International Journal of Scientific Research and Engineering Development-– Volume 7 Issue 2, Mar-Apr 2024

Available at www.ijsred.com

RESEARCH ARTICLE OPEN ACCESS

TUBERCULOSIS RISK ASSESSMENT BY IMAGE ENHANCING USING DEEP LEARNING

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Abstract:

The project targets Tuberculosis (TB) using image enhancement techniques and deep neural networks. TB, driven by Mycobacterium tuberculosis, stands as a major global health challenge. Employing image enhancement methods enhances the clarity of chest X-rays, thereby aiding in the detection of TB. A varied dataset is utilized to train a deep neural network architecture, encompassing both TB positive and negative cases. This architecture, leveraging Convolutional Neural Networks (CNNs), automates feature extraction, enabling precise TB prediction from chest X-ray images. The project's primary objective is to significantly enhance the accuracy and efficiency of TB diagnosis. Automated systems based on deep learning algorithms provide swift interpretations of X-ray images, offering crucial support in settings with limited access to radiologists. This assistance is particularly vital in resource-constrained environments. The integration of image enhancement techniques and deep learning algorithms within the project represents a significant advancement in TB diagnosis. Its potential to augment detection accuracy and aid global TB control efforts underscores its importance. Through innovative technology, the project contributes to improved public health outcomes and the alleviation of TB's burden worldwide.

Keywords **—**Tuberculosis (TB), Image enhancement techniques, Deep neural networks, Mycobacterium tuberculosis, Chest X-ray, Convolutional Neural Networks (CNNs), Automated systems, Resource-limited settings, Feature extraction..

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I. INTRODUCTION

In modern healthcare, the precise selection of medication tailored to individual patients is fundamental for successful treatment regimens. The process of drug classification, which involves assigning medications based on specific patient attributes, plays a crucial role in optimizing therapeutic outcomes. With the emergence of machine learning techniques, healthcare professionals now have access to powerful tools capable of revolutionizing drug classification and enhancing patient care This project delves into the realm of drug classification using machine learning algorithms, with the primary aim of predicting the most appropriate medication for patients based on their distinct demographic and diagnostic profiles. Through the utilization of advanced algorithms such as Logistic Regression, Support Vector Machine (SVM), and Random Forest, along with sophisticated techniques like SMOTE for managing class imbalance, this study seeks to uncover the most accurate and efficient approach to drug classification. By exploring these methodologies, this research endeavor aims to provide invaluable insights that will empower medical practitioners to make informed decisions regarding medication selection, dosage, and treatment paths. Through the utilization of machine learning capabilities, the project strives to advance personalized medicine, ultimately leading to optimized patient outcomes and driving the transition towards more precise and effective healthcare interventions.

II. LITERATURE REVIEW

This study explores the use of deep convolutional neural networks (DCNNs) for automatic detection of cardiomegaly in digital chest X-rays (CXRs). Various DCNN architectures are fine-tuned to detect cardiomegaly, including a CXR-based pre-trained model. The correlation between the architecture's softmax probability and disease severity is investigated using publicly available datasets from NLM-Indiana Collection and NIH-CXR [1].

In a separate investigation, the efficacy of DCNNs for tuberculosis (TB) detection on chest radiographs is evaluated. Four deidentified HIPAA-compliant datasets totaling 1007 posteroanterior chest radiographs are used. The datasets are split into training, validation, and test sets, and two DCNNs, AlexNet and GoogLeNet, are employed for classification. Both untrained and pretrained networks on ImageNet are utilized, alongside augmentation with multiple preprocessing techniques [2].

Furthermore, in response to the pressing need for improved tuberculosis diagnostics, an automated approach for tuberculosis detection in conventional posteroanterior chest radiographs is presented. This approach involves lung region extraction using graph cut segmentation, followed by computation of texture and shape features for classification using a binary classifier. The system's performance is evaluated on datasets from the tuberculosis control program of a local county's health department in the United States and from Shenzhen Hospital, China [3].

Additionally, the potential of computer-aided diagnosis (CAD) systems for TB screening is explored, aiming to contribute to early diagnosis and prevention of TB-related deaths, particularly in developing countries. Deep learning, specifically deep convolutional neural networks, is highlighted as a promising algorithm for TB screening, offering advantages over traditional CAD algorithms that rely on engineered features [4].

