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Classification of Five Categories of Lung Disorder Patterns using Deep Learning Techniques

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ABSTRACT: Several studies were carried out to classify diffuse lung disease utilizing a variety of computational methods and technologies. However, due to the fact that identical traits in nature were discovered for the clinical signs of widespread lung diseases. The classification of the five different forms of diffuse lung infection for subsequent diagnosis and therapy is time-consuming and exhausting for the radiologist. Therefore, in this proposed research project, we seek to classify and identify each of the five types of clinical symptoms associated with widespread lung infection. Analyze the CT scan image patch patterns of the lung disorders using the CNN and VGG16 framework to classify five different types of lung diseases. We discovered that the suggested models successfully classified diffuse lung disease with an accuracy of 0.90.

KEYWORDS: Disease Classification, Lung Disease Pattern, CNN, VGG16.

I. INTRODUCTION

A set of lung diseases known as diffuse lung disease often affects the interstitial tissue. The interstitial, a connective tissue, provides support for the lungs alveoli (air sacs). It is common knowledge that as we breathe in, oxygen enters the bloodstream and fills the alveoli. In other words, during exhalation, carbon dioxide moves from the blood into the alveoli and is then expelled from the body.

The lung becomes inflamed and stiff when the interstitial disease is present, preventing the alveoli from expanding fully. It aids in lessening both the elimination of carbon dioxide from the body and the delivery of oxygen to the bloodstream. Despite being heterogeneous, diffuse lung diseases are discovered to have the most comparable clinical signs. Diffuse Breathing difficulties are brought on by lung disorders, which are brought on by carcinogens, pollens, dust, or autoimmune conditions. The clinical symptoms of diffuse lung diseases are somewhat comparable to those of high resolution computed tomography scans, which are frequently employed for precise diagnosis. Textural changes in lung parenchyma shown on computed tomography scans are a common symptom of diffuse lung disorders.

In order to prevent lung patterns linked to diffuse lung illnesses like emphysema, fibrosis, ground-glass opacity, and micro nodules, very high intensity of action must be done. Figure 1.1 shows two examples for each of the layout of healthy lungs as well as dispersed lung types. Even while there are enormous and numerous distinguishable visual variations between the tissue types, Fig. 1.1 makes it abundantly evident that there is still a higher degree of diversity in such an appearance within the same tissue type. As a result, detecting small changes in the lungs textural qualities early on should be necessary for the early detection of widespread diseases. Emphysema, fibrosis, ground glass opacity, micro nodules, and healthy lung are the most common lung patterns linked to diffuse lung diseases. A timely diagnosis of these disease patterns is essential for the treatment of interstitial lung disease, which is a set of diverse abnormal inflammations of the lung tissues. However, because the clinical signs of many diseases are similar, it is challenging to obtain a precise diagnosis. Computer-aided diagnosis methods have been created to help radiologists.

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1.1 Overview

Deep neural network-supported computer vision finds applications in every aspect of life, from the detection of diseases to the recognition of facial expressions of emotion. Computer-aided image analysis algorithms can now compete with experts in terms of accuracy thanks to recent technological advancements, but they are still unmatched in terms of speed and number of evaluated instances. Computers, as opposed to doctors, make swift, logical conclusions that are unaffected by feelings or fatigue. According to the most recent WHO (World Health Organization) study, over 1 million Americans alone seek medical attention for pneumonia each year, and there are around ten million cases of tuberculosis globally.

