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# Deep Learning Framework Based on Automated Detection and Classification of Pulmonary Diseases Using ResNet50 and VGG-16 Architectures

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***Abstract:*** Pulmonary diseases refers to the condition affecting lungs andrespiratory system .There are various pulmonary diseases, from the common cold to more serious conditions like asthma, lung cancer, and pneumonia. This project focuses on the developmentand implementation of Cnn for accurate and efficient detection of pulmonary diseases from medical imaging data. Deep learning are VGG16, ResNet to enhance the diagnostic capabilities of existing healthcare systems. The utilization of this techniques offers significant advantagesin automating the detection process, thereby reducing the dependency on manual interpretation.

Through this CNN framework we can detect early and classify Pulmonary diseases,which ultimately contribute to improve the patient outcomes for more effective healthcare delivery. Pulmonary diseases such as Pneumonia and its classes are Class 0 (Bacterial Pnuemonia), Class1 (Lung Cancer), Class2 (Normal),Class3 (Tuberculosis), Class 4(Viral Pneumonia).



***Keywords: Pulmonary Diseases, Deep Learning , VGG-16 and ResNet50 Architectures***

## I. INTRODUCTION

Pulmonary diseases constitute a global health concern, like conditions such as pneumonia, tuberculosis, and various forms of lung cancer affecting millions ofindividuals annually. Timely and accurate diagnosis is paramount for effective intervention and treatment planning. In recent years, the deep learning techniques, particularly Neural Networks (NNs), has revolutionized medical image diagnosis .

NNs excel in extracting intricate patterns and features from complex images, making them a powerful tool for automating the detection of abnormalities in medical imaging data. This project delves into theapplication of well-established NN architectures, including VGG16, ResNet50for development of robust framework for the automated detection and classification of pulmonary diseases. The Cnn architectures in this context addresses several critical challenges in pulmonary disease detection. Traditional methods often rely on manual inspection of radiological images, a time-consuming variability in diagnostic accuracy.By contrast, NNs have demonstrated remarkable proficiency in learning the hierarchical way of representations directly from the pixel-level data, enabling them to discernsubtle patterns indicative of pathology. Moreover, the transfer learning paradigm, a key strategy in this project, leverages pre-trained networks on large-scale image datasets, for the transfer of the learned features to a specific task of pulmonary disease detection and classification.

The expedites model training but also enhances generalization capabilities, particularly in scenarios where labeled medical image datasets may be limited. In addition to enhancing diagnostic accuracy, the proposed framework seeks to streamline clinical workflows by providing rapid and reliableassessments of pulmonary health. The integration of automated detection systems based on NN architectures could significantly alleviate the burden on healthcare professionals, allowing them to focus on treatment planning and patient care. Furthermore, by leveraging a diverse range of NN models, we aim to comprehensively evaluate their performance on various types of pulmonary disorders, ranging from the infectious diseases to malignant tumours.

Through rigorous experimentation and validation on diverse datasets, this research endeavour aspires establishment of a versatile and tool for the early detection and classification of pulmonary diseases, ultimately contributing to improved patient outcomes and more efficient healthcare delivery. Pulmonary disease classification using models, specifically ResNet50 and VGG16, has emerged as a promising approach in medical image analysis.

## II. PROPOSED CNN ARCHITECTURES

### *A. ResNet50 AND VGG-16*

ResNet50(Residual Network):ResNet is known for its use of residual blocks, This architecture helps inmitigating the vanishing the gradient problemand enables the training of very deep networks. The network starts with a convolutional layer and pooling layer, followed by multiple stages for its ownset of residual blocks. The last stage is followed by global average pooling, Flattening and fully connected layer forclassification.

***Overview of using ResNet for image classification:***

***Input Layer:*** Takes input images of a specific size.

***Convolutional Blocks:*** ResNet uses residual blocks with skip connections.

***Global Average Pooling:*** Instead of fully connected layers, ResNet typically ends with Global pooling.

***Early stopping****:* is a form of avoiding overfitting when training with iterative method. Such methods update the learner so as to make it better fit the training data with each iteration.

