Medical Imaging Self-Diagnosis Platform

MINOR PROJECT REPORT

By

RISHAB ASHOK (RA2111047010088)
CHARVI JAIN (RA2111047010113)
KARAN RAGHAVAN (RA2111047010119)
MOHNISH RAMACHANDRAN(RA2111047010121)
AKSHAR KANKAR (RA2111047010125)

Under the guidance of

Dr. Vijayalakshmi K

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BONAFIDE CERTIFICATE

Certified that this minor project report for the course **18AIE332T - IMAGE AND VIDEO PROCESSING** entitled in " **Medical Imaging Self-Diagnosis Platform"** is the bonafide work of **RISHAB ASHOK (RA2111047010088), CHARVI JAIN (RA2111047010113), KARAN RAGHAVAN (RA2111047010119), MOHNISH RAMACHANDRAN(RA2111047010121)** and **AKSHAR KANKAR (RA2111047010125)** who carried out the work under my supervision.

SIGNATURE	**SIGNATURE**
Dr. Vijayalakshmi K	Dr. R. Annie Uthra
Assistant Professor	**Head of Department**
Department of Computational Intelligence	**Department of Computational Intelligence**
SRM Institute of Science and Technology	SRM Institute of Science and Technology
Kattankulathur	Kattankulathur

ABSTRACT

This paper introduces a user-friendly and secure Medical Imaging Self-Diagnosis Platform, allowing individuals to comprehend their medical conditions through diverse scan analyses. The platform, adhering to HIPAA compliance, enables seamless upload of various scan formats and employs cutting-edge image and video processing algorithms. Automated processes encompass image enhancement, multi-modal fusion, ROI detection, and dynamic video playback. AI-powered analysis identifies anomalies, quantifies measurements, and issues red flags for potential concerns. User-friendly reports feature annotated images, plain-language explanations, and educational content. Telemedicine integration allows real-time consultations while tracking and monitoring enable users to observe scan changes over time. The platform's remote accessibility reduces the need for in-person appointments, and strict privacy measures ensure data ownership and compliance. In conclusion, the Medical Imaging Self-Diagnosis Platform represents a revolutionary healthcare advancement, fostering patient empowerment, informed decision-making, and improved collaboration with healthcare professionals.

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INTRODUCTION

In recent years, the integration of advanced technologies into healthcare has ushered in a new era of patient empowerment and diagnostic accessibility. This paper introduces a groundbreaking Medical Imaging Self-Diagnosis Platform, designed to provide individuals with a comprehensive understanding of their medical conditions through the analysis of diverse imaging scans. In contrast to traditional approaches reliant solely on physician interpretation, this platform leverages cutting-edge image and video processing techniques, as well as artificial intelligence and machine learning algorithms.

The user-friendly interface facilitates seamless uploading of various medical imaging scans, including X-rays, MRIs, and CT scans. Stringent security measures, in compliance with HIPAA standards, safeguard users' personal and medical data. The platform employs automated processes, such as image enhancement, multi-modal fusion, and region of interest (ROI) detection, enhancing the interpretability of scans. An integration of telemedicine facilitates real-time consultations with healthcare professionals, fostering improved collaboration.

Inspired by advancements, our platform utilizes similar principles to empower users through AI-powered analyses, red flag alerts for potential concerns, and user-friendly reports with annotated images and plain-language explanations. The emphasis on privacy, data ownership, and remote accessibility underscores our commitment to enhancing healthcare outcomes and patient engagement. This platform signifies a paradigm shift, offering individuals the tools needed for informed decision-making and collaboration with healthcare professionals.