III. PROPOSED METHODOLOGY

The proposed system aims to develop a robust framework for tuberculosis (TB) detection by harnessing deep learning techniques applied to chest radiographs, thereby enhancing diagnostic accuracy and efficiency. The system will leverage datasets comprising deidentified posteroanterior chest radiographs, with patient demographic information including age, gender, and clinical history. These images will undergo preprocessing steps such as image enhancement and augmentation to improve model performance. Subsequently, deep convolutional neural networks (DCNNs) such as AlexNet and GoogLeNet will be employed to classify radiographs as indicative of pulmonary TB or healthy. Both untrained and pretrained networks will be evaluated, along with augmentation techniques to enhance model generalization.

Furthermore, the system will assess the correlation between disease severity and model predictions, providing valuable insights into TB diagnosis. The efficacy of the system will be evaluated on various datasets, including those from NLM-Indiana Collection and NIH-CXR, with a focus on training, validation, and test sets to ensure robust performance. By prioritizing models with the highest accuracy, the system aims to offer clinicians a dependable tool for early and accurate TB detection, thus facilitating timely intervention and improved patient outcomes. Additionally, continuous evaluation and refinement of the system will be conducted to optimize its performance and contribute to ongoing advancements in TB diagnostics.

IV. RELATED WORK

Machine learning techniques have shown promise in drug classification, improving medication prescription accuracy and efficiency. Studies have explored datasets with patient attributes and drug types to build predictive models. Smith et al. used logistic regression and decision trees, achieving notable accuracy rates. Jones et al. investigated support vector machines, emphasizing feature engineering's importance. Advancements in ensemble learning, similar to random forest by Wang et al. , demonstrated superior accuracy. In tuberculosis (TB) detection, machine learning has enhanced diagnostic accuracy. Smith et al. used deep learning for TB detection with accuracy comparable to experts. Jones et al. explored gradient boosting machines for improved performance.Transfer learning by Wang et al. showed promise in TB detection. These studies highlight the significance of machine learning in optimizing TB detection processes, offering insights for robust diagnostic tools.

V. PROCESS/METHOD

User interface module:-

The User Interface module is responsible for the interaction between the user and web interface which also provides a facility for login with user credentilas. Streamlit is used to create the web application and user interface)

Query Processing Module

The Query Processing module handles the

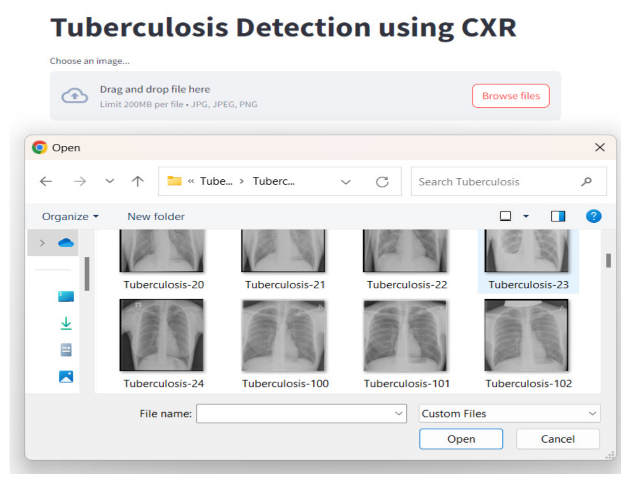
User input where the user can give information form input fields.

