Early Detection of Tuberculosis Using Deep Neural Networks

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1 Abstract

This project leverages deep learning techniques to improve the early detection of tuberculosis (TB), a critical global health issue. Through the implementation of a custom neural network architecture, the project analyzes patient data to provide rapid TB diagnosis. The model achieves a high sensitivity of 95% for TB detection, making it particularly valuable for initial screening in medical settings, despite challenges with false positives.

2 Overview

2.1 What is the problem?

Tuberculosis remains one of the leading causes of death worldwide, with millions affected annually. Traditional diagnostic methods like sputum smear microscopy are time-consuming, resource-intensive, and often inaccessible in many regions. The need for rapid, accurate, and accessible TB diagnosis is crucial for controlling the spread of this infectious disease.

2.2 Why is this problem interesting?

This problem addresses a critical healthcare challenge, particularly in resource-limited settings. Automated TB detection could significantly reduce the burden on healthcare systems and improve access to diagnosis in underserved areas. The solution could be integrated into existing medical facilities to provide rapid screening, potentially saving lives through earlier detection and treatment initiation.

2.3 What is the approach?

The project implements a custom neural network architecture for TB detection using patient medical data. The approach focuses on binary classification, distinguishing between TB and non-TB cases. The solution emphasizes high sensitivity to minimize missed TB cases, recognizing that false negatives in TB detection can have severe consequences.

2.4 What is the rationale?

Deep learning has shown remarkable success in medical diagnosis tasks due to its ability to identify complex patterns in data. While traditional machine learning approaches exist for TB detection, neural networks offer the potential for better feature extraction and pattern recognition from medical data. This approach differs from traditional methods by prioritizing sensitivity over specificity, acknowledging the greater cost of missed TB cases.

2.5 Key components and limitations

Key components include data preprocessing for handling medical records, a custom neural network architecture, and comprehensive performance evaluation. Primary limitations include a high false positive rate and significant class imbalance in the dataset (1522 non-TB vs 88 TB cases).

3 Experiment Setup

3.1 Dataset Description

The dataset comprises 1610 patient records in the test set, with 1522 non-TB and 88 TB cases. Each record includes various patient features such as demographics, medical history, and symptoms. The significant class imbalance (approximately 17:1 ratio) presented a major challenge in model training.

3.2 Implementation Details

The implementation was carried out using the following framework and specifications:

- **Framework:** TensorFlow with Keras API
- **Optimizer:** Adam optimizer
- **Loss Function:** Binary Cross-Entropy
- **Training Environment:** Google Colab with GPU support
- **Data Preprocessing:**
  - Standardization of numerical features
  - Encoding of categorical variables
  - Data splitting into training and validation sets

3.3 Model Architecture

The neural network architecture consists of multiple convolutional blocks with the following structure:

- **Base Architecture:** Multiple Convolutional Blocks
- **Each Convolutional Block:**

    - Convolutional Layer
    - Batch Normalization Layer
    - ReLU Activation Function

- **Activation Functions:**
    - ReLU for intermediate layers
    - Sigmoid for the output layer

- **Regularization:**
    - Batch Normalization for reducing internal covariate shift
    - Dropout layers for preventing overfitting

- **Output Layer:** Single unit with sigmoid activation for binary classification

4 Experiment Results

4.1 Main Results

The model achieved: - ROC-AUC score: 0.746 - Overall accuracy: 56% - TB detection sensitivity: 95% (84 out of 88 cases correctly identified) - Non-TB precision: 100%

The confusion matrix shows:

$$\begin{bmatrix} 817 & 705 \\ 4 & 84 \end{bmatrix}$$

4.2 Supplementary Results

Class-specific metrics:
- Non-TB cases: Precision = 1.00, Recall = 0.54, F1-score = 0.70
- TB cases: Precision = 0.11, Recall = 0.95, F1-score = 0.19
- Macro avg: Precision = 0.55, Recall = 0.75, F1-score = 0.44
- Weighted avg: Precision = 0.95, Recall = 0.56, F1-score = 0.67

5 Discussion

The model's high sensitivity (95%) for TB detection makes it valuable for initial screening, though the high false positive rate suggests the need for secondary confirmation. The ROC-AUC score of 0.746 indicates good discriminative ability despite the significant class imbalance challenge.

Future improvements could include: - Implementing advanced class balancing techniques - Developing a two-stage classification system - Incorporating additional medical data types - Enhancing model interpretability

6 Conclusion

This project successfully developed a neural network-based TB detection system achieving 95% sensitivity in identifying TB cases. While the high false positive rate presents opportunities for improvement, the model's ability to catch almost all TB cases makes it a valuable tool for initial screening in medical settings, particularly in resource-limited environments.

7 References

Chest TB X Ray,
Lung Segmentation Dataset,
X Ray Dataset
GitHub Repository