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AI-BASED TUBERCULOSIS AND PNEUMONIA DETECTION

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Abstract : Tuberculosis and Pneumonia are significant global health concerns, particularly in resource-constrained and underserved areas Accurate and timely diagnosis of these diseases is critical, yet often impeded by the lack of clinical experts and appropriate diagnostic tools. Our research presents an innovative approach to address this challenge using Artificial Intelligence and deep learning. We propose a deep-learning CNN model with multilayer classification and identification of TB and Pneumonia. Our model uses image processing techniques and CNN functions for feature extraction and retrieve the probabilities of the Chest-Xray images of the respiratory diseases[1], we have trained the 5323 images with the dataset of 1776 images of Pneumonia, similarly 1776 of TB and 1772 for the normal x-ray images with the help of the CNN we have calculated the accuracy rate of 96.8% of the correct classification and detection of the respiratory diseases as per their class.

IndexTerms - Pneumonia ,Tuberculosis ,CNN ,Chest x-ray, Diagnosis

Introduction

The domain of disease diagnosis, particularly in low and middle-income nations, is consistently marked by difficulties arising from limited resources and inadequate healthcare infrastructure. Respiratory diseases, including pneumonia and tuberculosis (TB), pose a significant health burden worldwide. These diseases affect the lungs and respiratory system, creating a serious threat to public health.

A significant portion of the population in these regions continues to face barriers to accessing timely and accurate diagnostics. This results in delayed treatment and compromised health outcomes. Our project aims to narrow this significant gap by utilizing the capabilities of machine learning algorithms to facilitate timely and accurate disease detection in rural regions. The core objective is the early diagnosis of patients from underserved areas for rapid decision treatment.

Pneumonia, a severe respiratory disease, is a leading cause of death, particularly among children under five in resource-constrained settings. Annually, it claims over 1.1 million lives, surpassing the combined mortality rate of HIV/AIDS, malaria, and tuberculosis[2]. Thus in many low and middle-income countries, there is a significant shortage of these diagnostic tools and clinical experts, leading to delayed and often inaccurate diagnosis. However, the diagnosis in most cases should be made as quickly as possible to initiate medical treatment.

In many developed and developing countries, air pollution has reached a peak due to factors such as industrial growth, automobiles, and dust. This has led to a large population suffering from various kinds of respiratory disorders, with TB being one of them. TB bacteria can also influence other organs of the body if not treated on time because the harmful TB bacteria spread very rapidly[3]. The signs of Tuberculosis include cough, chest pain, weakness, weight loss, fever, and sweating.

This paper presents an AI-based approach for the detection of Tuberculosis and Pneumonia, aiming to contribute to the efforts of disease control and prevention, particularly in resource-constrained settings. We are using Convolutional Neural Networks (CNN) and other neural network architectures for feature extraction from Chest X-ray (CXR) images. These images serve as a valuable resource for training our models, enabling them to accurately identify patterns indicative of Tuberculosis and Pneumonia.

Methods

The data used in this study comprises Chest X-ray (CXR) images, which are crucial for the detection of Tuberculosis and Pneumonia. These images were collected from various regional hospitals and pathology labs. The collection process was carried out under strict ethical guidelines, ensuring patient confidentiality and consent. The dataset includes a diverse range of cases, encompassing different stages of the diseases, and varying patient demographics[4]. This diversity is crucial for training robust machine learning models that can generalize well to unseen data. The collected CXR images form the basis for the subsequent steps of preprocessing, feature selection, and classification in our study.

1. Preprocessing:

The preprocessing stage is crucial in preparing the Chest X-ray (CXR) images for further analysis. This stage involves several steps:

- Data Augmentation: To increase the diversity and quantity of our training data, we use data augmentation techniques. These may include transformations such as rotations, translations, zooming, flipping, etc. This helps to make our model more robust and better generalized to unseen data.
- Resizing: Given that the original CXR images can vary in size, we resize all images to a standard size. This ensures that our model receives consistently sized inputs, which is a requirement for many machine-learning algorithms.
- Normalization: We scale the pixel values of the CXR images to a certain range, often between 0 and 1. This process, known as normalization, helps to reduce the influence of illumination differences in the images and aids in the convergence of the model during training.
- Noise Reduction: CXR images can often contain 'noise' or unwanted variations in brightness or color information[5]. We apply noise reduction techniques, such as smoothing filters, to reduce this noise and enhance the quality of the images.
- Segmentation: This involves dividing the image into regions or categories, which can simplify the image analysis and allow for more precise feature extraction. In the context of CXR images, segmentation can help to highlight regions of interest, such as the lung fields.