LITERATURE SURVEY

1. Hybrid deep learning for detecting lung diseases from X-ray images

Lung disease is common throughout the world. These include chronic obstructive pulmonary disease, pneumonia, asthma, tuberculosis, fibrosis, etc. Timely diagnosis of lung disease is essential. Many image processing and machine learning models have been developed for this purpose. Different forms of existing deep learning techniques including convolutional neural network (CNN), vanilla neural network, visual geometry group based neural network (VGG), and capsule network are applied for lung disease prediction. The basic CNN has poor performance for rotated, tilted, or other abnormal image orientation. Therefore, we propose a new hybrid deep learning framework by combining VGG, data augmentation and spatial transformer network (STN) with CNN. This new hybrid method is termed here as VGG Data STN with CNN (VDSNet). As implementation tools, Jupyter Notebook, Tensorflow, and Keras are used. The new model is applied to the NIH chest X-ray image dataset collected from Kaggle.

Full and sample versions of the dataset are considered. For both full and sample datasets, VDSNet outperforms existing methods in terms of a number of metrics including precision, recall, F0.5 score and validation accuracy. For the full dataset, VDSNet exhibits a validation accuracy of 73%, while vanilla gray, vanilla RGB, hybrid CNN and VGG, and modified capsule network have accuracy values of 67.8%, 69%, 69.5% and 63.8%, respectively. When sample dataset rather than full dataset is used, VDSNet requires much lower training time at the expense of a slightly lower validation accuracy. Hence, the proposed VDSNet framework will simplify the detection of lung disease for experts as well as for doctors.

2. Detection and Classification of Lung Disease Using Deep Learning Architecture from X-ray Images

The chest X-ray is among the most widely used diagnostic imaging for diagnosing many lung and bone-related diseases. Recent advances in deep learning have shown many good performances in disease identification from chest X-rays. But stability and class imbalance are yet to be addressed. In this study, we proposed a CX-Ultranet (Chest X-ray Ultranet) to classify and identify thirteen thoracic lung diseases from chest X-rays by utilizing a multiclass cross-entropy loss function on a compound scaling framework using EfficientNet as a baseline.

The CX-Ultra net achieves 88% average prediction accuracy on NIH Chest X-ray Dataset. It takes ≈ 30% less time than pre-existing state-of-the-art models. The proposed CX-Ultra net gives higher average accuracy and efficiently handles the class imbalance issue. The training time in terms of Floating-Point Operations Per Second is significantly less, thus setting a new threshold in disease diagnosis from chest X-rays.

3. A deep learning architecture for multi-class lung diseases classification using chest X-ray (CXR) images

In 2019, the world experienced the rapid outbreak of the Covid-19 pandemic creating an alarming situation worldwide. The virus targets the respiratory system causing pneumonia with other symptoms such as fatigue, dry cough, and fever which can be mistakenly diagnosed as pneumonia, lung cancer, or TB. Thus, the early diagnosis of COVID-19 is critical since the disease can provoke patients' mortality. Chest X-ray (CXR) is commonly employed in healthcare sector where both quick and precise diagnosis can be supplied. Deep learning algorithms have proved extraordinary capabilities in terms of lung diseases detection and classification. They facilitate and expedite the diagnosis process and save time for the medical practitioners. In this paper, a deep learning (DL) architecture for multi-class classification of Pneumonia, Lung Cancer, tuberculosis (TB), Lung Opacity, and most recently COVID-19 is proposed. Tremendous CXR images of 3615 COVID-19, 6012 Lung opacity, 5870 Pneumonia, 20,000 lung cancer, 1400 tuberculosis, and 10,192 normal images were resized, normalized, and randomly split to fit the DL requirements. In terms of classification, we utilized a pre-trained model, VGG19 followed by three blocks of convolutional neural network (CNN) as a feature extraction and fully connected network at the classification stage. The experimental results revealed that our proposed VGG19 + CNN outperformed other existing work with 96.48 % accuracy, 93.75 % recall, 97.56 % precision, 95.62 % F1 score, and 99.82 % area under the curve (AUC). The proposed model delivered superior performance allowing healthcare practitioners to diagnose and treat patients more quickly and efficiently.