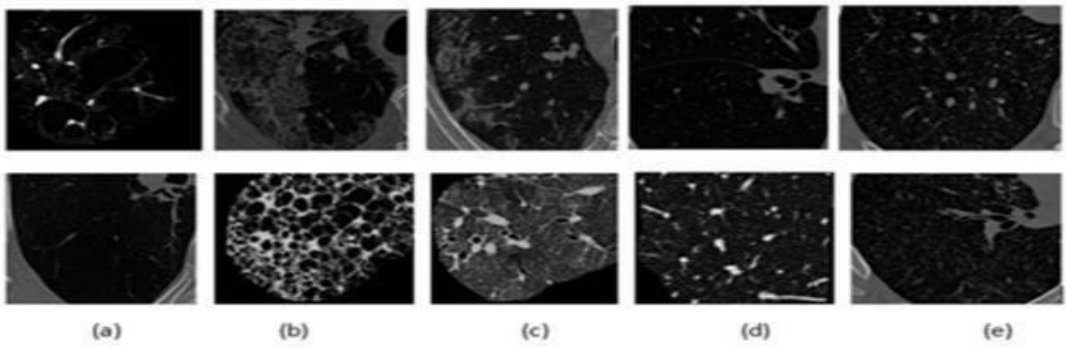

Figure 1.1: Interstitial Lung Disease patches sample images

II. MOTIVATION AND BACKGROUND

Traditional radiological screening techniques and manual identification were previously used in biomedical image analysis to diagnose diseases like Emphysema, Fibrosis, Ground Glass, Micro Nodules, and Healthy. This method is found to be rather time- consuming, and it has also been discovered that patients suffer from a number of serious limitations, such as the subjectivity of the diagnosed result and the variability between different laboratories. Additionally, a wide range of biomedical images have been created employing a variety of modalities with the use of extremely sophisticated medical imaging instruments, such as Computerized Tomography, X-Ray, Microscopic, Ultrasound, and Magnetic Resonance Imaging.

As a result, manually labeling and annotating every piece of data that was gathered from a huge number of patients every day had become a typical unfeasible chore for many specialists. A large number of publicly accessible biomedical image data sets were easily accessible and have been used for biomedical image analysis, in line with recent developments in the field of biomedical image technology. Biomedical Image classification and retrieval have been considered the important components and challenging tasks in such an analysis, and as a result, biomedical Image analysis based on computer technology and its Platform has become especially essential in computer-aided detection and diagnosis systems.

Thus, this study uses deep learning technology to classify biomedical images automatically. It also discovered that this technology has the potential to help radiologists and other medical professionals by speeding up diagnosis by cutting down on screening and processing times. Additionally, the work considerably increases the results reproducibility and gets beyond all of these obstacles by providing a quick, stable, and categorization that supports and helps the experts make decisions. However, achieving a high and dependable accuracy for automatic image classification is a difficult issue; this is also evident in numerous previously published literary works.

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III. PROBLEM STATEMENT

The precise classification of biomedical images is essential for the clinical diagnosis of many medical illnesses that might be identified from such images. Traditional image classification methods, as well as hand-crafted image feature descriptors and other classifiers, fall short of the exacting classification requirements for biomedical images and are unable to considerably improve accuracy rates. The same is true for artificial neural network models that are directly used as a "black box" to extract deep features from a different remote dataset or that are directly trained utilizing sparse biomedical images as training material. In this paper, we provide an end-to-end classifier for all kinds of biological images that is based on deep learning and transfer learning.

IV. OBJECTIVES

- To ascertain and classify Interstitial Lung Disease radiographic patterns as soon as feasible using CT images.
- To offer a quick, precise, and effective detection technique.
- Create an early screening model to distinguish patients of interstitial lung disease from those who are healthy using deep learning techniques.
- To use image processing to develop a promising supplementary diagnostic tool for clinical doctors on the front lines.

V. DATASET

The classification of diffuse lung disease uses the TALISMAN benchmark data set, which is open to the public. With the help of secondary data integration techniques, the TALISMAN data collection aims to offer image-based diagnostic support for ILDs. Emphysema, ground-glass opacity, micro nodules, fibrosis, and healthy are among the 103 picture series of DLD categories included in the data set. Radiologists with experience have annotated a total of 1363 two dimensional Regions of Interest. 14,356 overlapping patches with a size of 32 x 32 are taken from these annotated ROIs to represent the DLD pattern.