2. Feature Selection:

Feature selection is a critical step in the machine learning pipeline. It involves identifying the most informative features in the data that contribute significantly to the predictive performance of the model. In the context of our study, features could be derived from the pre-processed Chest X-ray (CXR) images.

The goal of feature selection is two-fold:

- Improving Model Performance: By selecting only the most relevant features, we can reduce the dimensionality of the data, which can help to improve the model's performance by reducing overfitting and improving generalization.
- Increasing Computational Efficiency: Reducing the number of features can also decrease the computational cost of training and inference, making the model more efficient to run, especially on resource-constrained devices.

In the context of CXR images, features could be pixel intensities, textures, shapes, or other identifiable aspects of the image. The choice of features can depend on the nature of the data and the specific requirements of the task. For instance, texture features might be particularly informative for lung disease detection, as diseases like Tuberculosis and Pneumonia can cause visible changes in the texture of lung tissues in CXR images.

3. Classification:

Classification is the final step in the deep learning pipeline, where the prepared data is used to train a model that can predict the class or category of new, unseen data. In the context of our study, the goal is to classify the Chest X-Ray (CXR) images into different categories, such as 'Healthy', 'Tuberculosis', or 'Pneumonia'.

For this task, we leverage the power of Neural Networks, particularly Convolutional Neural Networks (CNN). CNNs have shown great success in image classification tasks due to their ability to automatically learn hierarchical feature representations from the data, eliminating the need for manual feature extraction[7]. This makes them particularly suitable for tasks that involve complex patterns and structures, such as our CXR image classification task.

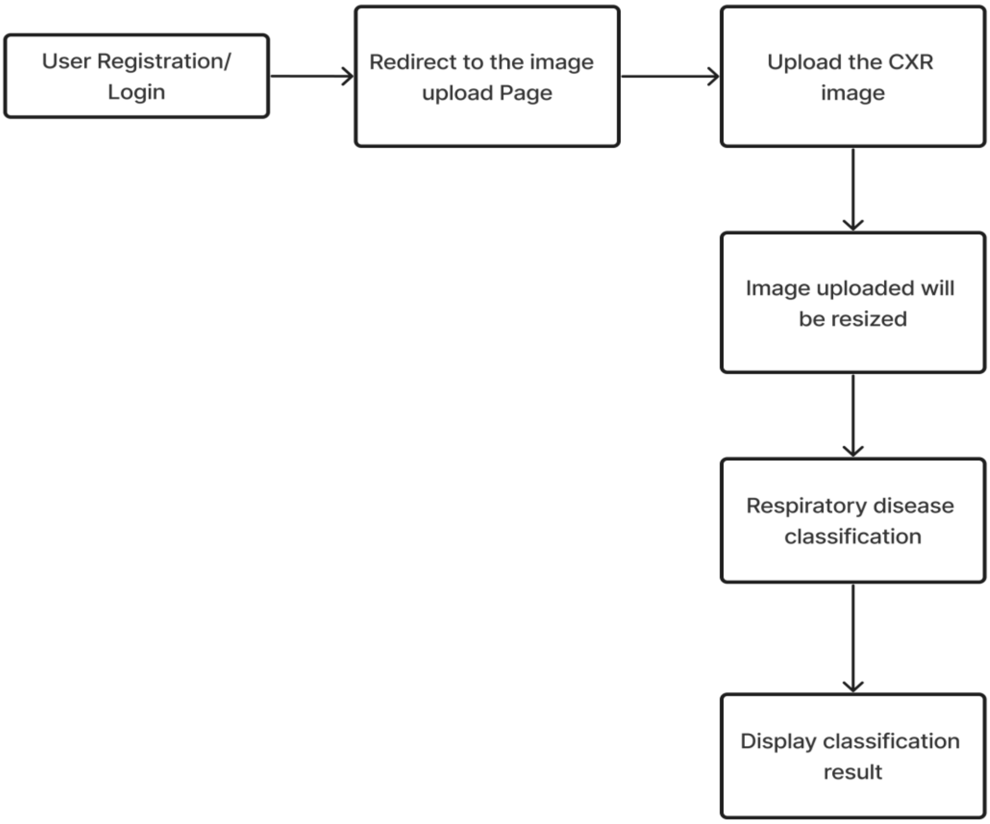
The architecture of our CNN model is designed to effectively capture the intricate patterns in the CXR images that are indicative of 'Healthy', 'Tuberculosis', or 'Pneumonia' classes. The model is trained using a large dataset of labeled CXR images, and its performance is evaluated using metrics called accuracy.

