International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

Automated Tuberculosis Detection using Transfer Learning

Rayapati Vyshnavi[1], Tirumalaraju Amrutha[2], Tumpilli Santhosh[3], Potnuru Ajith[4], Nunna Tarun Venkata Sai[5]

[1]Rayapati Vyshnavi, Information Technology, Rajam, Andhra Pradesh
[2]Tirumalaraju Amrutha, Information Technology, Rajam, Andhra Pradesh
[3]Tumpilli Santhosh, Information Technology, Rajam, Andhra Pradesh
[4] Potnuru Ajith, Information Technology, Rajam, Andhra Pradesh
[5] Nunna Tarun Venkata Sai, Information Technology, Rajam, Andhra Pradesh

ABSTRACT -

Tuberculosis detection has advanced significantly with the integration of artificial intelligence (AI) and machine learning, facilitating early and accurate diagnosis. Traditional diagnostic methods rely heavily on radiologists to interpret chest X-rays (CXRs), a process that can be time-consuming, subjective, and prone to inconsistencies. AI-driven deep learning models have transformed this process by automating the analysis of CXRs, allowing for the rapid and precise identification of TB-related abnormalities. Convolutional neural networks (CNNs) are employed to extract intricate patterns and features from the X-ray images, which are indicative of TB. In addition, attention mechanisms focus on the most critical regions of the images, further enhancing the model's ability to detect subtle abnormalities. Wavelet transforms and eigen domain feature extraction techniques are also applied, providing deeper insights into the morphological structures within the images. Furthermore, graph-based neural networks analyze the spatial relationships between affected regions, improving detection accuracy. AI-powered models offer several advantages, reducing the reliance on specialist radiologists and making TB detection more accessible, particularly in low-resource areas. These models also help accelerate the diagnostic process, ensuring quicker decision-making and timely treatment interventions, which are vital for combating TB effectively. The integration of AI into healthcare systems not only makes TB diagnosis faster, more reliable, and cost-effective but also plays a crucial role in the global fight against tuberculosis. Ultimately, it leads to improved patient outcomes, enhanced public health responses, and greater global awareness and control of the disease.

Key Words: Tuberculosis, Artificial Intelligence, Deep Learning, Transfer Learning, Attention Mechanisms.

1. INTRODUCTION

Automated tuberculosis detection using transfer learning enhances the accuracy and efficiency of diagnosing TB from chest X-ray images. Traditional diagnostic methods rely on radiologists, which can be time-consuming and subject to variability. Transfer learning leverages pre-trained deep learning models to extract crucial features from X-rays, improving detection accuracy even with limited datasets. By focusing on TB-related abnormalities, AI-driven models help identify the disease more precisely while reducing dependency on medical specialists. This makes diagnostics more accessible, particularly in low-resource settings where expert radiologists may not always be available. Faster diagnosis ensures timely treatment, which is crucial for patient recovery and disease control. AI-powered detection also minimizes human error and enhances reliability in medical imaging. Additionally, the cost-effectiveness of this approach makes TB detection more affordable and scalable across different healthcare systems. By integrating transfer learning into medical diagnostics, healthcare providers can improve early detection, leading to better patient outcomes and more effective TB management. TB remains a major global health concern, especially in low-income and densely populated regions. The disease is classified into two forms: latent TB, where the bacteria remain dormant without causing symptoms, and active TB, which leads to severe respiratory issues. Artificial intelligence (AI) and deep learning models, such as those using transfer learning, are being explored to improve TB detection from chest X-rays. Preventive measures like improving living conditions, ensuring proper ventilation, and early screening can help reduce TB transmission. Public awareness and access to healthcare play a crucial role in controlling the disease. Despite medical advancements, TB continues to be one of the deadliest infectious diseases, requiring global efforts to eliminate it. Ongoing research and technological advancements are essential in achieving effective TB prevention and treatment strategies.

2. LITERATURE SURVEY

The paper highlights the global health challenge posed by tuberculosis (TB), particularly in developing countries, where it remains a significant health issue. Montgomery Dataset This dataset contains 138 frontal chest X-ray images, with 80 classified as normal and 58 as having TB manifestations. Tuberculosis (TB) Chest X-ray Dataset this dataset consists of 700 images diagnosed with tuberculosis and 3500 normal images. The proposed model, CBAMWDnet, incorporates CBAM, which enhances the model's ability to focus on important features in the input data. The performance of deep learning models like CBAMWDnet heavily relies on the availability of large datasets of labeled medical images. Obtaining such datasets can be difficult due to privacy concerns and the limited availability of validated open-source data. [1]

The study utilized a well-curated dataset comprising chest X-ray and CT scan images, which included both healthy and TB-infected cases. The dataset's quality and diversity were ensured through collaboration with hospitals and the use of publicly accessible datasets. The methodology involved a pre-processing module that enhanced the clarity and visibility of TB-related features in the X-ray images. Techniques such as noise reduction, histogram equalization, and contrast augmentation were employed to improve image quality. A Convolutional Neural Network (CNN) was employed as the classification model, leveraging learned representations from the extracted features to identify tuberculosis patterns effectively. The CBAMWDNet model used in the study is highly parameterized, making it computationally intensive. [2]

3. PROPOSED SYSTEM

The proposed methodology for automated Tuberculosis (TB) detection from chest X-ray (CXR) images involves a systematic pipeline comprising multiple stages: *Input Acquisition, Pre-processing, Lung Region Segmentation, Feature Extraction, TB Abnormality Detection, Classification*, **and** *Deployment*. The entire process is designed to leverage the power of transfer learning with deep learning models to ensure high diagnostic accuracy, even in resource-constrained settings. This automated TB detection framework leverages advanced deep learning techniques to achieve high accuracy in diagnosis.