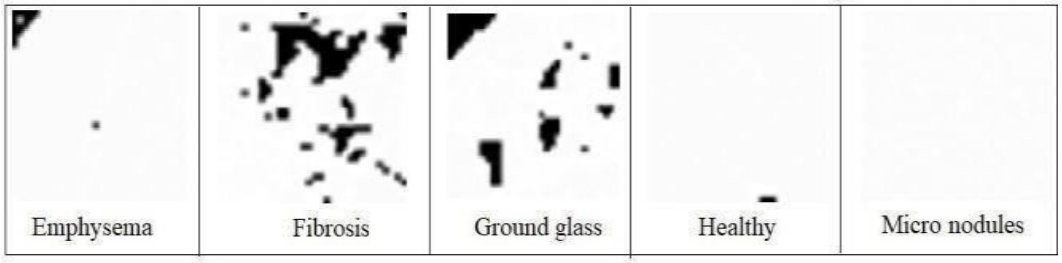

Figure 1.5: Five types of patches

VI. RELATED WORK

In the realm of medical image diagnosis, there are numerous studies and research projects being conducted using AI and deep learning datasets like TALISMAN (Texture Analysis of Lung Images for Medical diagnostic AssistaNce). The local Rotational invariant Gabor Texture Descriptor and Multi coordinate Binary Patterns (RGLBP) were created by Song et al. in 2013 [1]. For the five classification criteria, they proposed a brand-new classification technique called the patch-adaptive sparse approximation (PASA) method. Each image patch was classified using a coefficient vector and 0.80 precision was attained. The classifier offers a new Large Margin Local estimate (LMLE) model for the classification of medical images every two years, according to the same study team. In 2014, Kuruvilla et al. [2] introduced five feed-forward algorithms and a number of statistical factors. To obtain the best assembly settings, a back propagation neural network with 13 training functions is used. SCRF for lung cancer classification from segmented CT scans, but because these works don't always function perfectly, they help researchers learn about artificial neural networks.

Convolutional neural networks (CNNs), a common type of deep neural network, have been applied to image categorization with success in recent years. 2014 saw the proposal of customizable convolution by Li et al. [3]. To

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classify lung image patches with interstitial lung disease, convolutional neural networks (CNN) with a shallow convolution layer were used (ILD). ILD database 16220 image patches from 92 HRCT image sets are publicly available. These patches include 4348 normal patches, 1047 emphysema patches, 1953 ground glass patches, 2591 fibrosis patches, and 6281 micro nodules patches and images patches of 32*32 pixels. Results in terms of accuracy were 0.83 in CNN, 0.71 in SIFT, 0.72 in LBP, and 0.80 in RBM. Christodoulidis et al's CNN architecture and transfer learning were proposed in 2016 [4], and this research detailed a training technique for enhancing a CNN's accuracy and robustness when applied to classify lung tissue patterns.

To increase performance, multiple knowledge transfers from six texture databases were used. Accuracy of Ensemble of CNNs of 0.8817, Compressed 8- layer CNN of 0.8751, and Multi-task Learning of 0.8631. Convolutional neural network (CNN) methodology was proposed by Anthimopoulos et al.[5] for the classification of interstitial lung disease (ILD) patterns. The ability of CNNs to analyze lung patterns was proved by their classification accuracy of 85.5. Sensitivity to patterns ranged from 99 (consolidation) to 69. (honeycombing). Deep CNN was proposed by Christe et al.[6] in 2016. To divide lung CT patches into seven categories. The capability of CNNs in evaluating lung patterns is demonstrated by the use of 14696 image patches created from 120 CT scans for training and evaluation. The classification accuracy of these image patches is 85. For various (ILD) patch types, CNN methodology was proposed by Hattikatti et al. [7]. Pictures from CT scans show a variety of pulmonary textural patterns linked to various diseases. The radiologist finds it challenging to distinguish between these images various patterns in order to make a diagnosis.

1. Challenges

Obtaining medical images for deep learning is difficult for a number of reasons:

- In comparison to common images, they are expensive and difficult to obtain.
- Experts must be used in order to accurately annotate bio-images.
- Unlike the cutting-edge image analysis datasets (ImageNet, AlexNet, GoogLeNet, and VGGNet), which contain thousands or even millions of instances of real images, the medical database capacity is typically insufficient.
- The diffuse lung patterns in the data set exhibit both intra- and inter-class heterogeneity. We can see from the dataset that there is sample imbalance between the various tissue patterns.