***Output Layer****:* The final layer with the softmax activation layer for classification.

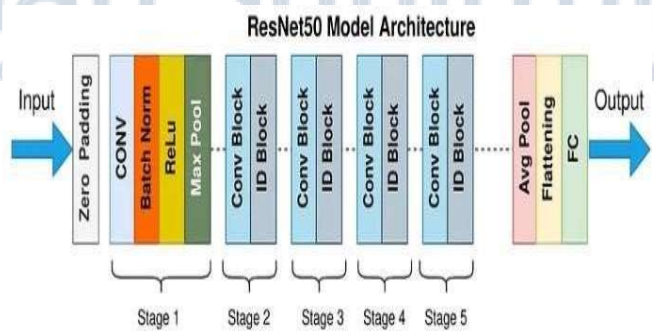


**Fig 1: Architecture of ResNet50**

From fig 1 ResNet-50, as the namesuggests, has 50 layers. The architecture of ResNet- 50 can be several stages,each containing set of the residual blocks. The network starts with a convolutional layer anda pooling layer, followed by multiple stages,with its own set of residual blocks. The last stage is followed global average pooling, Flattening and a fully connected for classification.

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***Input:***
The network can take the input imageheight, width as multiples of 3as channel width. we will consider the input size as 224 x 224 x 3. Every ResNet architecture performs the initial convolution and max-pooling using 7×7 and 3×3 kernel sizes respectively.

***Zero padding:***
It is a technique used in neural networks to add extra pixels around the borders image or a feature map. Padding involves adding rows and columns of zeros to the input data, creating a border of zeros around the existing data. The primary purpose of zero paddingis to preserve spatial information and to avoid the loss of information at the edges .

***Convolutional layer:***
Convolutional layer has Max pooling Residual Stage 1 to 5 (multiple residual blocks) The residual path it consists ofa series of convolutional layers that transform the input. These layers learn to capture the residual information that needs to be added for identity path. The max pooling operation is performed independently on each depth of the input.

***Skip Connections:***
Skip connections, is residual connections, are a fundamental component in the design, particularly in architectures like ResNet (Residual Network). Skipconnections aim to address the challenges associated with training very deep networks by allowingthe gradient to flow more easily through network

***Global Average Pooling:***
After the convolutional layers and pooling layers, the dimensions of the feature maps are reduced. Instead of using traditional fully connected layers, some architecturesopt for global average pooling. Global Average Pooling involves taking the average of the image of the each feature map across its entire spatial dimensions. For each feature map, thisoperation produces a single value, effectively reducing the spatial dimensions to 1x1.The output of global average pooling is a vector with one value of featuremap, and thisvector is then fed directly into the fully connected layer.

***Fully Connected Layer (Output Layer):***
The output of global average pooling or the preceding layers is typically flattened into a 1D vector. This vector is then connected to fully connected layer. In the context of image classification, the number of neurons layer corresponds to the number of classes in classification task. Each neuron in the fully connected layer is connected every element in the flattened vector, and weights are learned during training process. The final layer often architecture, consists of multiple convolutional layers with small 3x3 filtersand max-pooling layers can be used image classification From fig 2 VGG-16 consists of 13

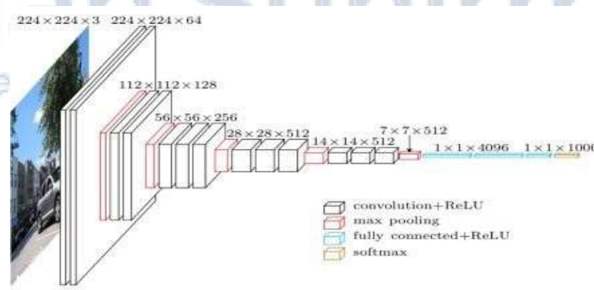


**Fig 2: Architecture of VGG-16**

***Convolutional Layers and the Fully Connected Layersbrief look at architecture of VGG-16:***

***Input Layer:*** Takes input images of fixed size (e.g., 224x224 x3 pixels).

***Convolutional Blocks:*** 13 blocks of convolutional layers with ReLU, each followed by max-pooling.

***Fully Connected Layers:*** After the convolutional blocks, there are one or morefully connectedlayers with ReLU

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***Output Layer***: The final layer softmax activation for classification.

