**Multi-Class Lung Diseases Classification from Chest X-Ray and CT images**

*A Report on Mini-project Submitted in the*

*Partial Fulfillment of the Requirements for the Award of the Degree of*

**BACHELOR OF TECHNOLOGY**

**IN**

**ELECTRONICS AND COMMUNICATION ENGINEERING**

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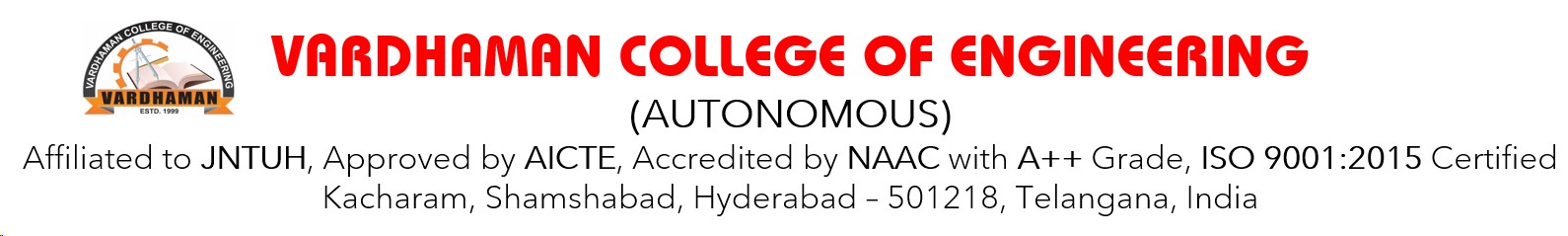
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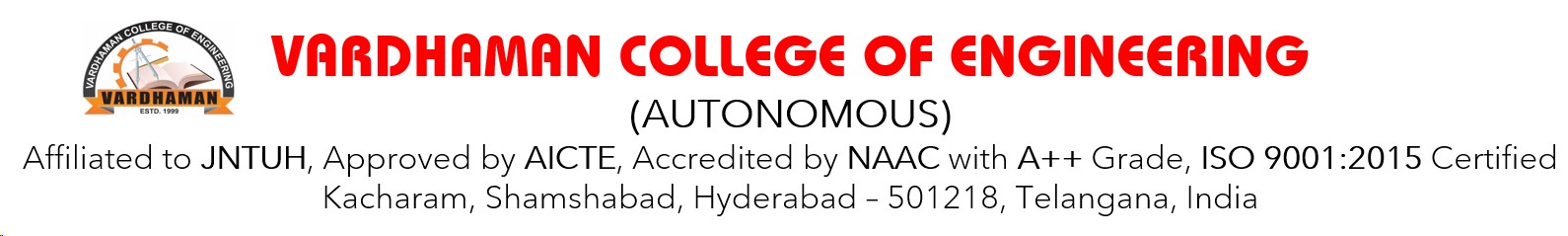
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# Abstract

Deep learning techniques have made great progressin medical image analysis, especially in classifying lung diseasesusing chest X-rays.To better understand condition of the lungdisease, chest X-Ray is used for identifying the disease spreadin the lungs.In this report, we have used Chest X-Ray images toclassify multiple types of lung diseases. We used COVID-19 Radiology Database in CNN models, including Xception Model, ResNet50 models todetect various diseases like Viral Pneumonia,Lung Opacity andCOVID-19 cases. The Xception Model has achieved the highestTrain Accuracy and Percentand Test accuracy compared to other model ResNet50. Additionally, we compared the performance of different models.

The Department is headed by Dr. P. Nageswara Rao having vast teaching experience and ably supported by highly qualified faculty with an unparallel level of expertise in their field. The Department constitutes 10 Professors, 12

Associate Professors and 30 Assistant Professors.

The UG Program has been accredited by the National Board of Accreditation (NBA) till the year 2025.

*Keywords*: X-rays, Lung Diseases, CNN Models, COVID-19, Viral Pneumonia, tuberculosis, Xception Model.