VII. PROPOSED ALGORITHM

One of the most outstanding deep neural networks, CNN uses numerous hidden layers that execute convolution and sampling to extract small amounts of input data to significant amounts. This network demonstrated strong performance across several areas, particularly in computer vision. CNN can use a variety of convolutional layers, with feature vectors serving as both the input and output of the succeeding layers. The information is tangled up in several pathways at every layer. The depth of the feature maps that are generated is comparable to the quantity of filters used during the convolution process.

1. CNN Method

This Section Describe CNN method consisting of two phases:

- Data Engineering
- Model training and validation

Data Engineering

The data set is known as the TALISMAN data set. There are 14356 overlapping patches in the total data set, each measuring 32 by 32, representing five different forms of interstitial lung diseases: Ground glass, micro nodules, fibrosis, emphysema, and healthy patches The data set contains only actual images. Below is a summary of the data's final division:

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Training: 7011 image patches of different diffuse lung diseases. Test: 1399 image patches of different diffuse lung diseases.

Image Pre-processing

Before being fed into the model for training, the data set's images are preprocessed. Among the steps in image pre-processing are image scaling and tagging. It improves some characteristics, which aids in enhancing the model's functionality.

- Resize: The data set is made up of various-sized photos that have been scaled down to a base size, which serves as the input image size for the model.

- Labeling: Images are labeled so that the model may be trained appropriately and extract features based on the labels. Before performing model training, the size of the pre- processed images is decreased to 32 x 32 x 3 and they are uniformed.

Model Training and Validation

Three measures are used to assess the trained models: accuracy, F1, and F2.The greater the metric, the better. To fine-tune the hyper parameters, use the validation set. The model is then tested. It is possible to diagnose novel coronaviruses from lung CT scans using an image classification technique. Test A pre-trained transfer learning model's accuracy is defined as its capacity to distinguish between multiple classes of diffuse lung disease patches, such as emphysema, fibrosis, ground- glass opacity, and micro-nodules, and healthy patches.

3.2 CNN Architecture

The five convolutional layers of the layered sequential model architecture for classifying CT scan images are shown in Fig. 3.1. CNN's building. There are 64 filters in the first convolutional layer, 256 filters in the second, 256 filters in the third, 256 filters in the fourth, and 528 filters in the final layer. The number of filters equals the number of characteristics that may be extracted at each layer by the network. Because the lower layers of the proposed network only detect features in a relatively limited portion of the image and discover hidden patterns during network training, the number of filters is gradually increased. With increasing network depth, the CNN layer architecture's receptive field expands. As a result, the network pulls the data from a bigger portion of the original image as the number of layers increases since deeper layers will be able to recognize higher-level information. At the convolutional layer, we fixed the default kernel size to 3x3 and used a non- linear ReLU activation function. Similarly, to contain the more complicated visual patterns in the training network, three max-pooling layers and a kernel window of size 2x2 are employed with the increasing number of filters in each layer.

The developed CNN model was then applied to the chosen data set, which contained five distinct patterns of diffuse lung disease. Using learning parameters and the distributions of the training, validation, and testing datasets, the learned model will adjust it.

1. Gather all healthy and positive photographs and place them in the data folder.
2. Image resizing/labeling and model training using a deep learning algorithm
3. Testing.
4. Retrain the model if necessary, then deploy or export it for offline use.

The tasks listed below are used to train the model using the aforementioned dataset:

1. Defining the model's parameters before training it.
2. Using the dataset obtained in step 1 to train the model for the specific character detection job.
3. Following model training.

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Once the model has been trained to a suitable level of content, the following procedures will be carried out for validation against testing:

1. Assessing the model using the testing and validation set.
2. Giving the validation model a label.
3. Obtaining the multiclass categorization for deployment and testing.