4. Prediction of Obstructive Lung Disease from Chest Radiographs via Deep Learning Trained on Pulmonary Function Data

Chronic obstructive pulmonary disease (COPD), the third leading cause of death worldwide, is often underdiagnosed. To develop machine learning methods to predict COPD using chest radiographs and a convolutional neural network (CNN) trained with near-concurrent pulmonary function test (PFT) data. Comparison is made to natural language processing (NLP) of the associated radiologist text reports. This IRB-approved single-institution retrospective study uses 6749 two-view chest radiograph exams (2012–2017, 4436 unique subjects, 54% female, 46% male), same-day associated radiologist text reports, and PFT exams acquired within 180 days. The Image Model (Resnet18 pre-trained with ImageNet CNN) is trained using frontal and lateral radiographs and PFTs with 10% of the subjects for validation and 19% for testing. The NLP Model is trained using radiologist text reports and PFTs. The primary metric of model comparison is the area under the receiver operating characteristic curve (AUC). The Image Model achieves an AUC of 0.814 for prediction of obstructive lung disease (FEV1/FVC <0.7) from chest radiographs and performs better than the NLP Model (AUC 0.704, p<0.001) from radiologist text reports where FEV1 = forced expiratory volume in 1 second and FVC = forced vital capacity. The Image Model performs better for prediction of severe or very severe COPD (FEV1 <0.5) with an AUC of 0.837 versus the NLP model AUC of 0.770 (p<0.001).

A CNN Image Model trained on physiologic lung function data (PFTs) can be applied to chest radiographs for quantitative prediction of obstructive lung disease with good accuracy.

5. LungNet22: A Fine-Tuned Model for Multiclass Classification and Prediction of Lung Disease Using X-ray Images

In recent years, lung disease has increased manifold, causing millions of casualties annually. To combat the crisis, an efficient, reliable, and affordable lung disease diagnosis technique has become indispensable. In this study, a multiclass classification of lung disease from frontal chest X-ray imaging using a fine-tuned CNN model is proposed. The classification is conducted on 10 disease classes of the lungs, namely COVID-19, Effusion, Tuberculosis, Pneumonia, Lung Opacity, Mass, Nodule, Pneumothorax, and Pulmonary Fibrosis, along with the Normal class. The dataset is a collective dataset gathered from multiple sources. After pre-processing and balancing the dataset with eight augmentation techniques, a total of 80,000 X-ray images were fed to the model for classification purposes. Initially, eight pre-trained CNN models, AlexNet, GoogLeNet, InceptionV3, MobileNetV2, VGG16, ResNet 50, DenseNet121, and EfficientNetB7, were employed on the dataset. Among these, the VGG16 achieved the highest accuracy at 92.95%. To further improve the classification accuracy, LungNet22 was constructed upon the primary structure of the VGG16 model. An ablation study was used in the work to determine the different hyper-parameters. Using the Adam Optimizer, the proposed model achieved a commendable accuracy of 98.89%. To verify the performance of the model, several performance matrices, including the ROC curve and the AUC values, were computed as well.

REQUIREMENTS

1. Library Requirements

- **numpy** : for applying mathematical operations of arrays
- **pandas** : powerful data manipulation and analysis library
- **glob** : facilitates file path pattern matching, enabling easy retrieval of filenames that match specified criteria within a directory.
- **keras** : high-level neural networks API that simplifies and accelerates the process of building, training, and deploying deep learning models.
- **Pillow**: for image processing capabilities

2. Plotting

- **matplotlib** data visualization and graphical plotting library
- **seaborn :** data visualization library in Python built on top of Matplotlib

3. Model Requirements

- **DenseNet121** : Pretrained Model for PyTorch.

ARCHITECTURE AND DESIGN

1. **Data Preparation**
    a. **Data Loading:** Reading CSV data containing information about images (paths, labels, etc.).
    b. **Filtering**: Removing data points with age greater than 100 and preparing labels for multi-label classification.