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# Abbreviations

|  |  |
| --- | --- |
| **Abbreviation** | **Description** |
| VGG16 | Visual Geometry Group 16 |
| VGG19 | Visual Geometry Group 19 |
| Densene | Densely Connected Convolutional Networks. |
| ResNet | Residual Networks |
| Ild | interstitial lung disease |

**CHAPTER 1**

**Introduction**

## 1.1 Introduction

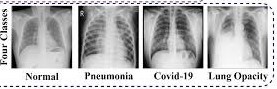
Lung diseases are a significant global health burden, affecting millions of people worldwide. Early and accurate diagnosis of these conditions is crucial for effective treatment and management. Radiological imaging, including chest X-rays (CXR) and computed tomography (CT) scans, plays a pivotal role in the diagnosis and monitoring of lung diseases. However, the interpretation of these images can be challenging and time-consuming, often requiring the expertise of highly trained radiologists. More than 200 chronic lung tissue inflammation types are grouped as interstitial lung disease (ILD), which can severely impact the pulmonary interstitial and potentially make it difficult for the patient to breathe. Consequently, early detection of these disorders is crucial for developing deci sions regarding decisions. Data-driven decisionmaking is growing in popularity in the healthcare sector because it can quickly collect and analyze complete and reliable data [1] .Millions of people get infected with pulmonary diseases around the globe each year, and thousands of them fail to survive due to age factor, under lying health conditions, and late diagnosis. Historical studies showed that pulmonary diseases are curable if diagnosed and treated at an early stage. [2]

**1.1.1 Lung disease**

## 1.2 Motivation

According to a research study called “The Global Impact of Respiratory Disease,” 10.4 million people suffered mild or severe symptoms of tuberculosis, and 1.4 million of those affected died as per the survey reported . Lung diseases kills an astounding number of people every year. More than 1.6

1



**Figure 1.1:** pneumonia,covid,lung opacity,normal

million people were reported to have died in the year the survey was carried out. Pneumonia is one of the top respiratory diseases and 1.23 million children under the age of 5 died due to pneumonia. Hence, early detection of lung diseases has become more important as shown in Figure **??**.

## 1.3 Objectives

The project aims to create an automated system for detecting lung diseases in X-ray and CT scans using deep learning techniques.

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**CHAPTER 2**

**Literature Survey**

## 2.1 Survey

To screen for probable disease, the majority of the ILD classifiers now in use manually identify regions of interest (ROI). Two deep learning network models used for ILD classification are connected by the hybrid deep learning network model described in this research. The proposed method’s schematic diagram is displayed in Figure 1. It accepts input from all HRCT images and outputs the ILD class label. From the HRCT images, the segmentation is done in the first stage using an improved U-Net++ model for segmenting the lung region. From the first stage’s segmented lung HRCT images, another deep learning-based RAPNet model was used to extract the features. Additionally, in the second stage, ILDs have been classified using the features produced by the RAPNet model using the memory-efficient network model MobileUNetV3. The hybrid deep learning network model employed in the proposed strategy has been briefly described in the following sentences.

### 2.1.1 Servey by various publishers

Hong et al. in [3] used transfer learning on six models to classify lung diseases like pneumonia, pneumothorax, and normal cases from chest X-ray images. The models were VGG19, DenseNet201, Vanilla EfficientNetB7, EfficientNetB7 with preprocessing, EfficientNetB7 with Multi GAP, and EfficientNetB7 with preprocessing and Multi GAP. They tested these on the NIH dataset. EfficientNetB7 with preprocessing and Multi GAP performed best, with 85.32 percent accuracy. They also applied transfer learning on the same set of models to classify pneumonia, pneumothorax, tuberculosis, and normal cases from their own chest X-ray dataset. Again, EfficientNetB7 with preprocessing and Multi GAP outperformed the rest, achieving 96.10 percent accuracy. Al-

3

shmrani et al in [4] Used Five deep learning models for transfer learning tasks.

They’re VGG19, MobileNetV2, Inception, Xception, and InceptionResNetV2. Classifying lung diseases like pneumonia, COVID-19, and normal instances involved CXR images from an internal dataset. Among these models, VGG19 performed best with 93.48Kim et al in [5] used transfer learning on Xception models for the study. Their goal was to identify different lung conditions like tuberculosis, pneumonia, COPD, pneumothorax, lung cancer and normal cases. They analyzed CXR images from NIH and their own datasets. The Xception model showed amazing results with 97.30sensitivity at 97.20other techniques used in the study. Shamrat et al in [6] Created LungNet22 by fine-tuning Several models employed transfer learning for identifying chest X-ray lung conditions (normal or tuberculosis). DenseNet121 was the top performer. Its accuracy hit 83.50 percent. Among positives, it identified 82.20 percent. Its specificity, ruling out negatives, was 84.90 percent. Specifically, Liu et al. trained six networks: DenseNet121, InceptionV3, NASNet, ResNet50, VGG16, Xception. On the in-house dataset images, DenseNet121 outshone the others classifying these pulmonary ailments. Lyu et al in [7] developed a two-part technique utilizing deep learning. The approach aimed to identify lung conditions like pneumonia and tuberculosis. It leveraged chest Xray images from a dataset curated in Shenzhen. Firstly, UNet localized the relevant lung region.

