Interstitial Lung Disease Classification using Transfer Learning Pre-trained Deep Neural Network

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DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING
Dr. B.C. ROY ENGINEERING COLLEGE, DURGAPUR, WB.

DECLARATION

We, the undersigned, hereby declare that our B.Tech. final year Project entitled "**Interstitial Lung Disease Classification Using Transfer Learning Pre-trained Deep Neural Network**" is original and is our own contribution. To the best of our knowledge, the work has not been submitted to any other Institute for the award of any degree or diploma. We declare that we have not indulged in any form of plagiarism to carry out this project and/or write this project report. Whenever we have used materials (data, theoretical analysis, figures, and text) from other sources,we have given due credit to them by citing in the text of the report and giving their details in the references. Finally, we undertake the total responsibility of this work at any stage here after.

Signature of the Students

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RECOMMENDATION

This is to recommend that the work undertaken in this report entitled, "**Interstitial Lung Disease Classification Using Transfer Learning Pre-trained Deep Neural Network**" has been carried out by "**D Mohit, Binoy Kumar Mondal, Ashish Raj, Arunava Kirtan**" under my/our supervision and guidance during the academic year 2021-22. This may be accepted in partial fulfillment of the requirements for the award of the degree of Bachelor of Technology (Computer Science and Engineering).

____

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APPROVAL

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Board of Examiners

DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING
Dr. B.C. ROY ENGINEERING COLLEGE, DURGAPUR, WB.

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With great pleasure and deep sense of gratitude, we convey our indebtedness to our respected teacher (**Prof. Sanjib Saha)** for his inspiring guidance, constructive criticism and valuable suggestions throughout the project work.

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CHAPTER 1

ABSTRACT

Interstitial Lung Disease (ILD) is a whole term used to express various variations of lung diseases that harm humans. Due to the trouble of classifying ILD, analyzing the type of ILD from CT images by radiologists is very time consuming. To excite the detection, Computer-Aided Diagnostic (CAD) technology has been built. In this project, one such method that relies on Convolutional Neural Networks (CNN) is introduced to detect ILD from CT scans images. We explored how a pre-trained neural network compares to a domain-specific neural network. We introduced various approaches to improve a CNNs capability in categorizing ILD and observed how our CT images influence the capability for all the models. The **test accuracy** on 4 types ILD detection (**Pulmonary Fibrosis**, **Hypersensitivity Pneumonitis**, **Tuberculosis**, and **Healthy**) on **DenseNet121**, **VGG16**, **InceptionV3**, **Xception**, **ResNet50**, and our **own CNN** model are **82%**, 75%, 68%, 65%, 34%, and 34% respectively. The best validation and test accuracy are achieved by **DenseNet121.**

CHAPTER 2

INTRODUCTION

Interstitial lung disease recites a broad group of diseases, most of them are the reason for cumulative damage of lung tissue. The damage is collaborated with interstitial lung disease which reduces one's lung's capability to inhale and get adequate oxygen into one's alveoli. Interstitial lung disease occurs by working with or around asbestos, coal dust, cotton dust, and silica dust (called occupational lung disease).Many category of auto-immune diseases, such as rheumatoid arthritis, also can develop interstitial lung disease. In very few cases, however, the reason remains unrevealed.Once lung infection starts, it's commonly not reversible. Medicines may sluggish the infection of interstitial lung disease, but numerous patients have never recovered full usage of their lungs. Patients who have interstitial lung disease Lung transplant is a last option for them.

In a recent survey it was published that on an average 80 per 100,00 male experience hardship from ILD while 67 per 100,00 female experience hardship from ILD in India [1]. On present-day the rates of new cases of 31.5% for male and 26.1% for female are contributed per year and the numbers are actually raised for COVID-19 cases.

The medical experts have created and published the MedGIFT dataset, which comprises branded sections in computed tomography (CT) scans.The ILD MedGift data set contains CT images of 103 Patients and 14 different types of ILDs are associated with them.

