. predicted labels.

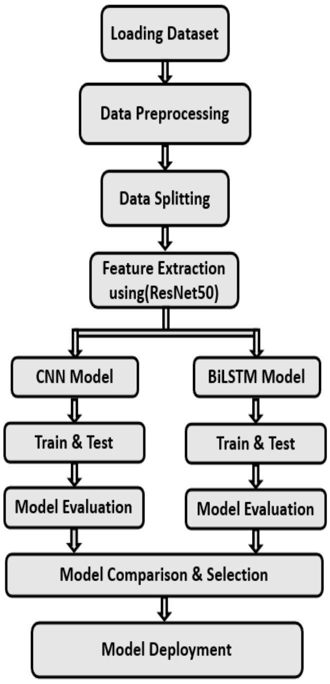

Fig 1: Flow Diagram Implementation

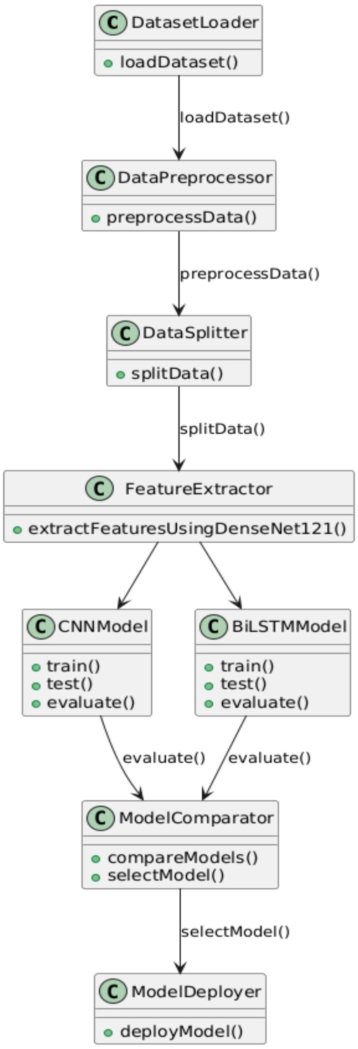

Fig 2: Class Diagram

5. RESULTS

Model's Accuracy:

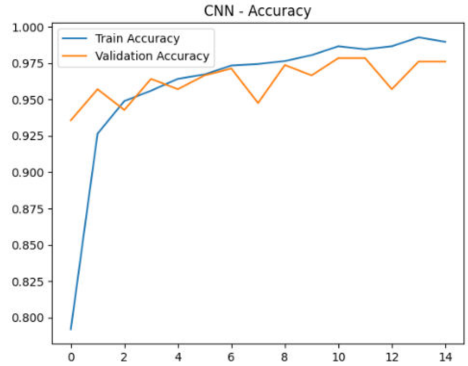

Fig 3: CNN - Accuracy

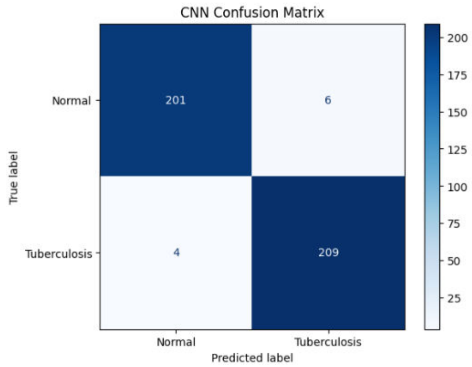

Fig 4: Confusion Matrix - CNN

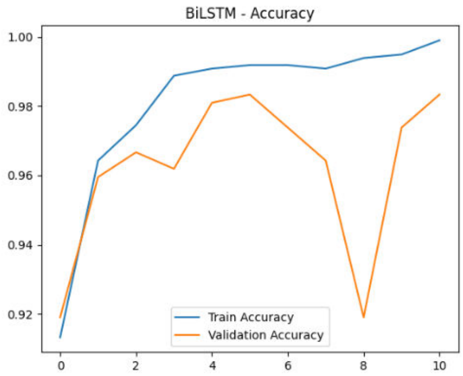

Fig 5: BiLSTM - Accuracy

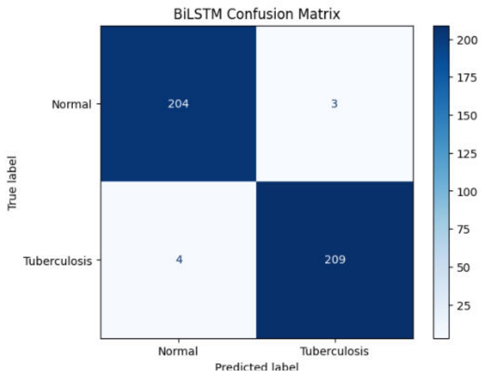

Fig 6: Confusion Matrix - BiLSTM

Result Conclusion:

BiLSTM model demonstrates better overall performance with fewer misclassifications, showing higher reliability in detecting both Normal and Tuberculosis cases compared to the CNN model. The confusion matrices align with the earlier classification report and specificity analysis, reinforcing BiLSTM as the preferred model for this task.

6. CONCLUSION

This study presents an advanced machine-lerning approach for detecting tuberculosis (TB) using chest radiography images, emphasizing improved computational efficiency and accuracy. The methodology integrates Convolutional Neural Networks (CNNs) for extracting detailed spatial features and Bidirectional Long Short-Term Memory (BiLSTM) networks for capturing temporal dependencies and sequential patterns within the images. By employing data preprocessing techniques such as data augmentation and class balancing, the model effectively addresses class imbalance issues common in medical datasets, leading to enhanced performance. To further improve robustness and generalization, the study of incorporates ReduceLROnPlateau callback, which dynamically adjusts the learning rate during training to prevent overfitting.

The results demonstrate that this approach is particularly promising for TB detection in resource-limited settings, where both accuracy and computational efficiency are crucial. The model's simplicity, coupled with careful hyperparameter tuning, contributes to its strong performance metrics, highlighting its potential for reliable TB identification. Future research will aim to refine the model by exploring new architectures and techniques to develop more lightweight models, ensuring that TB screening remains accessible and efficient across diverse healthcare environments.

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