Subsequently, transfer learning was applied to three models: VGG16, ResNet50, and InceptionV3 - with weights pre-trained on ImageNet data. Among these models, inceptionV3 exhibited superior performance, achieving 82Malik et al in [8] A two-step deep learning technique was proposed by Tian et al. to classify lung diseases, pneumothorax versus normal, on chest X-ray images from NIH and their inhouse SAHZUSM data sets. First, the lung region of interest was segmented using U-Net. Next, transfer learning was applied to six models, Inception-ResNetV2, DenseNet, InceptionV3, VGG, NasNet, and ResNet, with pre-trained weights from ImageNet. The Inception-ResNetV2 model achieved the highest performance with an accuracy of 97.30Ibrahim et al in [9] have implemented transfer learning on seven models. These were: VGG16, VGG19, DenseNet201, Inception-ResNetV2, InceptionV3, ResNet50,

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and MobileNetV2. Their goal is to Classify lung diseases like pneumonia, coronavirus, COVID-19, and normal cases. Using chest X-rays and CT scans from their own dataset. InceptionResNet v2 performed best. It achieved

92.1892.11

**CHAPTER 3**

## Chapter 3

Background Work Background work for this project involves

Classification: This is the most likely background word. Classification refers to the process of assigning data points (in this case, chest X-ray and CT images) to one of a set of predefined categories (in this case, different lung diseases). The ”multi-class” aspect indicates that there are more than two possible categories for the images to be classified into.

Diagnosis: Diagnosis is the identification of a specific disease based on various pieces of evidence, including medical imaging like chest X-rays and CT scans. While classification is a step in the diagnosis process, it’s not the entire picture. Classification focuses on grouping images, while diagnosis focuses on identifying the specific disease behind the image.

## 3.1 Traditional Methods

Lung disease detection is currently performed through an examination of CXR images by a professional radiologist, due to its convenient and noninvasive assessment for overall findings of the chest situation in brief. It is also suitable for follow-up examination since disease changes can be observed more easily and earlier. However, there is a common human error that may be caused by the misreading of a CXR image due to the complex anatomical structure of the chest.

CNNs have significantly advanced the field of multi-class lung diseases classification from CXR and CT images by automating feature extraction and leveraging hierarchical feature learning. Techniques like transfer learning and data augmentation, combined with powerful CNN architectures, have led to substantial improvements in diagnostic accuracy and efficiency. Despite the challenges, CNNs have proven to be a transformative tool in medical image analysis, enabling more accurate and early diagnosis of lung diseases.

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**Figure 3.1:** Reading X-ray scan

## 3.2 Preexisting Techniques

Convolutional Neural Networks (CNNs) have been extensively applied to the classification of lung diseases from chest X-ray (CXR) and computed tomography (CT) images. Below are some of the notable techniques and methods developed using CNNs:

1. CheXNet:

Overview: Developed by Rajpurkar et al. in 2017, CheXNet is a 121-layer DenseNet model designed to classify 14 different thoracic diseases using CXR images. Dataset: Trained on the NIH ChestX-ray14 dataset, which includes over 100,000 frontal-view X-ray images. Performance: Achieved performance comparable to radiologists in identifying pneumonia, with high accuracy and

robustness.

1. CheXpert:

Overview: Introduced by Irvin et al. in 2019, CheXpert addressed the challenge of label uncertainty in medical images by using a combination of convolutional and recurrent neural networks. Dataset: Used the CheXpert dataset containing 224,316 chest radiographs from 65,240 patients. Uncertainty Labels: Employed techniques to handle uncertainty in the labels, improving the model’s ability to generalize and perform accurate classification across

multiple diseases.

1. Attention-Based CNNs:

Overview: Attention mechanisms have been integrated into CNN architectures to improve focus on the most relevant regions of the image. Techniques: Methods like Spatial Attention and Channel Attention enhance the interpretability and accuracy of the models by highlighting important features in the images. Applications: These techniques have been used to detect diseases like tuberculosis and pneumonia with improved diagnostic performance.

1. Multi-Scale and Multi-View CNNs:

Overview: These techniques involve processing images at multiple scales or from multiple views to capture a broader range of features. Multi-Scale Networks: Utilize different levels of image resolution to detect both fine-grained and coarse-grained features. Multi-View Networks: Combine information from different views (e.g., frontal and lateral CXR images) to improve classification accuracy. Benefits: Enhanced ability to detect various lung conditions by integrating diverse spatial information.