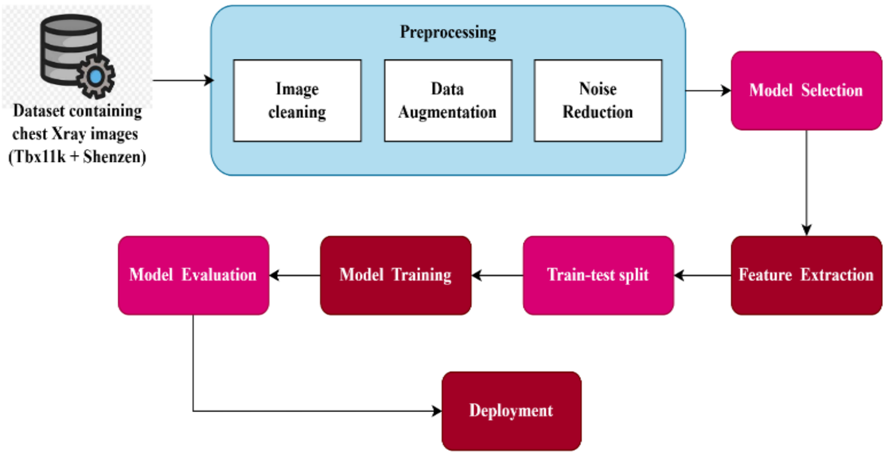

Fig. 1: System Architecture

A. Dataset (Tbx11k+shenzen):

The process starts with a dataset containing chest X-ray images. It specifically uses the Tbx11k and Shenzen datasets, which are known TB X-ray image collections. These datasets contain both TB-positive and TB-negative chest X-rays.

B. Preprocessing:

This stage consists of three key steps:

- Image cleaning: Removes artifacts, enhances image quality, and standardizes the images.
- Data augmentation: Creates variations of existing images through techniques like rotation, flipping, scaling to increase the training data. We used this technique like rotation, flipping, scaling, and brightness changes to generate more diverse chest X-ray samples. This helped improve our model's robustness and accuracy, especially since medical datasets are often limited and imbalanced.
- Noise reduction: Filters out unwanted noise from X-ray images to improve image quality.

C. Model Selection:

This step involves choosing the appropriate pre-trained deep learning model. Common choices might include ResNet, or DenseNet architectures. The model is selected based on its performance on similar medical imaging tasks.

D. Feature Extraction:

Uses the pre-trained model to extract relevant features from the X-ray images. These features might include patterns, textures, and structures indicative of TB. The pre-trained model's early layers are typically frozen to retain learned features.

E. Train-Test Split:

Divides the processed dataset into training and testing sets. Ensures proper model evaluation by keeping test data separate. Typically uses a ratio like 80/20 or 70/30 for train/test split.

F. Model Training:

Fine-tunes the selected model on the TB dataset. Adjusts the model's parameters to optimize TB detection. Uses transfer learning to leverage pre-trained weights while adapting to TB detection.

G. Model Evaluation:

Assesses the model's performance using metrics like accuracy, sensitivity, and specificity. Validates the model's ability to correctly identify TB cases. May include cross-validation for robust performance assessment.

H. Deployment:

The final stage where the validated model is prepared for real-world use. Includes model optimization for deployment. Makes the model available for clinical use in TB screening.

This workflow utilizes transfer learning to create an efficient TB detection system, reducing the need for training from scratch and potentially improving accuracy through pre-learned features from large image datasets.

4. RESULT

In this final evaluation step, we assessed the performance of the EfficientNetB7 model integrated with the Convolutional Block Attention Module (CBAM). The model achieved an impressive 97% overall accuracy. To make the chest X-ray classification process interactive and user-friendly, we integrated the EfficientNetB7 + CBAM model with a Gradio web interface.