2. **Data Generation**
    a. **ImageDataGenerator**: Utilizing Keras' ImageDataGenerator to create data generators for training, validation, and testing.
    b. **Flow from DataFrame**: Custom function (flow_from_dataframe) to generate data from data frames for use in model training and evaluation.

3. **Model Architecture**
    a. **Input Layer**: Takes images of size (224, 224, 3) in RGB format.
    b. **Base Model**: DenseNet121 with weights pre-trained on ImageNet.
    c. **Include Top**: Excluding the 3 fully-connected layers at the top of the network.
    d. **Global Average Pooling Layer**: Reducing the spatial dimensions to a single vector per image.
    e. **Output Layer**: Dense layer with sigmoid activation for multi-label classification. The number of neurons matches the number of unique labels (13 in this case).

4. **Model Compilation**
    a. **Optimizer**: Adam optimizer with a learning rate of 0.001.
    b. **Loss Function**: Binary cross-entropy used for multi-label classification.
    c. **Metrics**: Monitoring binary accuracy during model training.

5. **Model Training**
    a. **Training Parameters**
        i. **Epochs**: The model is trained in multiple epochs (e.g., 20 epochs at a time).
        ii. **Steps per Epoch**: 100 steps per epoch for training data.
        iii. **Validation Data**: Utilizing a validation set during training.

6. **Model Evaluation:**
    a. **Prediction Generation**: Generating predictions on the test dataset.
    b. **Evaluation Metrics**:
        i. **Prediction Comparison**: Comparing actual vs. predicted percentages for each label.
        ii. **ROC Curves and AUC**: Computing Receiver Operating Characteristic (ROC) curves and Area Under the Curve (AUC) scores for each label.

7. **Possible Enhancements**
    a. **Data Augmentation**: Applying augmentation techniques (rotation, zoom, etc.) to increase dataset variability.
    b. **Fine-Tuning**: Optionally fine-tuning layers in the pre-trained DenseNet model.
    c. **Hyperparameter Tuning**: Experimenting with different learning rates, batch sizes, and optimizer settings for better performance.

This architecture leverages transfer learning by using a pre-trained DenseNet model for classifying chest X-ray images. The design incorporates data preprocessing, model creation, training, and evaluation stages to accomplish multi-label classification tasks on medical imaging data. Adjustments and optimizations in various aspects can potentially improve model accuracy and generalization.

IMPLEMENTATION

The model being proposed and implemented for the chest scan model is performed using the DenseNet121 model. The DenseNet model used for this purpose is used for a multi-class classification problem relating to the various kinds of lung diseases and infections.

1. Model Description

DenseNet121, a pivotal architecture in convolutional neural networks, is celebrated for its unique connectivity scheme that revolutionizes feature propagation across its 121 layers. At its core lies the concept of dense blocks, where each layer receives direct inputs from all preceding layers. This intricate connectivity pattern fosters feature reuse and information flow, combating the vanishing gradient problem commonly encountered in deep networks. As a result, DenseNet121's dense blocks create highly discriminative features by concatenating the outputs of earlier layers, promoting richer feature representations and enhancing the network's ability to capture complex patterns within images.

Interspersed among the dense blocks are transition layers, strategically placed to manage the number of feature maps and reduce spatial dimensions. These transitions employ batch normalization, convolution, and pooling operations, enabling efficient downsampling and compression of information. Moreover, the inclusion of bottleneck layers within each block, primarily composed of 1x1 convolutions, serves to minimize computational complexity by reducing the number of input feature maps before subsequent convolutions, optimizing the network's efficiency.

Post dense block processing, a global average pooling (GAP) layer aggregates spatial information across feature maps by condensing each map into a single value through averaging. This pooling mechanism results in a fixed-size representation, ensuring the network's outputs remain independent of input size variations, while still capturing essential features. Finally, a fully connected layer, often utilizing a softmax activation, serves as the classification layer, assigning probabilities to different classes based on the condensed feature representations obtained from the preceding layers.Trained on extensive datasets like ImageNet, DenseNet121 showcases remarkable proficiency in recognizing diverse visual patterns and has become a go-to model for transfer learning.