Once the CNN model is trained, it can be used to predict the class of new, unseen CXR images. This allows for timely and accurate disease detection, particularly in resource-constrained settings where access to expert radiologists may be limited.

Proposed Work and Implementation

In this study, we propose a solution for AI-Based Tuberculosis and Pneumonia Detection that leverages the power of Convolutional Neural Networks (CNN), a type of machine learning model particularly effective for image analysis tasks. Our approach aims to facilitate timely and accurate disease detection, especially in resource-constrained settings.

1.Flowchart:



1.User Registration and Login: The user registers and logs into the system. This ensures that each user's data and results are securely stored and accessible only to them.

2.Redirect to Image Upload Page: After login, the user is redirected to the image upload page where they can upload their Chest X-ray (CXR) images.

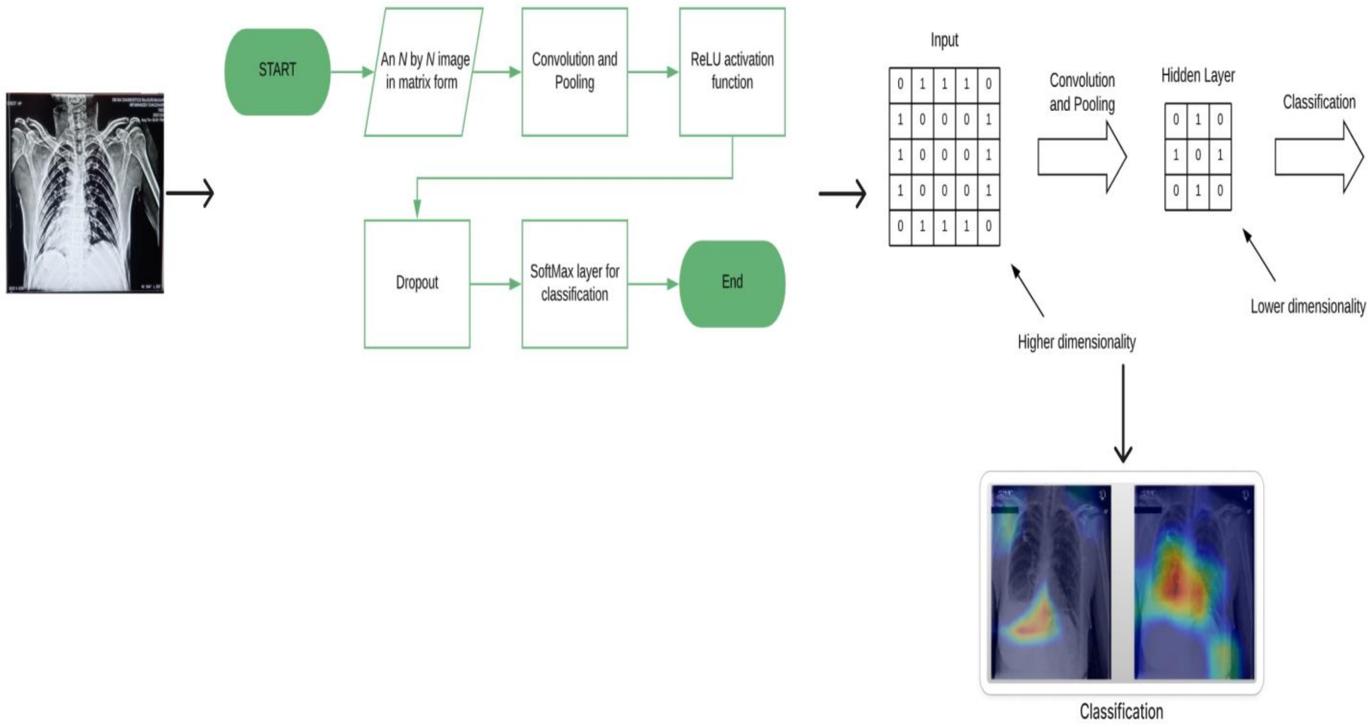
3.Upload the CXR Image: The user uploads the CXR image that they want to analyze. The system verifies that the uploaded file is an image and meets any size or format requirements.