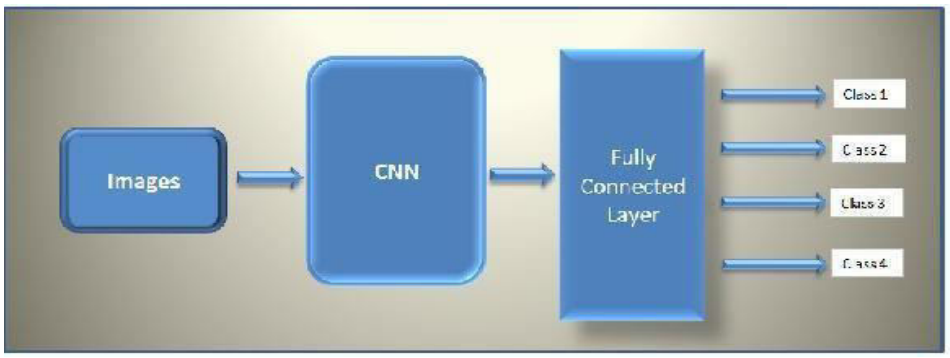

Figure 3.1: High Level Design

High Level Planning The suggested approach uses patches for interstitial lung diseases to automatically detect and localize various diffuse lung disorders. A revolutionary model called CNN is suggested Low Level Design in light of the benefits. Convolutional and pooling layers are stacked to create CNN, which has an output layer after several completely linked layers. The pooling layer shrinks the size of the feature map while the convolutional layer's goal is to represent features. Conv layer uses the training image's raw pixel values as input to extract features from it. Through the use of tiny squares of input data, this layer learns visual attributes to guarantee the spatial relationship between pixels.

Rectified Linear Unit (ReLU) layer, which uses a threshold operation to set any values less than zero to zero for each element of the extracted feature cube. When the ages are too big, the pooling layers part would lower the amount of parameters. Spatial pooling, also known as subsampling or down sampling, lowers the dimensionality of each map while preserving crucial data.

Dropout is a method for avoiding over fitting in models. When the training phase updates, Dropout operates by arbitrarily setting the outgoing edges of concealed units to 0. (Neurons that make up hidden layers). Adding another layer of pooling would reduce computing costs.

Dropout is a technique for keeping models from over fitting. Dropout functions by irrationally setting the outgoing edges of concealed units to zero during training phase updates (neurons that make up hidden layers). The cost of computing would be reduced by adding another layer of pooling. Special information is not preserved by a layer that is fully connected. It applies a fully connected layer. A dense, fully linked layer with one neuron that is softly maximally activated (output unit). Classification of test picture patches is done using the activation function soft max. Max soft Given that it offers a good probability function, regression is frequently employed for classification purposes.

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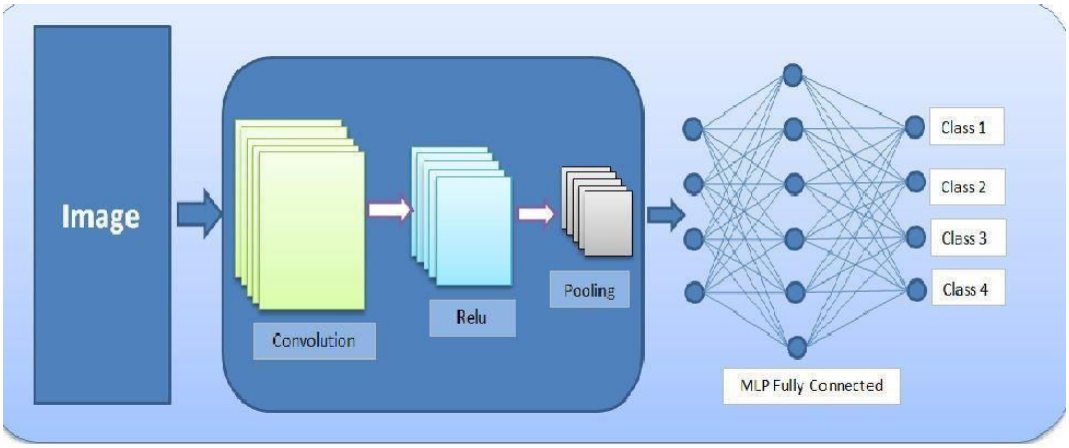

Figure 3.2: Low Level Design

3.3 Algorithm

Steps for classification interstitial lung diseases:

Step 1: Input Image patches - Eachinput shape of (32, 32, 3) is fed into the neural network.