The identification of an ILD requires asking the patient about their clinical history.The conventional way to detect ILDs is to take a chest CT scan image and consult with a doctor or a radiologist for detection of various ILDs.The Most common ILDs are reticulation, honeycombing, ground glass opacity, Consolidation, micronodules etc.In some less number of incidents correct detection cannot be assured radiologically. Although the nature of all ILDs belongs to the same type.Their HRCT images are very similar to each other so identification of critical features of a CT images is very strenuous for expert doctors and experienced radiologists and also the pressure of work where radiologists have to scrutinize multiple patients CT images, X-Ray images etc.. The mistake could happen very easily and many patients could suffer from this mistake. Which is estimated as close as 50%. To abate these mistakes CAD (computer aided diagnosis) [3] system is introduced.

It is comprised of three stages:
Lung segmentation
Lung disease quantification
Differential diagnosis
The first part mentions how to identify the lung boundary.The second part mentions identification and validation of the various tissue disorders and also predicts their spread in the lung.The third part aggregates the results and indicates a probable type of ILDs.

This project analyzes and inspects how to use a Convolutional Neural Network (CNN). which is one of the popular deep neural networks for multilayer image classification.Here we will use DenseNet (a reputed and trusted pre trained CNN model) for detection of various ILDs and we will identify the patient who has been infected with a particular ILD and this earlier detection of particular ILD may lead to more cures or longer survival. This possibility has led to public health programs which recommend populations to have periodic screening examinations for detecting specific chronic diseases, for example, cancer, cardiovascular disease and so on.

A. Convolutional Neural Networks

Convolutional Neural Network is a well-known Deep Learning algorithm which takes an image as an input and allocates priority (biases and learnable weights) to different objects/aspects in the input image and they are able to do classification one image from the other image. The pre-processing necessary in a Convolutional Neural Network is much lesser as compared to other categorization algorithms. While in archaic techniques patterns are hand invented, with adequate training, Convolutional Neural Networks have the capability to detect these patterns and characteristics.

Convolutional neural networks are prominent from various other neural networks

By their state of the art capability with input image, voice or frequency signal inputs.

They have three main category of layers :

- Convolutional layers
- Pooling layers
- Fully connected layers

The blueprint of a convolutional neural network is resembling that of the connected design of Neurons in the Human Brain and was motivated by the institution of the Visual Cortex. particular neurons respond to stimuli only in a confined area of the optical field known as the Receptive Field. A composition of such areas overlaps to shield the complete optical region.

A path to instinctively understand CNNs in that way: The first few layers extract the elementary features of the input image and the denser the network goes the complexity also increases accordingly.In this stage pooling and convolutions layers assist to extract texture and dimensions.

The pre final layers assign weights to all the extracted textures to determine the critical features which are required for image classification.

The final layer is the output layer that outputs the predicted assumption along with their accuracy.

The reason why CNN is largely famous is because of their building design. The excellent thing is there is nothing required for feature extraction [4]. The model learns to do feature extraction and the main objective of CNN is, it uses convolution of the input image and filters the image to generate unique features which are passed onto the next layer as an input. The features in the next layer are convoluted with various filters to generate more unique features and the procedure carry on till one gets the final feature (let say face of Y) which is unique to obstruction.

Also, another key attribute is that dense convolutional neural networks are capable and work properly on input images. As one researchist finds out, convolutional dense layers take advantage of the fact that an excellent filter can resurrect anywhere in the region of the input image, and regions are adjacent blocks of the pixel. But one of the major objectives why researchers are augmented about deep neural networks is the potential for the network to adopt necessary features from immature data. Now, convolutional networks can identify important patterns from the images, reducing the necessity of ancient manual image processing techniques.

Premiere tech companies created their custom made CNNs according to their needs. The custom made CNNs are trained on state of the art CPU and GPUs with the dataset that contains millions of images such as “ImageNet” that comprises 1.2 millions images. The pretrained CNNs used for this project are DenseNet, InceptionV3. All the networks are provided by the keras library [6] that were pre trained on “ImageNet”.