4.Image Resizing: The uploaded CXR image is resized to a standard size to ensure consistency in the analysis process.

5.Respiratory Disease Classification: The resized image is then passed through our Convolutional Neural Network (CNN) model. The model extracts features from the image and classifies them into one of the categories: 'Healthy', 'Tuberculosis', or 'Pneumonia'.

6.Display Classification Result: The result of the classification is then displayed to the user. They can see whether the model predicts the image to be 'Healthy', 'Tuberculosis', or 'Pneumonia'.

2.Preferred Architecture:



1.Start: We begin with an input image of size N by N in matrix form. Each element of this matrix corresponds to a pixel value in the image .

2.Convolution and Pooling : The image is passed through several convolutional layers, where filters are convolved with the image to extract features. Pooling layers are used to reduce the spatial dimensions of the image while retaining the most important information.

3.ReLu Activation Function: The Rectified Linear Unit (ReLU) activation function is applied to introduce non-linearity into the model. It replaces all negative pixel values in the feature map with zero.

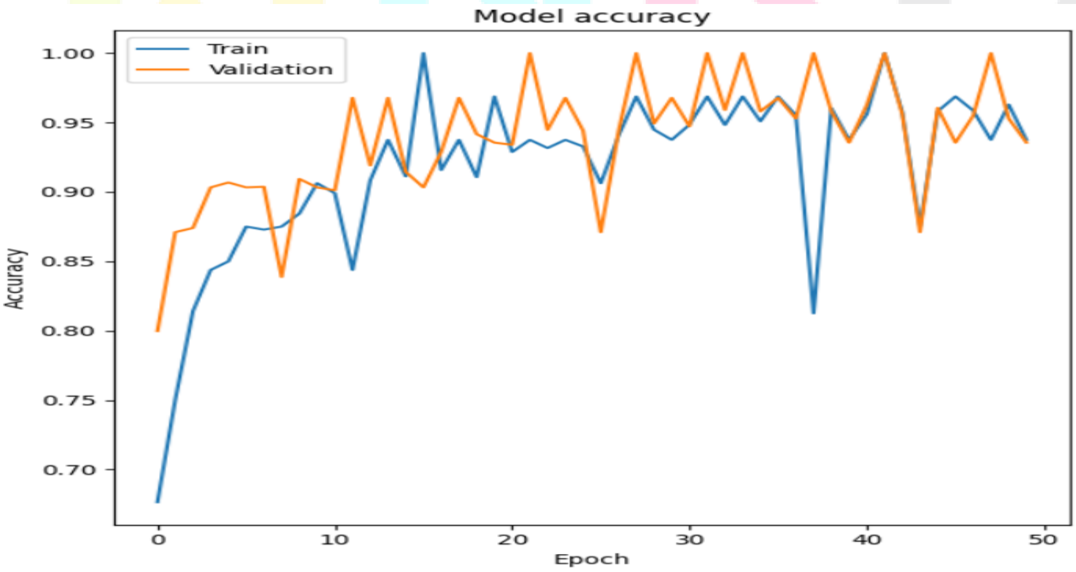
4.Dropout: Dropout is a regularization technique that randomly sets a fraction of input units to 0 at each update during training time. This helps to prevent overfitting.

5.Softmax layer for Classification: The SoftMax function is used in the output layer of the model to output a probability distribution over the target classes. The class with the highest probability is chosen as the output prediction.

6. End: The output of the SoftMax layer is the final prediction of the model.

Results And Discussion

Model accuracy



1.Evaluation Metric: The model's performance was evaluated using accuracy as a key metric.