## III. IMPLEMENTATION

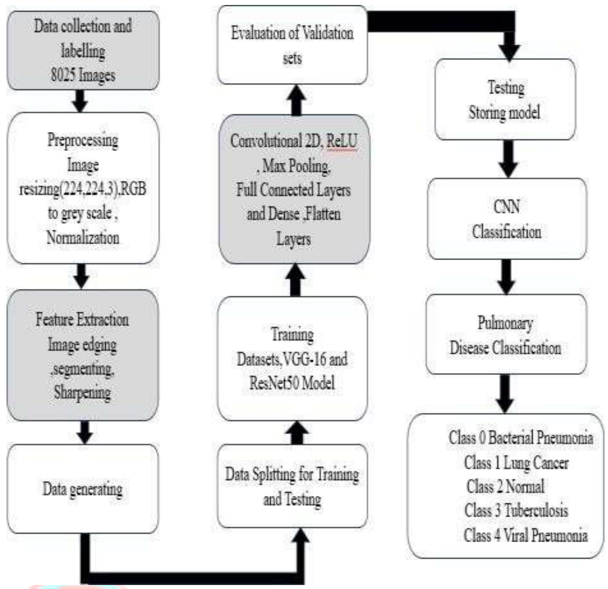


**Fig 3 Flow diagram of Proposed Method**

The Proposed above model collects input data from open source Kaggle.com andthese data is helpful for preprocessing and feature extraction of Segment, Edges and Sharpening for higher resolution then model performs training and testing for model accuracy and image classification and detection of pulmonary detection using VGG- 16 and ResNet50 Architectures. .

## IV. FEATURE EXTRACTION

Extracted edge information can used as features in higher-level analysis tasks such as object recognition, shape analysis, and scene understanding Segments or regions from image segmentation can serve as features for characterizing different regions of interest within an image Sharpening Enhanced images obtained through sharpening techniques provide more detailed and discriminative featuresfor subsequent analysis and classification tasks.