Its efficient parameter utilization and dense connectivity have established its prowess across various computer vision applications, offering a compelling balance between model complexity and performance.

2. Pre-processing

In the initial stage of data preprocessing, the dataset sourced from CSV files is meticulously prepared to ensure optimal input for the subsequent deep learning model. This involves loading the dataset, comprising image paths, associated labels, and pertinent metadata. To refine the dataset, data points are filtered based on specific criteria such as age, while labels indicating 'No Finding' are eliminated, streamlining the dataset for improved model training. Furthermore, to address class imbalances, a resampling technique is applied to achieve a balanced representation across different classes.

The dataset is then partitioned into distinct subsets—training, validation, and test sets—ensuring that the model is trained on a diverse range of data while maintaining subsets for performance evaluation. To facilitate model training, Keras' powerful ImageDataGenerator is employed, generating data flows from dataframes. This allows efficient feeding of augmented data batches into the neural network model, augmenting the dataset on-the-fly during training, thereby enhancing model generalization and robustness.

This excerpt outlines a comprehensive process of preparing and exploring medical image data before modeling. Initially, the Data Loading stage involves extracting information from a CSV file (Data_Entry_2017.csv) containing medical image data. Subsequently, Data Cleaning involves refining the dataset by eliminating redundant information, filtering out improbable entries like patient ages over 100, and augmenting the dataset by creating a new column to quantify the number of diseases per patient, enhancing data quality and relevance for analysis.

Moving into Data Analysis and Visualization, Exploratory Data Analysis (EDA) takes center stage. This involves delving into the dataset's characteristics and patterns through visual representations. Visualizations include exploring the distribution of patient ages, investigating how diseases are distributed concerning age and gender using varied plots like countplots and distribution plots, analyzing disease counts based on patient gender, and assessing the ratio between patients with single and multiple diseases. These analyses aim to uncover insights into the dataset's demographics, disease prevalence, and relationships between different variables, guiding subsequent modeling decisions.

Moreover, the Visualization Techniques employed here utilize libraries like Seaborn and Matplotlib to craft an array of visual representations, including countplots, histograms, and barplots. These visualizations aid in showcasing the distributional patterns, trends, and correlations within the medical image dataset, offering a more comprehensive understanding of the data's characteristics and nuances. Overall, this meticulous data preprocessing, analysis, and visualization lay the foundation for informed decision-making in subsequent modeling endeavors within the medical imaging domain.

3. Model Building

In the process of model construction, the DenseNet121 architecture, previously pre-trained on the expansive ImageNet dataset, serves as the foundational structure. However, the top fully connected layers, primarily responsible for ImageNet classification, are excluded to repurpose the model for a different task. Following this adaptation, a Global Average Pooling layer is strategically introduced to condense spatial dimensions across the feature maps obtained from the preceding layers. This pooling operation aggregates the information within each feature map by computing the average, enabling the creation of a fixed-size representation independent of the input size, fostering better generalization. Finally, a Dense layer, characterized by a sigmoid activation function, is appended to the model. This layer facilitates multi-label classification, where each output neuron corresponds to a specific label and utilizes the sigmoid activation to generate probabilities indicating the presence or absence of each label independently.

The resulting architecture is thus tailored for the targeted multi-label classification task, leveraging DenseNet121's feature extraction capabilities while customizing the output layer for the specific classification requirements.