Step 2: Conv layer with a 3×3 filter size is applied. Activation function RELU is used after the convolutions layer. Then a 2x2 filter size is used with Max Pooling. 64 filters make up the first convolution layer.

Step 3: Repeat step 2 and add Dropout Layer with (0.5). 256 f ilters make up the second convolution layer.

Step 4: Repeat step 2. 256 filters make up the third convolution layer.

Step 5: Conv layer with filter size of 3 x 3 is applied. ReLU activation function is used and Dropout Layer with (0.5) is applied. The fourth conv layer has 256 filters.

Step 6: Once again Repeat step 2. The last conv layer has 528 filters.

Step 7: Flatten Layer is applied.

Step 8: Three more Dense Layer is added with the ReLU activation function.

Step 9: Dense layer with a sigmoid activation function is used.

Step 10: Soft max is used for classification of test image patches into different types of diffuse lung diseases classes.

IV. IMPLEMENTATION

In contrast to other neural networks, CNN automatically derives the characteristics from the raw data set. Through the use of pertinent filters, CNN may effectively capture the spatial and temporal dependencies in a picture. The entire CNN is initially trained to learn weights. The first fully connected layer's output is then triggered and utilized to create an extracted feature vector with a smaller dimensionality.

For the extraction of picture features, the traditional CNN model structure was employed. To avoid over fitting and to solve the generalization problem, pooling processes were also used for the dimensional reduction of data. The output of the convolution layer was flattened to a 528 dimensional feature vector, which was then transformed using a full- connection network into a 1 dimensional feature vector.

The relative distance-from-edge value for the location-attention network was concatenated to this full-connection network structure after first being normalized to the same order of magnitude. Following the softmax layer, four full-connection layers were used to output the final classification result and the confidence score.

With feature extraction and classification occurring within the same CNN architecture, this gives us the most straightforward classification model. The deep CNN makes use of the adjusted weights and predicts the results directly.

Convolutional and pooling layers are stacked to create CNN, which has an output layer after several completely linked layers. The convolutional layer's goal is to represent features, while the pooling layer shrinks the feature map's size. Special information is not preserved by a layer that is fully connected. Since Softmax Regression offers a good

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probability function, it is frequently utilized for classification applications. The pooling feature map is flattened into a single column using the flatten function, which then sends the results to the fully connected layer.

Layer	Type	Maps	Size	Filter Size	Activation
Out	Dense	--	1	--	Sigmoid
dense_2	Dense	--	32	--	ReLU
dense_1	Dense	--	64	--	ReLU
dense	Dense	--	128	--	ReLU
flatten	Flatten	--	528	--	--
max_pooling2d_3	MaxPooling2D	528	1x1	2x2	--
conv2d_4	Conv2D	528	2x2	3x3	ReLU
dropout_1	Dropout	256	4x4	--	--
conv2d_3	Conv2D	256	4x4	3x3	ReLU
max_pooling2d_2	MaxPooling2D	256	6x6	2x2	--
conv2d_2	Conv2D	256	12x12	3x3	ReLU
dropout	Dropout	256	14x14	--	--
max_pooling2d_1	MaxPooling2D	256	14x14	2x2	--
conv2d_1	Conv2D	256	29x29	3x3	ReLU
max_pooling2d	MaxPooling2D	64	31x31	2x2	--
conv2d	Conv2D	64	62x62	3x3	ReLU
In	Input	64	64x64	3X3	--

Table 3.1: CNN Summary Table

V. TRANSFORM LEARNING

Transfer learning uses instruments that have already been trained to perform a different task to optimize the training process. An already-trained model is used as the foundation for another activity. Transfer learning is the process of learning a new activity better by transferring knowledge from a previously acquired, related one. When data resources are scarce, deep neural networks are often used in computer vision-related applications.

We therefore use the pre-trained models adept in resolving comparable issues to establish a starting point for a new work. Due to the limited sample amount, this method is essential in the processing of medical images. Deep neural networks do feature extraction by running raw data through models that are trained to perform different tasks. Here, we can make reference to deep learning models like VGG16, where data from the final layer is used as features for a new classifier.