1. Transfer Learning:

Overview: Leveraging pre-trained models on large datasets (e.g., ImageNet) and fine-tuning them on medical imaging datasets. Techniques: Commonly used pre-trained models include VGG, ResNet, Inception, and DenseNet. Advantages: Reduces the need for extensive training data and computational resources, while improving model performance by using pre-learned features.

1. Ensemble Learning:

Overview: Combining multiple CNN models to form an ensemble, which aggregates predictions from different models to enhance overall performance. Techniques: Methods like bagging, boosting, and stacking are used to create robust ensemble models. Applications: Used to improve the reliability and accuracy of lung disease classification by mitigating the weaknesses of individual models.

1. Generative Adversarial Networks (GANs) for Data Augmentation:

Overview: GANs are used to generate synthetic medical images that can augment training datasets, addressing issues of data scarcity and imbalance. Techniques: Models like CycleGAN can generate realistic medical images that enhance the training process. Benefits: Improves the generalization and robustness of CNN models by providing more diverse and representative training data.

1. U-Net and Variants for Segmentation and Classification:

Overview: Originally designed for image segmentation, U-Net and its variants have been adapted for lung disease classification by segmenting lung regions and then classifying the diseases. Techniques: Combining segmentation and classification in a single architecture to focus on relevant regions within the lung. Applications: Particularly effective for tasks where precise localization of disease is crucial, such as identifying nodules or lesions in CT images.

Preexisting techniques for multi-class lung diseases classification using CNNs include a variety of innovative methods that leverage deep learning to improve accuracy and reliability. Techniques like CheXNet and CheXpert have set benchmarks in the field, while attention mechanisms, multi-scale and multi-view networks, transfer learning, ensemble learning, GANs, and U-Net variants have contributed to the ongoing advancements. These methods collectively enhance the ability to diagnose multiple lung conditions accurately and efficiently from CXR and CT images, supporting better clinical decision-making and patient outcomes.

### 3.2.1 CNN Models

In this context, convolutional neural networks (CNNs) are particularly effective for image classification tasks due to their ability to automatically learn spatial hierarchies of features.The performance of CNN architecture is exceptional inseveral computer vision tasks such as classification, object detection, image reconstruction, etc. These architectures arewidely adopted in the medical domain for disease classification due to their capability of extracting extraordinaryfeatures. The practice of utilizing the built-in architectures ofCNN is also found to be beneficial in several domains due to their stable architectural setting. The most commonly usedbuilt-in architectures include Inception, AlexNet, DenseNet,and ResNet models. Although, the utilization of these builtin architectures is still limited inthe medical field due tothe domain shift since these models are trained on ImageNetdataset containing generic images.To this end, the first CNN learns the discriminativefeatures, whereas the second fuses the features for grading. This simulation ofthe human grading process combined with an ensemble of network architecturesgreatly enhanced the diagnostic accuracy.

**Applications in Medical Imaging:** CNNs have been applied to various medical imaging tasks, including tumor detection, segmentation of anatomical structures, and classification of disease states. For instance, CNNs have shownDepartment of Electronics and Communication Engineering 18 high accuracy in detecting diabetic retinopathy from retinal fundus images, identifying lung nodules in chest X-rays, and classifying skin lesions as benignor malignant. The ability of CNNs to learn complex patterns directly fromimages makes them well-suited for tasks that involve high-dimensional data such as medical images.

**Transfer Learning:** One of the key advancements in deep learning is the concept of transfer learning, which involves pre-training a CNN on a large dataset and then fine-tuning it on a smaller, task-specific dataset. Thisapproach has been particularly useful in medical imaging, where annotated datasets are often limited. Pre-trained models can leverage the knowledge gained from large-scale image datasets such as ImageNet, enabling them to achieve high performance even with relatively small medical image datasets. Despite the success of CNNs in various applications, their deployment in clinical practice requires addressing several challenges. These include the needfor large annotated datasets, the interpretability of model predictions, and theintegration of AI tools into existing clinical workflows. The following sectionswill discuss these challenges in more detail and explore the specific datasets used in

classfication of lung diseases.