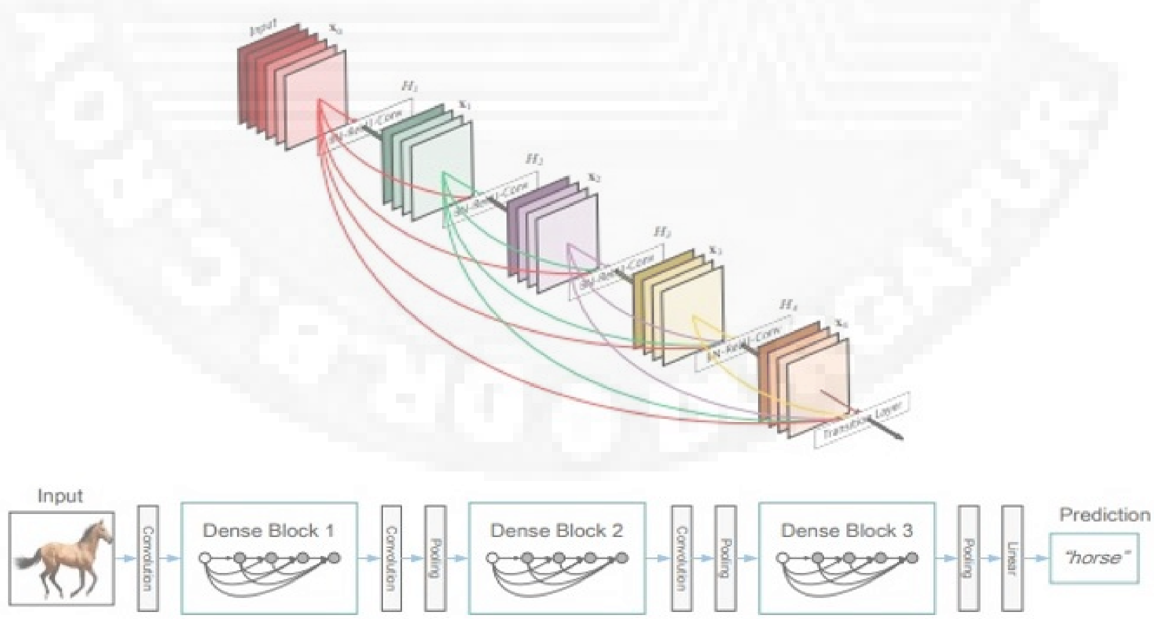


Figure 1: Various blocks and layers in DenseNet (Source: Original DenseNet paper)

CHAPTER 3

METHODS

A. TRANSFER LEARNING

The limitation of image classification in the medical field is that there is not a very good scope to collect adequate images to train our model so we opt for a method which is called transfer-learning [2]. It is a very good option for fixing the issue of less images to train our model.The method of Transfer learning is an extension that consents significant advancement or elevated execution when modeling is the secondary task.

It is a well-known direction in the field of deep learning where pre-trained models are utilized as the inception point on computer visualization and natural voice processing works given the huge enumerate and time required building a deep neural network model on these hurdles and from the big jumps in proficiency that they come up with related objectives.

Typically so-called pre-trained models were trained on a relatively large standard dataset.

Steps to train our pre-trained model

Select a Source Model. A trained source model is selected from obtainable trained models. Many major tech giants release models on huge and various mix datasets that may be added in the combination of trained models from where to choose them.

Reuse Model. The pre-trained model can be used as the inception point for a trained model on the secondary task of interest. This may include exploiting all or features of the trained model, relying on the modeling method used.

Tune Model. Electively, the pre-trained model may require accommodating or purifying on the input-output data obtainable for the work of interest.