1. Pre-trained Models Approach

Pre-trained models are a popular method for doing transfer learning in deep learning situations. Here, we can differentiate between the three methods listed below: Model Reuse True Model Choose Source Model Reuse Model, the first choice, asserts that a model that has already been trained can serve as a foundation for another model that will be utilized for a different job. This entails incorporating the entire model or some of its components. In the second strategy, it may or may not be necessary to refine an adopted model using the input-output data for the new task.

The third choice takes into account choosing one of the available models. Research organizations frequently disclose their algorithms that were developed using difficult datasets and may fully or partially address the issue raised by a new mission. By offering a sizable image data set, the ImageNet project aids computer vision researchers in their classification and detection tasks. This database has around
20.000 classes and roughly 14 million unique photos. Over a million photos from ImageNet are also provided with bounding boxes and comments for use with object localization issues. In this study, we will concentrate on two pre-trained models from the ImageNet dataset: VGG-16.

2. VGG16

Researchers A. Zisserman and K. Simonyan from the University of Oxford proposed the VGG model, a deep convolution neural network with over 138 million parameters. By altering the kernel size and replacing the 11x11 and 5x5 filters in the first two layers with numerous smaller 3x3 filters sequentially, this model was able to obtain a 7.4 error rate on the ImageNet dataset.

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3. VGG16 Architecture

The architecture of the 16-layer VGG model is shown in Figure 4.1. The 16-layer VGG convolution network was developed using
fixed-size images.

Figure 4.3: VGG16 Architecture

A series of convolution layers with small-size kernels and a 3x3 receptive field are used to process the input. The smallest size that still allows us to distinguish between up, down, right, left, and centre is this one. Additionally, the architecture uses 1x1 kernels, which can be understood as linear input transformation followed by nonlinearity. The spatial resolution remains the same after processing an input through a layer because the stride of convolutions, or the number of pixels that are shifted in every convolution - One pixel serves as the fixed step size. For example, the padding is fixed at 1 for 3x3 kernels. Five pooling (max-pooling) layers in succession, followed by some convolution layers, downsize the space.

Not all of them, nevertheless, are followed by maximum pooling. Max-pooling is performed over a fixed 2x2 pixel window with a 2 pixel stride. The final three Fully-Connected (FC) layers in this convolutional layer stack do a 1000-way classification using softmax, with the previous two layers each having 4096 channels. All hidden layers have the same non-linearity ReLU (rectification). Figure 4.1 visualizes the architecture of the VGG model with 16 layers.

4. VGG16 Algorithm

Using the ILD (TALISMAN) dataset, step 1 is to obtain images of both types of intestine lung disorders.
Step 2: Resize all of the photos to 224X224X3 using the VGG- 16 algorithm.
Step 3: Assign the fibrosis, micro nodules, and fibrosis class labels to the picture patches. Shattered glass, wholesome patches, and
Step 4: Using the training and testing datasets, categorize the photos by choosing from all of the class labels.
Step 5: Use 80 training photos to train the improved VGG-16 model. 20 testing photos are used to test the VGG-16 Model. Step 6: is where the various performance measure parameters are calculated. Determine whether the proposed Model is effective.

V. RESULTS

Evaluation Metrics

The performance of the suggested model has been assessed using the Confusion Matrix, Recall, Precision, and F1 score. In a confusion matrix, the row displays the predicted class and the column displays the actual class. The anticipated label and the genuine label are also displayed. Confusion matrix with testing data classification is shown in Figure 5.1.

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The model's accuracy indicates how frequently it predicts the right positive cases.

Precision = TP / TP+FP

The percentage of successful outcomes that are accurately classified is measured by recall.

Recall(r) = TP / TP+FN

The harmonic mean of the precision and recall scores is the F1 score.

F1Score = 2 (Precision×Recall / Precision+Recall)

Specificity measure of how well classifier identifies negative cases

Specificity = TN / (TN + FP)

The accuracy ratio measures the proportion of accurately predicted observations to all observations.