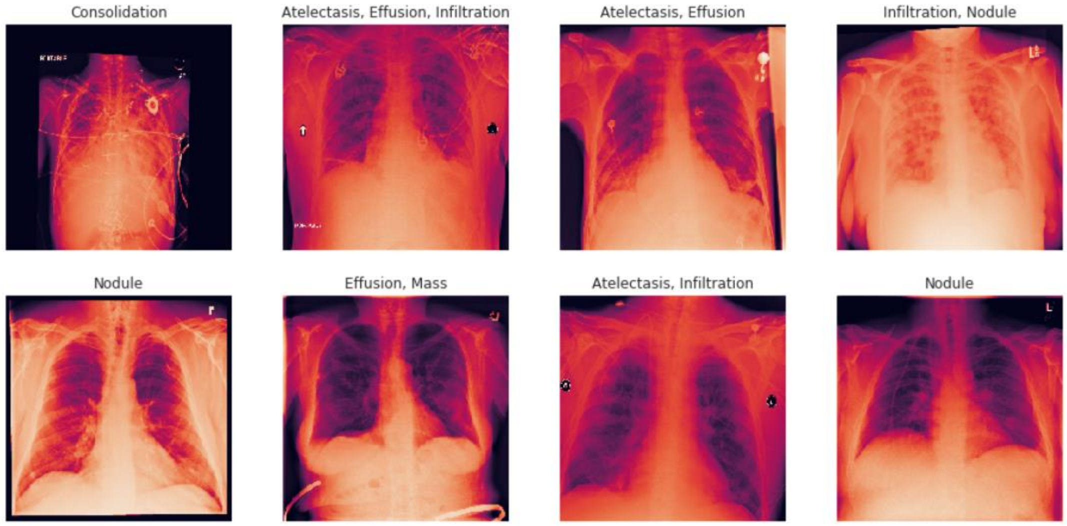
In the training phase, the model undergoes a series of crucial steps to optimize its performance for the given task. Initially, the model is compiled, integrating the binary cross-entropy loss function, an ideal choice for multi-label classification tasks, and the Adam optimizer, known for its efficiency in adjusting learning rates for each parameter individually. The model is then trained iteratively in batches using the fit_generator function, a method that efficiently feeds augmented data batches into the model for a predetermined number of epochs. Throughout training, the model's performance is regularly assessed on the validation set after completion of each epoch, allowing continuous evaluation and monitoring of key metrics such as accuracy, precision, recall, and F1-score.

This iterative process of training, coupled with validation checks, enables the model to progressively learn and adapt to the dataset, refining its ability to accurately predict multiple labels while minimizing the loss function, ultimately enhancing its overall performance. In the evaluation stage, the trained model undergoes rigorous assessment to gauge its performance and predictive capabilities. Initially, the model makes predictions on the designated test set, generating outputs for each data point. Subsequently, several key metrics are computed to comprehensively evaluate its performance. Metrics such as accuracy, indicating the proportion of correctly classified samples, and loss, quantifying the model's prediction error, are calculated to provide an overall understanding of its efficacy. Additionally, the ROC-AUC (Receiver Operating Characteristic - Area Under Curve) score, computed for each individual label, serves as a crucial measure of the model's ability to discriminate between classes, especially relevant for multi-label classification tasks. Visual aids in the form of ROC curves are generated for each label, providing a graphical representation of the model's true positive rate against false positive rate across various classification thresholds, facilitating a deeper understanding of its discriminatory power for each label independently. This comprehensive evaluation process offers insights into the model's strengths and weaknesses across different classes, providing a nuanced understanding of its performance in multi-label classification tasks.