Three examples of pre-trained models:

- DenseNet Model
- VGG Model [8]
- Inception Model
- Xception Model
- ResNet Model [9]

This pathway is useful because the input images are trained on a huge collection of images and train the model predict on a comparatively different big number of classes, severally keen on that the pre-trained model effectively learns how to identify patterns from images in order to predict well on the class.It makes sense to share such models because

1. They are reputed and thus useful to a wide range of researchers.
2. The training duration is non-significant on the normal user's computer.
3. most of the task is particularly the identification of patterns, ordering and pre-processing
4. using the same dataset makes the results repeatable and comparable.

Training a pre-trained model for this project transforms this model into our objective specific makes this model more useful.Transfer learning is done by replacing the classification layer with the untrained layers in the model.

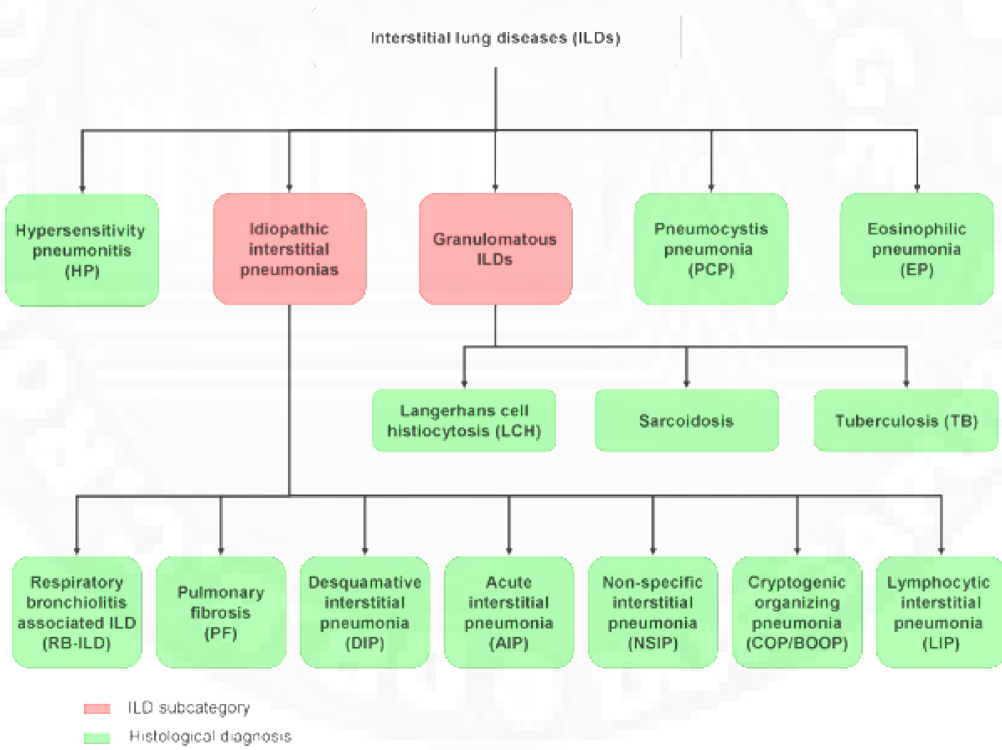
Our model consists of two fully connected layers and we have added 1024 dense layers with activation function “relu” along with one dropout layer. In the final stage our model has 4 different types of outputs with “softmax” activation function.

CHAPTER 4

DATASET

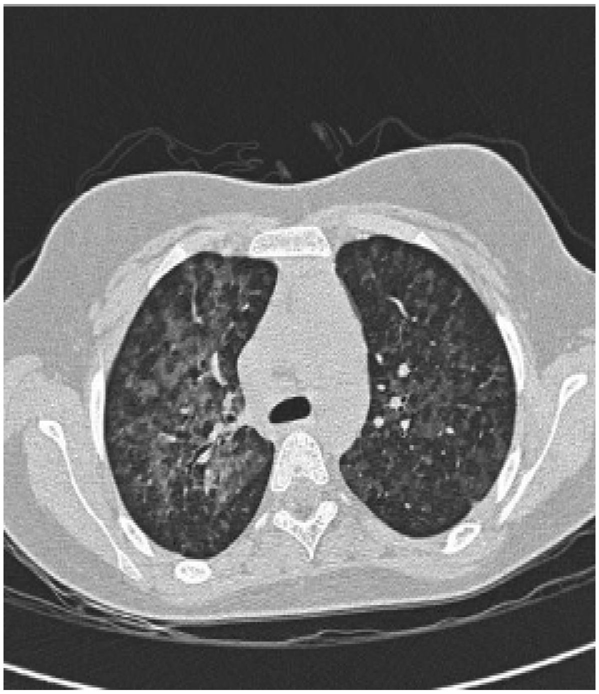
In this project we used ILD MedGIFT dataset to perform the detection.