**3.3 Challenges in Multi-Class Lung Diseases Clas-**

## sification

Even though CNNs have shown great promise in multi-class lung disease classification from chest X-ray and CT images, there are still several challenges to overcome:

1. **Data Availability and Imbalance:** Large datasets with well-annotated images for various lung diseases are crucial for training effective CNNs. Realworld datasets often suffer from imbalances, where some diseases are much less frequent than others. This can lead to the model favoring the majority class and underperforming on less frequent diseases.
2. **Class Similarities and Overlap:** Certain lung diseases can have subtle visual differences in chest X-rays and CT scans. This similarity can make it difficult for CNNs to distinguish between them, leading to misclassifications.
3. **Image Variability:** Chest X-rays and CT scans can vary significantly due to factors like acquisition techniques, patient positioning, and image quality.

CNNs need to be robust to these variations to maintain accurate classification.

1. **Model Explainability and Interpretability:** While CNNs excel at classification, understanding how they arrive at their decisions can be challenging. This lack of interpretability makes it difficult to identify potential biases or errors in the model and hinders its acceptance in clinical settings.
2. **Computational Cost:** Training complex CNNs can be computationally expensive and time-consuming, requiring powerful hardware and significant

resources.

1. **Generalizability and Real-World Applicability:** Models trained on one dataset may not generalize well to unseen data from different hospitals or imaging systems. Ensuring generalizability and real-world applicability requires careful data selection and validation strategies. Researchers are actively working on addressing these challenges. Techniques like data augmentation, transfer learning, and development of interpretable CNN architectures are helping to improve the performance and reliability of CNN-based lung disease classification systems.

## 3.4 Motivation for using CNN

The motivation for using Convolutional Neural Networks (CNNs) in glaucoma detection stems from their ability to automatically learn hierarchical features from raw images. This section outlines the key advantages of CNNs for this application:

**Feature Learning:** Traditional machine learning methods rely on handcrafted features, which can be labor-intensive and may not capture all relevant information. CNNs, on the other hand, learn features directly from the data through multiple layers of abstraction. This enables the model to identify complex patterns and structures that are indicative of glaucoma.

**Scalability:** Once trained, CNNs can process large volumes of images quickly and consistently, making them suitable for large-scale screening programs.

**Transfer Learning**: Transfer learning has emerged as a powerful technique in deep learning, particularly for medical imaging tasks where labeled datasets are often limited. Pre-trained CNN models, trained on large-scale datasets such as ImageNet, can be fine-tuned on smaller medical image datasets. This approach allows CNNs to leverage knowledge learned from general tasks (e.g., object recognition) and adapt it to specific medical imaging tasks like glaucoma detection.

**Automation and Efficiency:** CNNs offer the potential to automate the process of glaucoma detection, reducing the reliance on subjective human assessments. Automated systems can analyze retinal images rapidly and

consistently, providing clinicians with timely diagnostic support. This efficiency can lead to earlier detection of glaucoma and better patient outcomes.

**Integration with Clinical Workflow:** For CNNs to be clinically useful, they need to be integrated seamlessly into existing clinical workflows. This includes ensuring compatibility with imaging devices, electronic health records (EHRs), and other healthcare systems. Additionally, providing clinicians with intuitive interfaces for viewing model predictions and confidence scores is essential for fostering trust and adoption.

**Future Directions:** The field of deep learning for lung disease detection is evolving rapidly. Future research directions include improving model interpretability, enhancing robustness to image variability, and developing personalized diagnostic tools. Collaborations between researchers, clinicians, and industry partners will be crucial in advancing these technologies and translating them into clinical practice.

## 3.5 Methodology Overview

**Dataset Description** We have used COVID-19 RADIOGRAPHY DATABASE.

The dataset contains chest x-ray images of COVID-19, Normal, Lung Opacity,

Viral Pneumonia. All the images are in 299\*299 pixels resolution. In our Project we used 1300 images each of all classes because of resource contraints and time constraints. we reduced the pixel size to 70\*70 for further processing.

**Data Exploration And Preprocessing** In the Preprocessing we have done

* Contrast Analysis
* Removing images with letters or white rectangles.

We have done Contrast analysis on all the images and removed images with less contrast that is under a threshold value. and coming to images with letters and other white rectangles we analysed all the images and removed the images with white rectangles on them.

**Model Architecture:** A Convolutional Neural Network (CNN) architecture is chosen based on previous research and experimentation. The model typically consists of convolutional layers for feature extraction, pooling layers for spatial reduction, and fully connected layers for classification. Hyperpa rameters such as filter size, number of layers, and learning rate are tuned through

experimentation.

