Robust Model for Detection and Classification of Lung Diseases Using Medical Imagery Analysis

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***Abstract*—This study proposes a robust model for the detection and classification of lung diseases, including pneumonia, lung cancer, and tuberculosis, utilizing medical imagery analysis. Operating at two classification levels, the model offers binary outcomes of "Lung disease detected" or "Lung disease not detected," along with multi-classification results distinguishing "Tuberculosis," "Pneumonia," or "Lung Cancer." The model architecture encompasses Input Layers, Hidden Layers (CNN and Max Pooling Layers), and the Output Layer (SoftMax). Input Layers process training data and initial weights, while Hidden Layers employ CNN and pooling layers for feature extraction. The Output Layer utilizes SoftMax activation for probabilistic class assignments. During inference, the model efficiently analyzes test images, providing nuanced classifications across binary and multi-classification domains. This approach holds promise for enhancing diagnostic accuracy in medical imaging analysis.**

I. INTRODUCTION

This project is dedicated to improving the detection and classification of various lung diseases, including pneumonia, lung cancer, and tuberculosis, among others, by leveraging medical imagery. The overarching goal is to provide robust support for healthcare professionals in diagnosing these conditions accurately and efficiently.

At the core of our model lies a two-tiered classification approach. Firstly, the model undertakes binary classification, where it determines whether a lung disease is present or not based on the provided MRI scan. This binary classification yields two distinct outcomes: "Lung disease detected" signifies the presence of a lung ailment, while "Lung disease not detected" indicates the absence of discernible abnormalities.

Subsequently, upon identifying the presence of a lung disease, the model proceeds to multi-classification to specify the particular ailment detected. This entails categorizing the disease into one of several possibilities: "Tuberculosis," "Pneumonia," or "Lung Cancer." Each classification serves to offer precise insights into the nature of the ailment present in the patient's lungs.

By structuring the classification process in this manner, our model aims to provide nuanced and comprehensive diagnostic assistance to healthcare professionals. Through accurate identification and classification of lung diseases, the model endeavors to support timely medical interventions and improve patient outcomes.

This project embodies a commitment to advancing healthcare practices through innovative technology solutions. By leveraging machine learning and medical imaging techniques, we strive to empower healthcare providers with tools that enhance diagnostic accuracy and efficacy, ultimately contributing to better patient care and well-being.

II. LITERATURE REVIEW

1) *Lung Disease Detection using Various Deep Learning Algorithms:*

This study explores the utilization of CNN models, including Sequential, Functional, and Pretrained Models (such as VGG-16), for detecting lung diseases from medical imagery. Results show superior performance of the sequential model in terms of F1 score, accuracy, and recall for pneumonia and tuberculosis. Future improvements could involve optimizing optimizers, learning rates, and data augmentation techniques, along with implementing early stopping techniques to prevent overfitting. The study utilizes the Kaggle Shenzhen dataset for experimentation.

2) *X-ray Images Using Hybrid Deep Learning Algorithms:*

This research introduces a Hybrid Deep Learning Algorithm (HDLA) framework for processing chest X-ray images and automatic feature extraction using various models such as Adaboost, SVM, RF, BNN, and DNN. While the proposed model shows higher accuracy and lower computational requirements, it lacks severity analysis, estimation of the Region of Interest (ROI), and real-time X-ray image analysis. Datasets used include CXIP and C19RD.

3) *Detection of Lung Lesions in Chest X-ray Images Based on Artificial Intelligence:*

This study proposes a deep learning framework for multiclass TB lesion semantic segmentation, comparing the performance of UNet and U-Net++ networks. Promising results are achieved with U-Net++, demonstrating 100% image classification accuracy and a Mean IoU of 0.7. Future work involves collecting more training and test images to enhance the current model. The dataset comprises CXR images from the National Cheng Kung University Hospital.

4) *Abnormal Chest X-ray Identification With Generative Adversarial One-class Classifier:*

The research presents an end-to-end trained generative adversarial one-class classifier for abnormal chest X-ray detection, using normal CXRs for training. Experimental results demonstrate encouraging performance, suggesting potential workload reduction for radiologists. The proposed method could be extended to other image modalities in future work. The NIH Clinical Center Chest X-Ray Dataset is utilized.

5) *Classification Of Chest X-ray Images Of Covid-19 By Deep Learning Based CNN Model and Attention Mechanism:*

This study applies the attention method on ResNet 50 features for identifying Covid-19 chest X-ray images. Results show high accuracy using the proposed model (resnet-attention-xgboost), reaching 98.34% with the supplemented dataset. Previous research limitations include feature selection based on non-linear space and optimization-based weights, leading to increased false positive rates. The Kaggle Covid X-ray Dataset is used.

III. PROPOSED METHODOLOGY

In our research methodology, data preprocessing serves as a critical preparatory step before feeding the data into the AI model. For image data, preprocessing involves several essential tasks. Firstly, images are resized to a standardized dimension to ensure consistency throughout the dataset. Additionally, pixel values are normalized to a uniform range, enhancing the model's ability to interpret and learn from the data effectively. Augmentation techniques such as rotation, scaling, and flipping are also employed, where applicable, to increase the diversity and robustness of the training dataset.