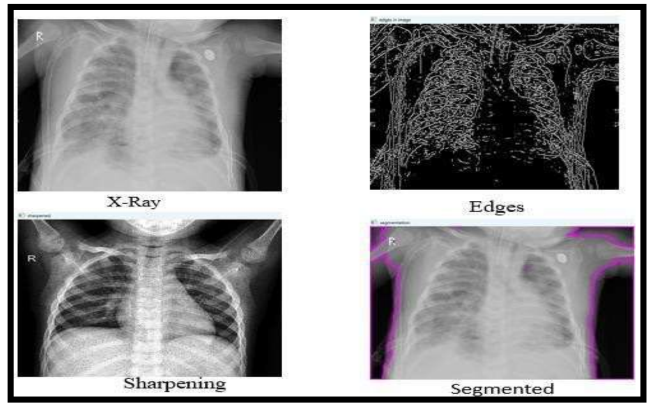


**Fig4 :Feature Extraction of Class0 Bacterial Pneumonia X-ray**

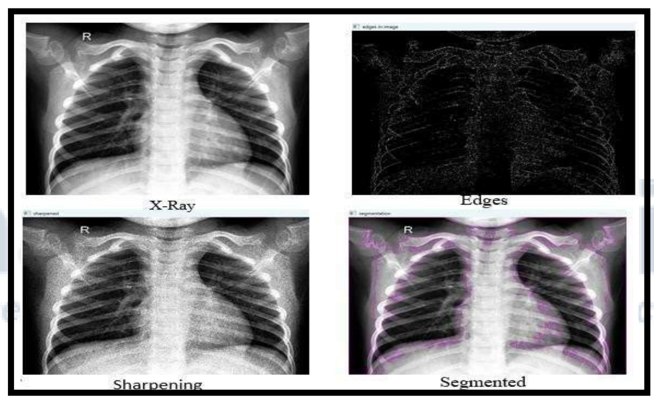


**Fig 5: Feature Extraction of Class1 Lung Cancer Xray**

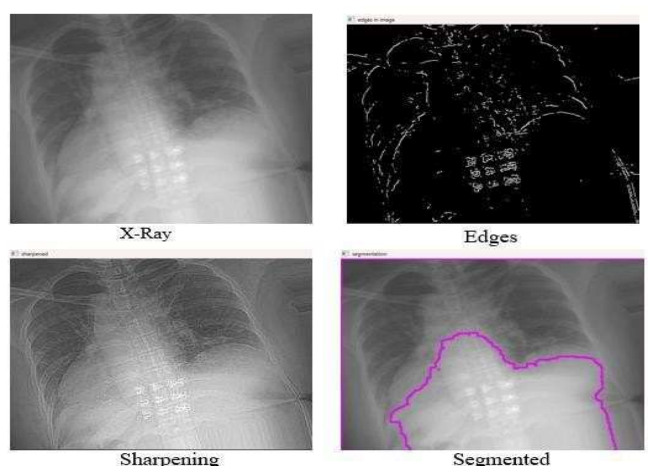


**Fig 6: Feature Extraction of Class2 Normal X-ray**

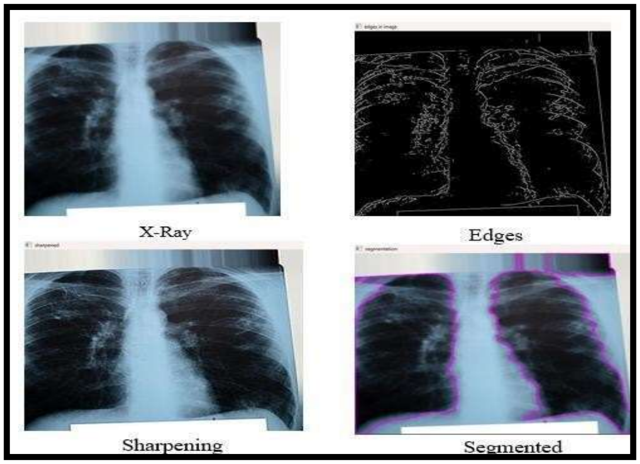


**Fig 7: Feature Extraction of Class 3Tuberculosis Xray**

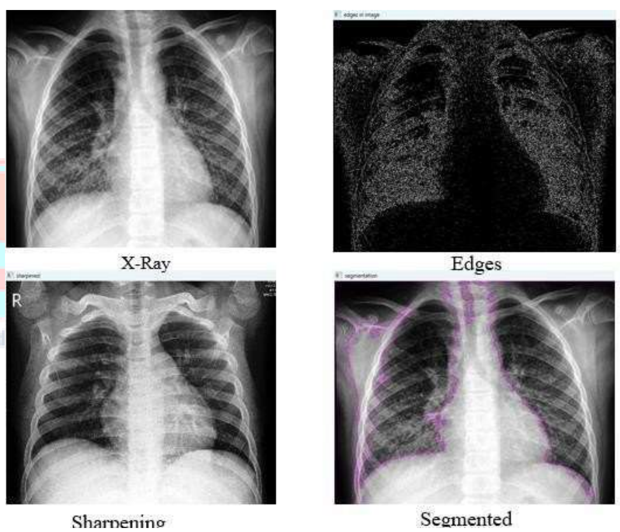


**Fig 8: Feature Extraction of Class4 ViralPneumonia X-ray**

## V. SIMULATED RESULTS OF VGG-16 ANDRESNET50 ARCHITECTURES

***i Training Results for 10 epochs and 20 epochs***

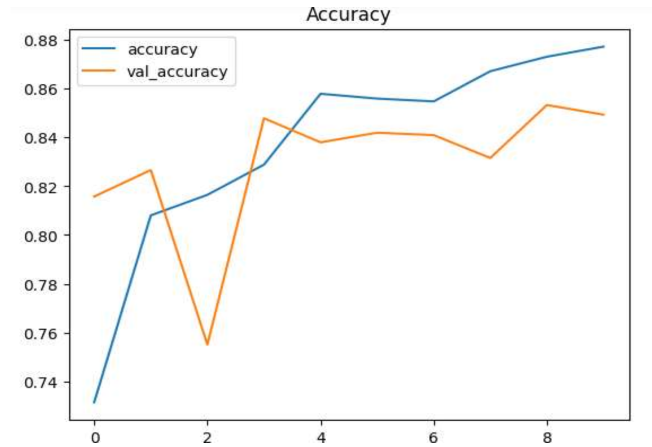


**Fig 9:VGG-16 Model accuracy for 10Epochs**

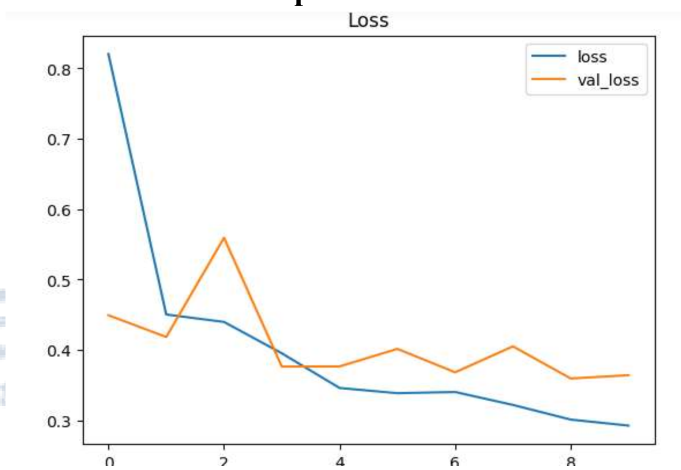


**Fig 10:VGG-16 loss Model for 10Epochs**

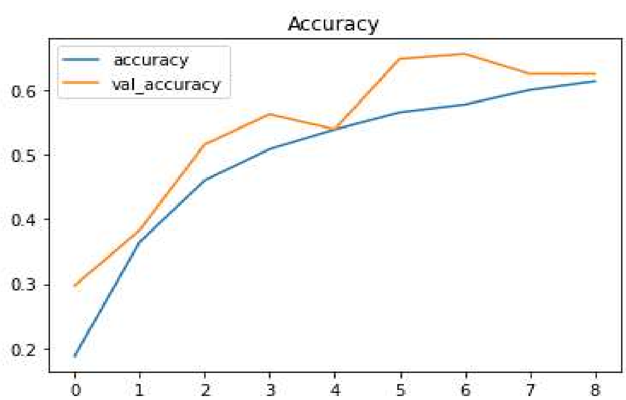


**Fig 11:ResNet50 accuracy Model for 10Epochs**

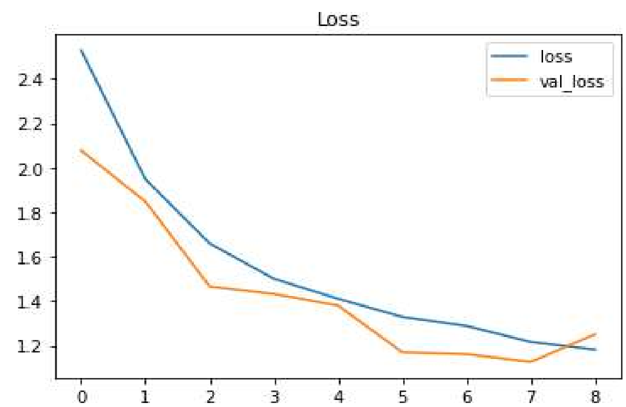


Fig 12:Resnet50 Model loss for 10Epochs

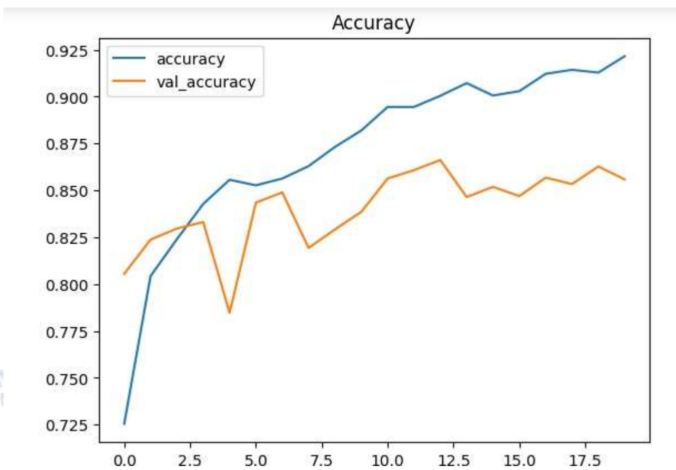


Fig 13:VGG-16 Accuracy Model for 20Epochs

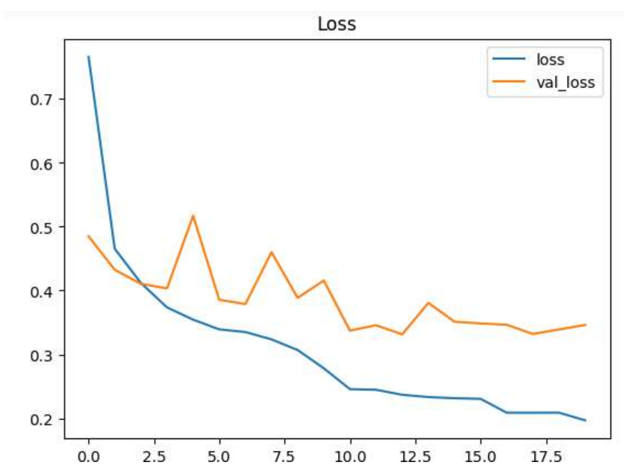


Fig 14: VGG-16 loss Model for 20Epochs

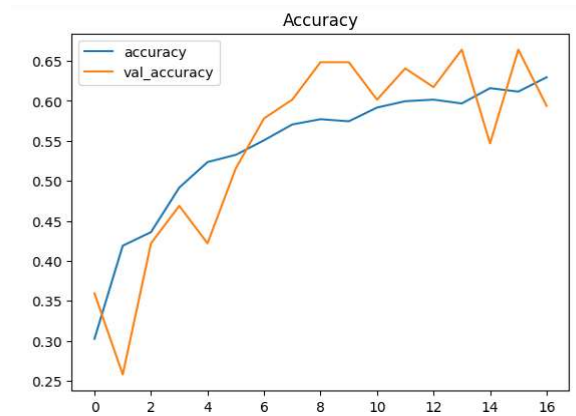