**Training:** The CNN model is trained using labeled datasets, with loss functions (e.g., binary cross-entropy) and optimizers (e.g., Adam) specified. Training involves iterative forward and backward passes to update model parameters based on the gradient of the loss function. Techniques such as early stopping and learning rate scheduling may be employed to prevent overfitting and improve convergence.

**Evaluation:** The trained model is evaluated on separate test datasets to assess its performance metrics such as accuracy, sensitivity, specificity, and area under the receiver operating characteristic curve (AUC-ROC). Crossvalidation or bootstrapping techniques may be used to validate model generalizability and robustness.

## 3.6 Experimental setup

**Dataset Description:** Detailed descriptions of the datasets used for training and testing the CNN model. Includes information on the number of images, distribution of classes , and any preprocessing steps applied to the

data.

**Model Selection:** Justification for selecting a specific CNN architecture (e.g., Xception, ResNet) or designing a custom architecture based on the requirements of the lung diesese detection task. Comparison with baseline models or previous studies may be included.

**Training Parameters:** Parameters used during model training, such as batch size, number of epochs, optimizer settings (e.g., learning rate), and augmentation techniques. Details on how hyperparameters were tuned and the rationale behind their selection.

**Hardware and Software:** Description of the computational resources used for training and testing, including CPU/GPU specifications, memory, and software frameworks (e.g., TensorFlow, Keras). Ensure transparency in hardware setup to facilitate reproducibility of results.

**Validation Strategy:** Details on how the performance of the trained model was evaluated, including metrics used for evaluation (e.g., accuracy, precision, recall). Cross-validation or hold-out validation strategies and their implications for model generalization.

**Experimental Protocol:** Step-by-step outline of the experimental protocol, including data partitioning into training, validation, and test sets, model training procedure, and performance evaluation metrics. Ensures transparency and reproducibility of experimental findings

**CHAPTER 4**

**Proposed Methodology**

## 4.1 Introduction

This chapter introduces the methodology for multi-class lung diseases classification from CXR and CT images using CNNs involves a systematic approach from data collection and preprocessing to model selection, training, evaluation, and deployment. By leveraging the capabilities of CNNs and addressing specific challenges in medical imaging, this methodology aims to contribute towards more accurate, efficient, and reliable diagnosis of lung diseases, ultimately improving patient care outcomes.

## 4.2 Dataset Description

We have used COVID-19 RADIOGRAPHY DATABASE. The dataset contains chest x-ray images of COVID-19, Normal, Lung Opacity, Viral Pneumonia.All the images are in 299\*299 pixels resolution. In our Project we used 1300 images each of all classes because of resource contraints and time constraints. we reduced the pixel size to 70\*70 for further processing. Here is a table attached :

|  |  |
| --- | --- |
| *Type* | *Imageno* |
| NORMAL | 1300 |
| COVID | 1300 |
| LUNG OPACITY | 1300 |
| PNEUMONIA | 1300 |

**Table 4.1:** Data Table

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**Figure 4.1:** Images with White Rectangles in them

## 4.3 Data Exploration And Preprocessing

In the Preprocessing we have done

* Contrast Analysis
* Removing images with letters or white rectangles.

We have done Contrast analysis on all the images and removed images with less contrast that is under a threshold value. and coming to images with letters and other white rectangles we analysed all the images and removed the images with white rectangles on them. A total of 58 images from COVID-19 images and 1 Normal image was removed from this analysis. Removing White rectangles: images are converted into grayscale first and then pixels which have above 10 are converted to 255 and rest 0 in this way we found the images with white rectangles and removed them from the dataset. As shown

in the4.1.

## 4.4 Model Architectures

Initially, we tried a CNN model from a research paper. This was our starting point to measure other models. We trained and tested this custom model. We wanted to see how well it did. After testing the custom model, we looked at other pretrained models. We used models like ResNet50, Xecption. These models were already trained on huge datasets. They are known to work really well for computer vision tasks. We wanted to use their learned skills.

We hoped they would do better than our custom model.

**ResNet50:** ResNet50 is a deep convolutional neural network architecture created by Microsoft Research in 2015. It’s a type of ResNet or ”Residual Network.” The ”50” signifies the 50 layers forming this network. ResNet50 excels at image classification, achieving top results when trained on large datasets. It employs a key innovation called residual connections. These allow the network to learn residual functions mapping inputs to outputs. Thanks to residual connections, ResNet50 can learn much deeper architectures without vanishing gradient issues hindering past models. ResNet50’s architecture consists four parts: the convolutional layers, the identity block, the convolutional block, and the fully connected layers. The convolutional layers are responsible for extracting features from the input image, while the identity block and convolutional block further process extracted elements. Finally, the fully connected layers are used to make the final classification. ResNet50 Which we used has a total of 24.1m parameters.