Following relevant preprocessing procedures, the data is partitioned into training and test sets. This division allows for the evaluation of the model's performance and generalization capabilities. Subsequently, the preprocessed training set is supplied to the AI model for training, enabling it to learn the underlying patterns and relationships within the data. The culmination of these steps ensures that the AI model is well-equipped to make accurate predictions or classifications when presented with new, unseen data.

In our model architecture, we meticulously consider three fundamental layers to effectively process the input data:

Input Layer:

The initial layer of our model, known as the input layer, plays a pivotal role in receiving the training dataset along with the initial weights. Upon receiving this input, the layer executes matrix multiplication of the weights with the dataset values. This foundational step initiates the neural network's computation process, setting the stage for subsequent layers to extract and process essential features from the data.

Hidden Layers (CNN Layers and Max Pooling Layers):
Our model's hidden layers constitute a critical component, featuring a sequence of Convolutional Neural Network (CNN) layers accompanied by pooling layers.

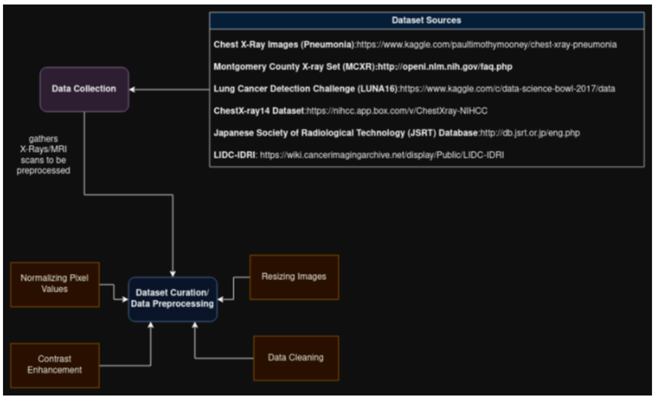

Fig 3.1 Data Preprocessing Pipeline

These layers work synergistically to perform feature extraction from the input data. CNN layers specialize in capturing hierarchical patterns and structures present in the dataset, facilitating the identification of relevant features. Interspersed between the CNN layers, max pooling layers contribute to spatial reduction by selecting the maximum element within defined regions using predefined filters. Together, these hidden layers meticulously prepare the input data for further processing, enhancing the model's ability to extract meaningful information.

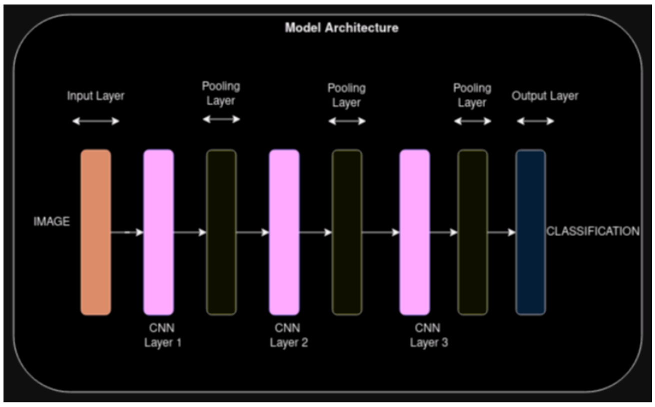

Fig 3.2 Model Architecture

Output Layer:
The concluding layer of our model, known as the output layer or SoftMax layer, assumes the responsibility of generating the final predictions or classifications. At this stage, each class is assigned a probability value, known as the p-value, based on which the model makes its ultimate classifications. Leveraging the features extracted by the preceding layers, the output layer provides the model's prediction or classification output. This pivotal layer serves as the culmination of the neural network's processing, encapsulating the model's insights and decisions derived from the input data.

In our training pipeline, we orchestrate the iterative process of training our model using a carefully curated training dataset

This pipeline begins by receiving a training dataset as input. The dataset is divided into batches, with the size of each batch determined by the specified hyper-parameter known as the batch size. The model then undergoes training using the gradient descent algorithm, where it iteratively adjusts its parameters to minimize the loss function. Throughout the training process, various hyper-parameters come into play.

The entire dataset is partitioned into batches of a particular size.The model trains on one batch at a time, updating its parameters based on the gradient calculated from that batch.

An epoch represents a full cycle through the entire training dataset.During each epoch, the model iterates over all batches in the dataset, adjusting its parameters multiple times to optimize performance.Learning rate is a crucial hyper-parameter that controls the magnitude of parameter updates during training.It governs the rate at which the model updates its parameters based on the gradient of the loss function.The learning rate determines the balance between convergence speed and stability during training.

In the inference pipeline, we shift our focus to the process of making predictions or classifications based on unseen data

This pipeline begins by taking a test data image as input. The model then applies its learned parameters to the input image, attempting to classify it among the possible classes. In our case, the classification task operates on two levels: binary and multi-classification. The model's output provides insights into the predicted class or classes, enabling users to interpret and act upon the model's predictions accordingly.