Fig 15 :ResNet50 accuracy Model for 20Epochs

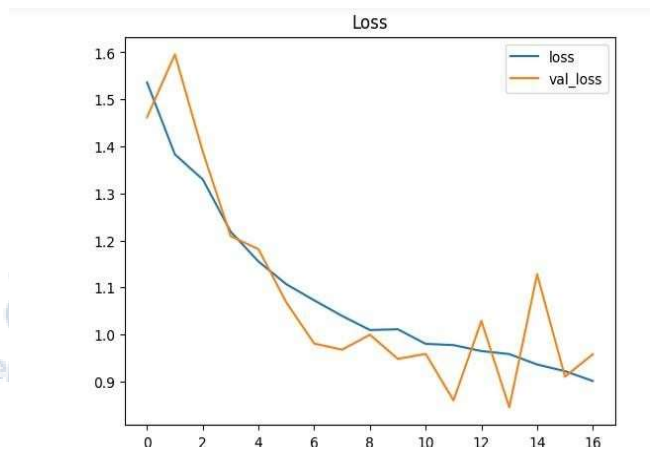


Fig16 :ResNet50 loss Model for 20Epochs

## VI. RESULTS

### *ii Training Results Comparison Tabulation*:

| No of Epochs | VGG-16 Training Performance Results | | | | | Resnet 50 Training Performance Results | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Accuracy | Validation accuracy | Loss | Validation Loss | Lr | Accuracy | Validation accuracy | Loss | Validation Loss |
| 10 | 87.7% | 84.9% | 29.2% | 36.4% | 2.7 | 59% | 58% | 98% | 92% |
| 20 | 92% | 85.5% | 19.6% | 34.6% | 0.001 | 62% | 59% | 90% | 95% |

Fig 17 :Training Results Comparison Tabulation

### *iii F .Testing Classification Percentage*

| Diseases Classification | VGG-16 | ResNet 50 |
|---|---|---|
| 1) Bacterial Pnuemonia | 81.2% | 44.1% |
| 2) Lung Cancer | 98.6% | 74.2% |
| 3) Normal | 98.3% | 93% |
| 4) Tuberculosis | 99.85% | 74.2% |
| 5) Viral Pnuemonia | 96.3% | 36.6% |

**Fig 18 :Testing Classification Percentage Results**

## VII. CONCLUSION

In conclusion Deep Learning Framework's training, testing results show that VGG-16 outperforms ResNet 50 interms accuracy, and the system's automated identification and classification ofpulmonary illnesses has been successfully completed. The project must be completed, which requires gathering input datasets for five classes and a total of 8050 images for 5classes.

The overall train dataset of five classes is6025 photos, and the total test dataset is 2025images. The training dataset consists of 1211images of each class, while test dataset consists of 403 images of each class. The initial preprocessing phase involved giving the data for rescaling from 255 to 1 pixel, resizing all the images to 224,224 with three channels.

Training part gave accuracy of 92.7% inVGG-16 and ResNet50 gave 60% results hence VGG-16 is superior then ResNet50. Testing part VGG-16 gave superior accuracyfor all 5 classes than ResNet 50 architectures.The accuracy for each class obtainedBacterial pneumonia using VGG-16 81.2% and Resnet-50 44.1%, Lung Cancer Using VGG-16 98.6% and Resnet-50 74.2% Normal VGG-16 97.3% and Resnet-50 93%,Tuberculosis VGG-16 99.85% and Resnet-50 74.2% ,Viral Pnuemonia VGG-16 96.3% and Resnet50 36.6% hence VGG-16 Performed well for all 5 classes than Resnet50 architectures

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