Accuracy = TP+TN / TP+FP+TN+FN

	precision	recall	f1-score	support
emp	1.00	0.73	0.84	1157
fib	1.00	0.97	0.98	1157
ground	1.00	0.93	0.97	1157
micro	0.97	0.89	0.93	1157
health	0.71	0.96	0.82	1156
micro avg	0.92	0.90	0.91	5784
macro avg	0.94	0.90	0.91	5784
weighted avg	0.94	0.90	0.91	5784
samples avg	0.90	0.90	0.90	5784

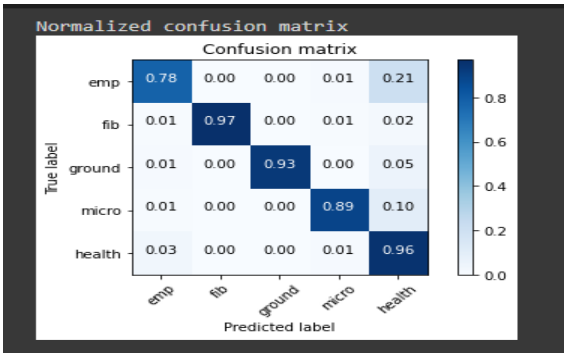

Figure 5.1: Confusion Matrix and Classification Report

5.1Result and Discussion

The experiments are conducted with the above discussed architecture and the data sets. The results are discussed.

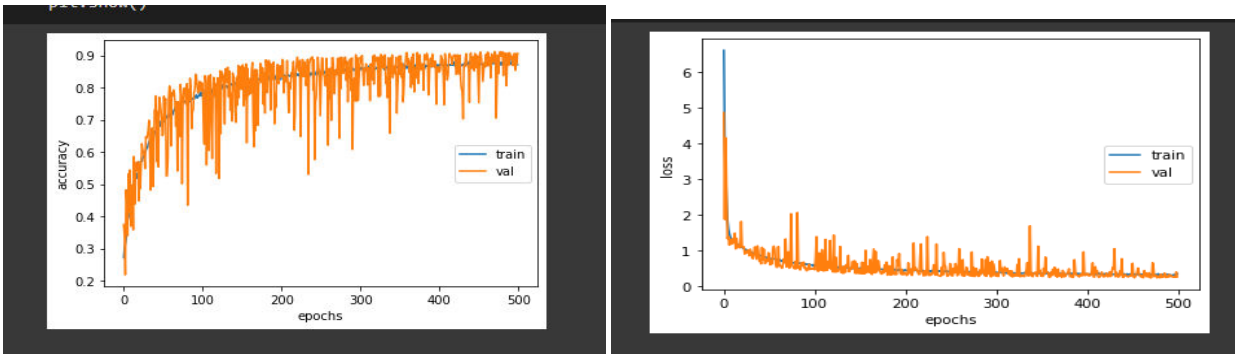

Figure 5.2: Training and Validation (Accuracy and Loss)

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VI. CONCLUSION AND FUTURE WORK

The main goal of this project is to identify and categorise the radiographic patterns of interstitial lung disease in CT scans as early as possible. To do this, we will consider five radiographic classes of lung tissues, including normal tissues, the five interstitial characteristics, and their subtypes. We used a TALISMAN benchmark dataset that is openly available to classify Diffuse Lung illnesses. Emphysema, micro-nodules, fibrosis, and healthy patches were all represented by 103 two-dimensional labeled sections. From those annotated ROIs, 14,356 overlapping patches with a size of 32 * 32 make up a diffuse pulmonary illness pattern. Here, the VGG16 framework has been applied. Emphysema, ground-glass fibrosis, micro nodules, emphysema, and fibrosis patches were used to classify five different forms of diffuse lung illnesses, and the accuracy was 0.90, respectively.Five classes of a network were trained. The system with the aforementioned accuracy rates was then trained using a small sample of input images, and it successfully categorised the Interstitial Lung disease categories. Finally, we could state that by utilising the VGG16 architecture, the suggested model had successfully achieved 0.90 percent accuracy in categorising the five categories of diffuse lung diseases.

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