**Xception Model:** Xception is a Convolutional neural network. It was made by Franc¸ois Chollet. Xception is good at computer vision tasks. It works well and doesn’t waste time. The network is based on inception. But it uses different convolution blocks. These blocks are called depthwise separable convolutions. They make the network better and faster. We have utilized the Xception model as a feature extractor, which means including the top (classification) layer of the pretrained Xception model. This allows us to use the pretrained Xception model as a feature extractor and add our own classification layers on top. We have also loaded the weights of the Xception model pretrained on the ImageNet dataset by setting weights to ’imagenet’. This initializes the model with weights learned from the ImageNet dataset, which can be beneficial for transfer learning tasks. we have defined additional layers to be added on top of the Xception base. These include a global average pooling layer (GlobalAveragePooling2D), a dropout layer (Dropout),

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batch normalization layer (BatchNormalization), and a dense output layer (Dense) with softmax activation function.

## 4.5 Training

At first the images are processed that is they are converted into NumPy arrays and the resulting array is stored to a CSV file for further process reducing the time to process images every time.Later all the images are resized to 70x70 pixels and normalized. After preparing the data, images and lablels are separated and the dataset is divided into training, testing and validation sets using train test split function. The training set consists of 80 percent and 20 percent into testing and validation sets.

## 4.6 Evaluation Metrics

**Performance Metrics:** Comprehensive suite of evaluation metrics used to assess model performance, including accuracy, precision, recall (sensitivity), specificity, and area under the receiver operating characteristic curve (AUCROC). Each metric’s significance in clinical diagnostics is highlighted.

**CHAPTER 5**

**Results And Discussions**

## 5.1 Introduction

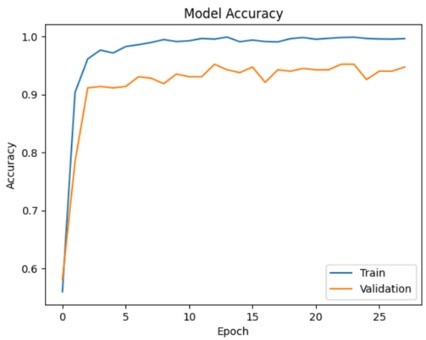
Chest X-ray (CXR) is widely used in detecting a variety of diseases affecting the chest area. This technology can help doctors detect a variety of diseases, such as a pneumonia, pulmonary edema, heart failure, lesions, lung cancer, tuberculosis, sarcoidosis, and pleural effusion. Therefore, various deep learning methods have been proposed to classify lung diseases on CXR images to improve the efficiency and accuracy of computer-aided diagnostic systems The process typically involves pre-processing of chest X-ray images, automatic feature extraction, and detection. The robust CNN is proposed using the pretrained model for automatic lung feature extraction. The extracted features are then classified using different machine learning classifiers. Initially, we tried a CNN model from a research paper. This was our starting point to measure other models. We trained and tested this custom model. We wanted to see how well it did. After testing the custom model, we looked at other pretrained models. We used models like ResNet50, Xception

## 5.2 Result-Performance Metrics

### 5.2.1 Accuracy, Precision, Recall, and F1-score

Accuracy: Measure of the model’s overall correctness in classifying lung diseases. Precision and Recall: Indicators of the model’s ability to correctly identify positive cases and avoid false positives. F1-Score: Harmonic mean of precision and recall, providing a balanced assessment of the model’s performance across all classes. AUC-ROC: Area Under the Receiver Operating Characteristic curve, assessing the model’s ability to distinguish between different classes.

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**Figure 5.1:** model-accuracy

|  |  |  |  |
| --- | --- | --- | --- |
| *Model* | *TrainAccuracy* | *TestAccuracy* | *V alidationAccuracy* |
| ResNet50 | 0.982 | 0.92 | 0.92 |
| Xception | 0.99 | 0.96 | 0.94 |

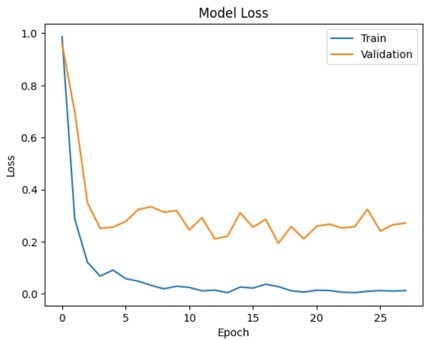
**Table 5.1:** COMPARISON OF TRAIN, TEST, AND VALIDATION ACCURACY FOR TWO MODELS

Out of al the models Xception model performed the best with accuracy of 99Xception model is trained with 50 epochs and batch size of 64. Validation loss did not improve and earlystopping occured at 28th epoch with a training accuracy of 0.99 and validation accuracy of 0.94.