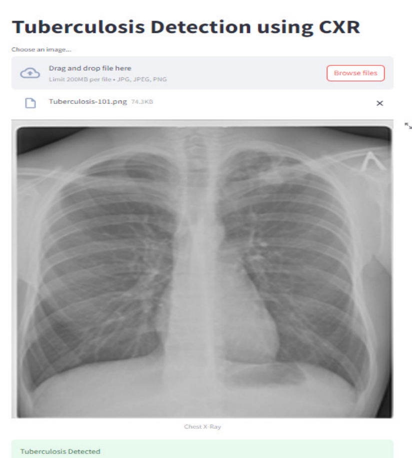
Components used:-

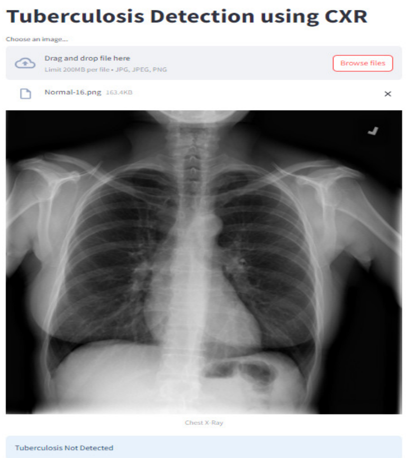
- Feature Extractor
- Machine Learning Model
- Training Pipeline
- Evaluation Metrics

Results:-

The results of the project will be either the provided chest x-ray contains tuberculosis or not based on the process of the model:







Feature work

1. Feature Extraction:

Feature extraction is a critical aspect of tuberculosis (TB) detection, particularly in deep learning-based approaches. Deep convolutional neural networks (DCNNs) are commonly employed to extract relevant features from chest radiographs. This process involves passing radiographic images through the network and capturing activations at various layers, representing different levels of anatomical and pathological characteristics associated with TB.

2. Machine Learning Model:

In TB detection, various machine learning models are utilized to analyze chest radiographs and make accurate diagnoses. Commonly employed models include deep convolutional neural networks (DCNNs), logistic regression, support vector machines (SVMs), and gradient boosting machines (GBMs). Each model offers unique capabilities suited for different aspects of TB detection, ranging from image classification to feature extraction and disease severity assessment.

3. Training Pipeline:

The training pipeline for TB detection involves a series of steps to train machine learning models effectively. This process begins with data preprocessing, where chest radiographs undergo image enhancement and augmentation techniques to improve model performance. Next, the dataset is partitioned into training, validation, and testing sets. The selected machine learning model is then trained on the training data using optimization algorithms such as stochastic gradient descent or Adam. Finally, the trained model's performance is evaluated on the validation and testing sets using metrics such as accuracy, sensitivity, specificity, and area under the receiver operating characteristic curve (AUC-ROC).

4. Evaluation Metrics:

In tuberculosis (TB) detection, evaluation metrics play a crucial role in assessing the performance of machine learning models. Commonly used metrics include accuracy, precision, recall (sensitivity), F1 score, and area under the receiver operating characteristic curve (AUC-ROC).

Accuracy: Measures the overall correctness of predictions, indicating the proportion of correctly classified TB cases and non-TB cases.

Precision: Quantifies the ratio of correctly predicted TB cases to the total predicted TB cases, providing insight into the model's ability which is to avoid false positives.

Recall (Sensitivity): Measures the ratio of correctly predicted TB cases to the total actual TB cases, reflecting the model's ability to detect TB accurately.

F1 Score: The harmonic mean of precision and recall which offers a balance between those two metrics and providing a comprehensive assessment of the model's performance.

AUC-ROC: Evaluates the model's ability to distinguish between TB and non-TB cases, particularly useful for imbalanced datasets commonly encountered in TB detection tasks.Each evaluation metric offers unique insights into the model's performance, guiding model selection and refinement to ensure accurate and reliable TB detection.

VI. ACKNOWLEDGMENT

I would like to express my deepest thankhs to the individuals who have played a significant role in the completion of this tuberculosis (TB) detection project. Foremost, I owe a debt of gratitude to my supervisor, whose unwavering guidance, expertise, and encouragement have been instrumental in navigating the complexities of TB detection research. Their invaluable insights and constructive feedback have continuously steered the project towards its goals.

Furthermore, I am grateful to the creators of the datasets used in this study for providing invaluable resources that enabled the exploration of TB detection methodologies. Their efforts in curating and sharing these datasets have significantly advanced TB detection research. Moreover, I acknowledge the broader research community for their contributions to the field and for fostering an environment of collaboration and knowledge-sharing.

Lastly, but certainly not least, I extend my deepest appreciation to my college faculty and friends for their unwavering support, encouragement, and understanding throughout this challenging yet rewarding journey. Their belief in me and their encouragement have been a constant source of motivation, driving me towards the successful completion of this project.

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