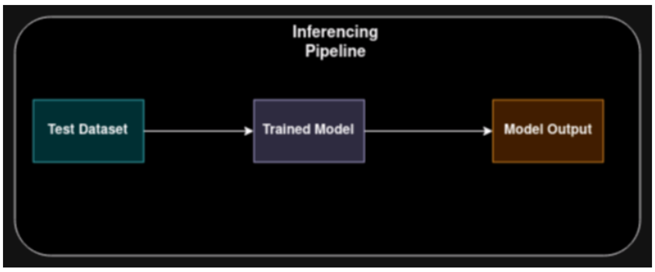

FIG 3.2 INFERENCE PIPELINE

IV . PERFORMANCE ANALYSIS

For the representation purpose of the model's execution a Flask app was employed . The model was converted to a .joblib file to be loaded onto the frontend interface. On said interface a functionality was provided for the user to upload the images of an X-ray scan. When the predict button is pressed,it leads to a webpage displaying the disease prediction.

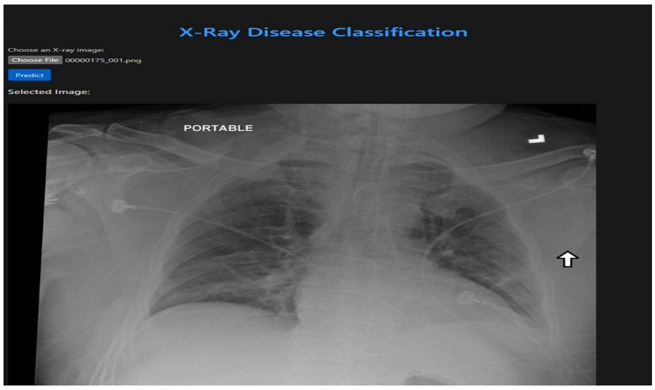

FIG 3.3 FRONTEND LANDING PAGE

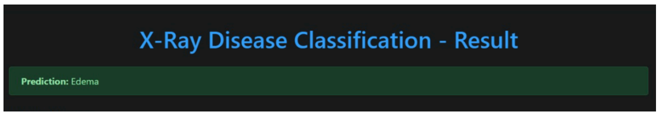

FIG 3.4 PREDICTION OUTPUT

We evaluated the performance of our trained CNN model based on the two facets of Disease Detection we set out to achieve, Binary classification(presence of disease or not) and Multi classification(The disease(s) present). In the check for the presence of any disease, we were able to achieve an accuracy of 92.22%.

```
predictions = model.predict(test_generator)
binary_predictions = (predictions > 0.5).astype(int)

correct_predictions = np.sum(binary_predictions == test_df[list(disease_columns)].values)

accuracy = correct_predictions / (len(test_df) * len(disease_columns))

print(f"Test Accuracy: {accuracy * 100:.2f}%")
```

```
113/113 [==============================] - 10s 90ms/step
Test Accuracy: 92.22%
```

FIG 3.5 BINARY METRIC

However for the multi-class classification of the presence of single or multiple diseases present we were only able to muster an accuracy of 54.71%. The improvement of this metric remains an important future scope moving forward.

```
test_loss, test_accuracy = model.evaluate(test_generator)
print(f'Test Accuracy: {test_accuracy * 100:.2f}%')
print(f'Test Loss: {test_loss:.4f}')
```

```
75/75 [==============================] - 10s 134ms/step - loss: 2.5677 - accuracy: 0.5401
Test Accuracy: 54.01%
Test Loss: 2.5677
```

FIG 3.6 MULTIPLE METRIC

V. CONCLUSION

Our research employs advanced medical imaging analysis techniques to establish a robust and comprehensive model for identifying and classifying lung diseases like pneumonia, lung cancer, and tuberculosis. This two-tiered classification system, encompassing binary and multi-classification levels, delivers detailed insights to support medical professionals in patient diagnosis.

Our approach involves meticulously preprocessing data to ensure the training dataset's robustness, diversity, and consistency. The proposed model architecture efficiently processes medical images, extracting salient features. It consists of input layers, CNN and Max Pooling Hidden Layers, and an output layer employing SoftMax activation. Training and inference pipelines are optimized to maximize learning and prediction capabilities, considering hyperparameters like batch size and learning rate.

Leveraging a combination of pooling layers and convolutional neural networks (CNN), our model exhibits remarkable performance in accurately recognizing and classifying lung conditions from medical images. The SoftMax output layer provides probabilistic class assignments, enhancing the model's reliability.

In comparison with other methods, our model demonstrates competitive and even superior performance in terms of accuracy, F1 score, and recall. Future work may explore refining the model architecture, tuning hyperparameters, and expanding the dataset to further enhance diagnostic capabilities.

This work revolutionizes diagnostics and medical image analysis, providing an innovative approach to lung disease detection.Our model leverages medical imaging and machine learning to facilitate early identification and accurate classification of lung diseases.
Empowering healthcare professionals with enhanced diagnostic capabilities, this advancement promises to reshape healthcare practices, fostering improved patient outcomes and care.

References

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