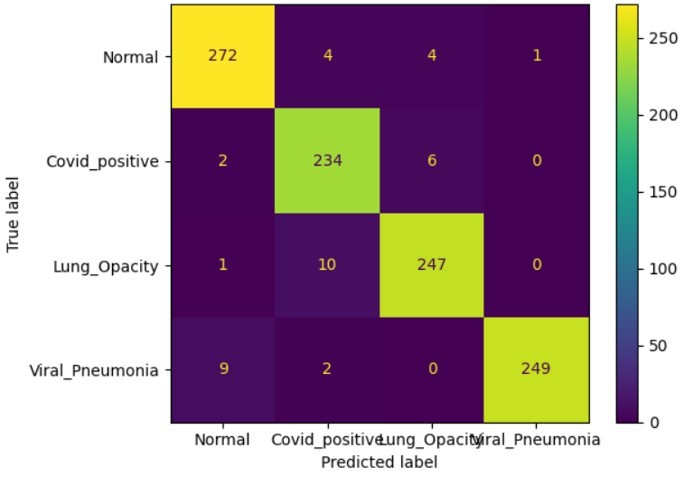
**Result:**These are the Confusion matrix and Precision, Recall, f1-score for Xception Model.

|  |  |  |  |
| --- | --- | --- | --- |
| *n* | *precision* | *recall* | *f*1 − *score* |
| Normal | 0.96 | 0.97 | 0.96 |
| Covid-positive | 0.94 | 0.97 | 0.95 |
| Lung-opacity | 0.96 | 0.96 | 0.96 |
| viral-pneumonia | 1.00 | 0.96 | 0.98 |

**Table 5.2:** Recall, Precision, f1-score for Xception Model



**Figure 5.2:** model-loss



**Figure 5.3:** Confusion Matrix for Xception Model

### 5.2.2 ROC Curve and AUC

The Receiver Operating Characteristic (ROC) curve and Area Under the Curve (AUC) were used to assess the model’s ability to distinguish between diffenent type of lung diseases cases across various thresholds.

## 5.3 Discussions

### 5.3.1 Interpretation Metric

The achieved metrics, including accuracy, precision, recall, and F1-score, were interpreted in the context of lung disease detection. Insights were drawn regarding the model’s ability to correctly identify the lung diseases.

### 5.3.2 Challenges and Limitations

Challenges Faced Challenges encountered during model development and evaluation were identified and discussed. These challenges may include dataset limitations (e.g., size, quality), interpretability of deep learning models, and generalizability to diverse patient populations. Limitations of the Study Limitations inherent in the study design and methodology were acknowledged. These may encompass biases in dataset selection, assumptions made during preprocessing, and the reliance on retrospective data.

**CHAPTER 6**

**Conclusion and Future scope References**

## 6.1 Conclusion

In Conclusion, We have looked at different Pre-trained deep learning models for this Lung disease classification. We trained and tested seven: EfficientNet-

B0, ResNet50, DenseNet121, VGG16, VGG19, DenseNet121 and a custom

CNN. The models, like Xception and ResNet50, worked better than the others. They were more accurate on test and validation sets. This shows using new techniques helps classify images better. From our experiments, we saw that updated architectures like Xception and ResNet50 did really well. Their test and validation scores were higher than other models we checked. The results clearly highlight how important it is to use the latest advancements to get improved classification performance. However, it is essential to acknowledge the limitations of our study, Where we have not used the full dataset and

other resource constraints.

## 6.2 Future Directions and Recommendations

some potential future directions and recommendations for multi-class lung disease classification from chest X-ray and CT images using CNNs: Data augmentation techniques: Artificially expanding datasets with techniques like rotations, flips, noise injection, and color jittering to address data imbalance and improve model robustness to image variations. Federated learning: Training models collaboratively across multiple institutions without sharing sensitive patient data, allowing for access to a wider range of data while preserving privacy. Attention mechanisms: Integrating attention mechanisms within CNNs to focus on specific regions of interest in the image that are most relevant for disease classification. Multimodal learning: Combining CNNs with

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other modalities like patient history or additional imaging data to improve

classification accuracy

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