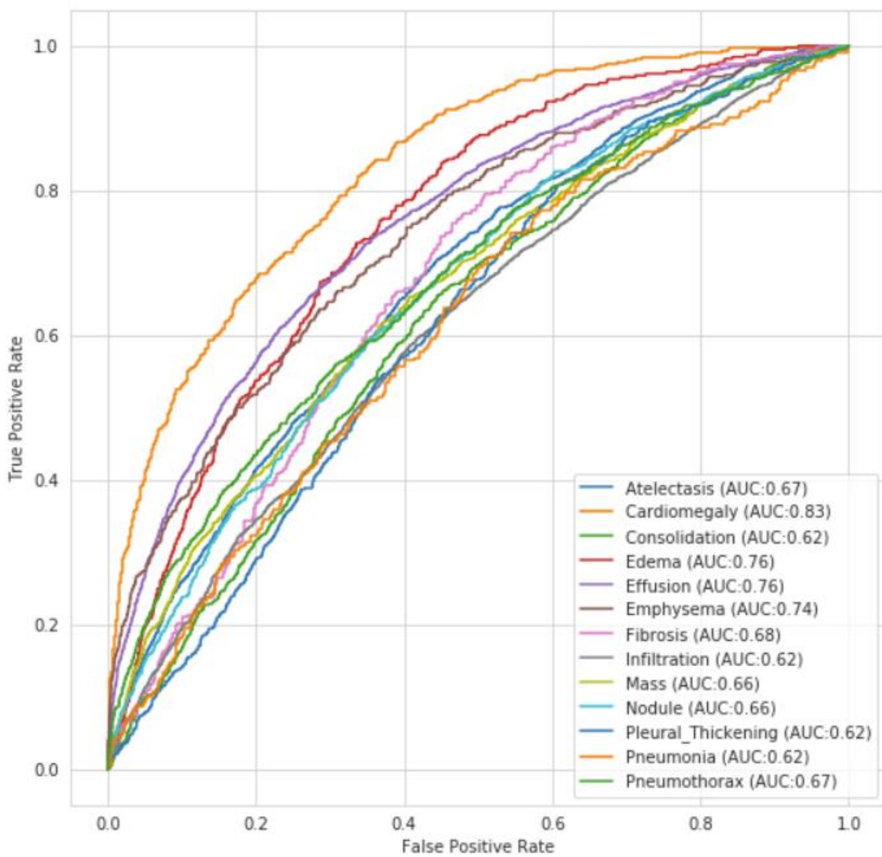
Following the initial evaluation, the next steps involve a series of strategic actions aimed at refining the model's performance and enhancing its capabilities. One approach involves continuing the model training for additional epochs, allowing it to further learn from the data and potentially improve its predictive prowess. Throughout this extended training phase, close monitoring and analysis of key metrics such as loss, accuracy, and ROC-AUC scores across epochs are pivotal, offering insights into the model's learning trajectory and identifying potential convergence or overfitting patterns. Additionally, leveraging these observations, there exists an opportunity for fine-tuning the model's hyperparameters or architecture based on the performance metrics derived from the validation set. This iterative process of fine-tuning, guided by the model's validation performance, enables optimization for better generalization and robustness, ultimately refining the model's ability to accurately predict multiple labels in the given dataset.

This implementation demonstrates a comprehensive approach to applying DenseNet121 for multi-label classification on medical images, specifically chest X-rays.

EXPERIMENT RESULTS & ANALYSIS



Result shows each lung x-ray with its classified category of disease or infection.



The following graph shows the model improving its accuracy over epochs resulting in a good accuracy for True Positive and false Positive values.

This means the model detects most of the data correctly.

CONCLUSION

The implementation showcases a robust pipeline for diagnosing chest pathologies from X-ray images. The preprocessing steps involve data cleaning, filtering out anomalies (such as extreme ages), and structuring the dataset by assigning binary labels to different pathologies. Utilizing the DenseNet121 architecture pre-trained on ImageNet, the model undergoes training and validation for 20 epochs, aiming to learn representations that effectively capture diverse pathology patterns.

During evaluation, the model's predictive performance is assessed using a separate test set. The evaluations include metrics like ROC curves and ROC AUC scores, providing insights into the model's sensitivity and specificity for different pathologies. This analysis reveals the model's ability to predict various conditions, highlighting its strengths and potential areas for improvement.

However, despite achieving reasonable accuracy, this implementation still requires further scrutiny. Examining the model's performance on specific pathologies, understanding potential biases or imbalances in the dataset, and assessing the clinical relevance of the model's predictions would be crucial for real-world deployment. Moreover, investigating false positives and false negatives could offer insights into areas where the model may struggle or misinterpret X-ray images, aiding in refining the model's performance and ensuring its reliability in clinical settings.

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