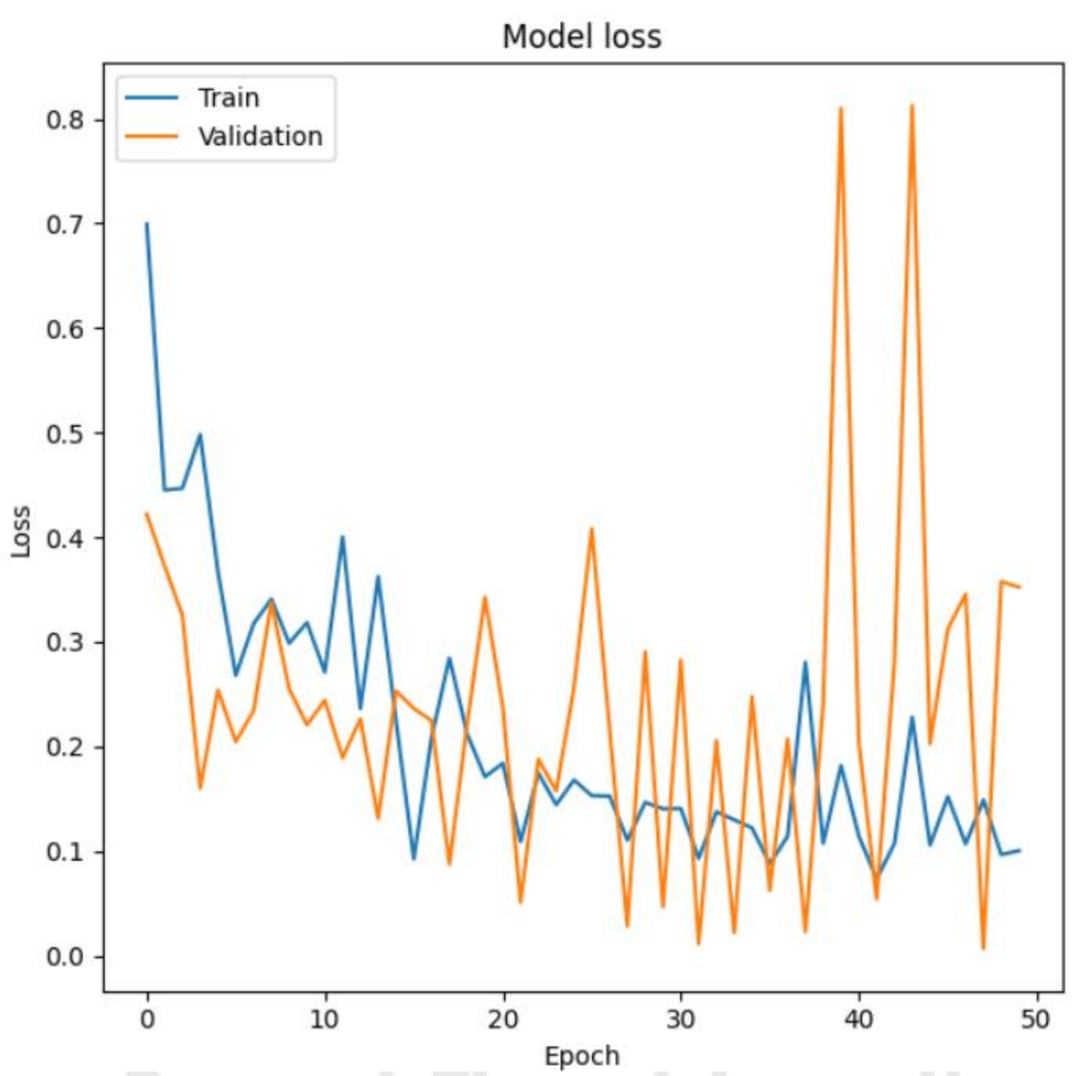
2.Training and Validation Datasets: The model's accuracy was assessed on both the training and validation datasets.

3.Visual Representation: A line graph was used to visually represent the model's accuracy over 50 epochs.

4.Training Data Accuracy: The model's accuracy improved as it learned from the training data, indicating effective learning.

5.Validation Data Accuracy: The model's accuracy on the validation dataset also showed a general upward trend, suggesting good generalization to unseen data.

Model loss



1.Evaluation Metric: The model's loss during the training and validation phases was another critical metric used to evaluate its performance.

2.Visual Representation: A line graph was used to depict the model's loss over 50 epochs.

3.Training Data Loss: The training loss showed a general downward trend, indicating that the model was learning effectively from the training data.

4.Validation Data Loss: The validation loss also decreased over time, suggesting that the model was generalizing well to new data.

Conclusion and Future Scope

our study on AI-based TB and pneumonia detection involves the accurate categorization of X-ray images into three classes: TB, pneumonia, and normal, along with their respective probabilities. Our focus lies on enabling timely diagnosis, which is critical for effective treatment, particularly in local and underserved areas where healthcare resources are scarce. Moving forward, the future scope of our study could entail leveraging large language models (LLMs) like GPT-3.5 to enhance accuracy and efficiency, enabling deeper analysis of clinical data, and potentially expanding the application to other medical imaging modalities for comprehensive diagnostic support.

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