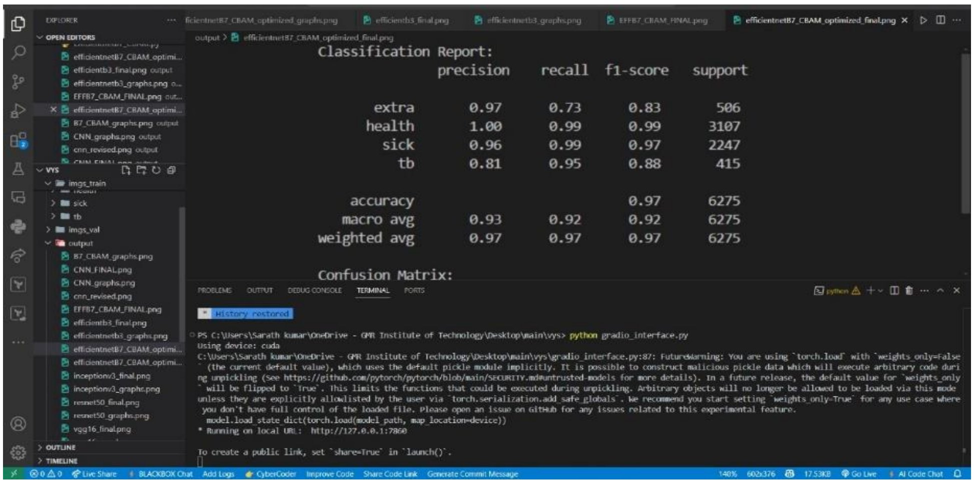

Fig. 2: Classification Report and Confusion Matrix for EfficientNetB7 with CBAM

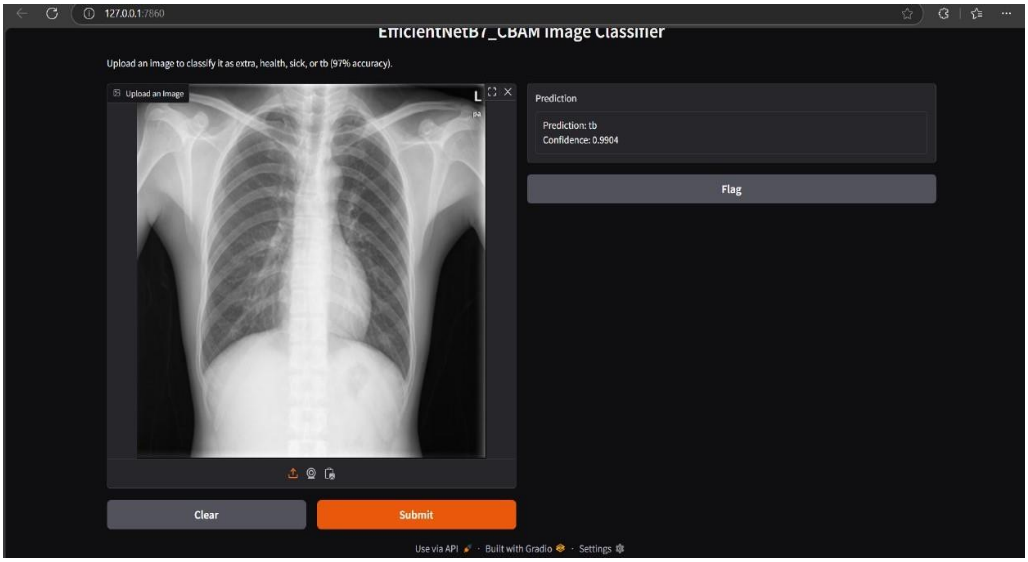

Fig. 3: Web Interface Output using Gradio for EfficientNetB7 with CBAM

5. CONCLUSION

The fusion of EfficientNet-B7 with CBAM, coupled with Gradio's interactive capabilities, represents a significant advancement in automated TB detection. This integrated approach offers a high-accuracy, user-friendly solution that holds substantial promise for improving TB diagnostics, particularly in resource-limited environments where rapid and reliable detection is essential. Furthermore, deploying this advanced model through Gradio integration has facilitated the development of an interactive web interface, streamlining the diagnostic workflow.

6. LIMITATIONS

High-end GPU resources are needed to train and fine-tune deep models like EfficientNet-B7, which limits deployment in resource-poor settings. Use of clinical images may raise data privacy concerns, and deployment for diagnosis may require medical device regulatory approval.

REFERENCES

[1]. Huy, V. T. Q., & Lin, C. M. (2023). An improved dense net deep neural network model for tuberculosis detection using chest x-ray images. IEEE Access, 11, 42839-42849.

[2]. Ramachandra, H. V., Nithin, B., Reddy, A. N., & Anirudha, B. (2024, July). Tuberculosis Detection using Image Pre-Processing. In 2024 Asia Pacific Conference on Innovation in Technology (APCIT) (pp. 1-5). IEEE.

[3]. Kotei, E., & Thirunavukarasu, R. (2024). Tuberculosis detection from chest x-ray image modalities based on transformer and convolutional neural network. IEEE Access.

[4]. Chokchaithanakul, W., Punyabukkana, P., & Chuangsuwanich, E. (2022). Adaptive image pre-processing and augmentation for tuberculosis screening on out-of-domain chest X-Ray dataset. IEEE Access, 10, 132144-132152.

[5]. Kabi, S. K., Tripathy, R. K., Patra, D., & Panda, G. (2023). A Novel Approach for the Detection of Tuberculosis and Pneumonia Using Chest X-Ray Images for Smart Healthcare Applications. IEEE Sensors Letters, 7(12), 1-4.