The ILD MedGift data set contains CT images of 103 Patients and total 14 different types of ILDs are associated with them.In below figure different types of ILDs are classified-



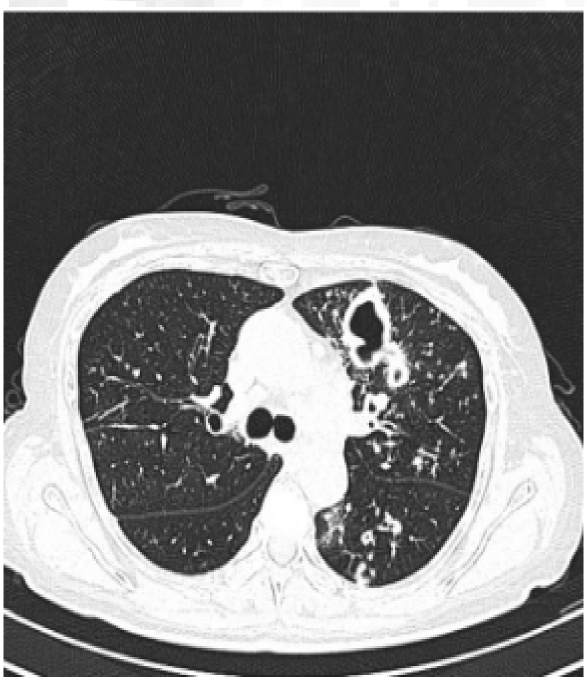
We have chosen 4 ILDs and selected the best CT images of those ILDs.Those ILDs are a) Hypersensitivity Pneumonitis, b) PulmonaryFibrosis, c)Tuberculosis., d)Healthy.

In below figure some different types of CT images of ILDs are presented

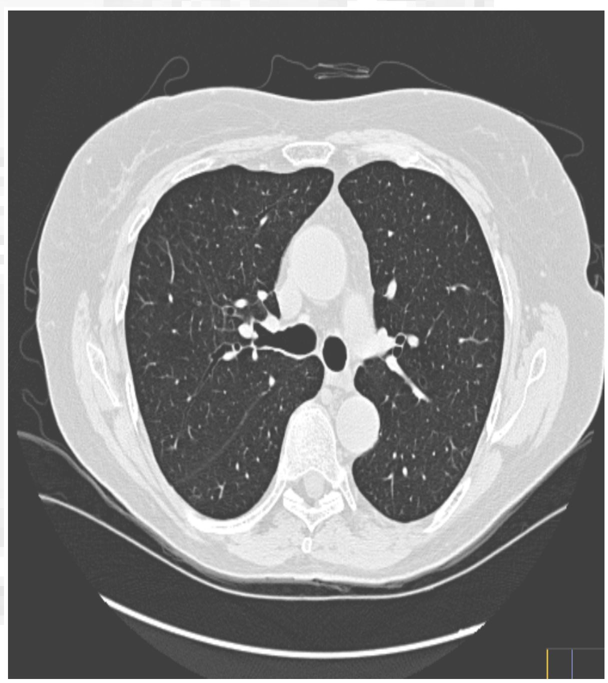


a)Hypersensitivity Pneumonitis

b) Pulmonary Fibrosis



c)Tuberculosis



d) Healthy

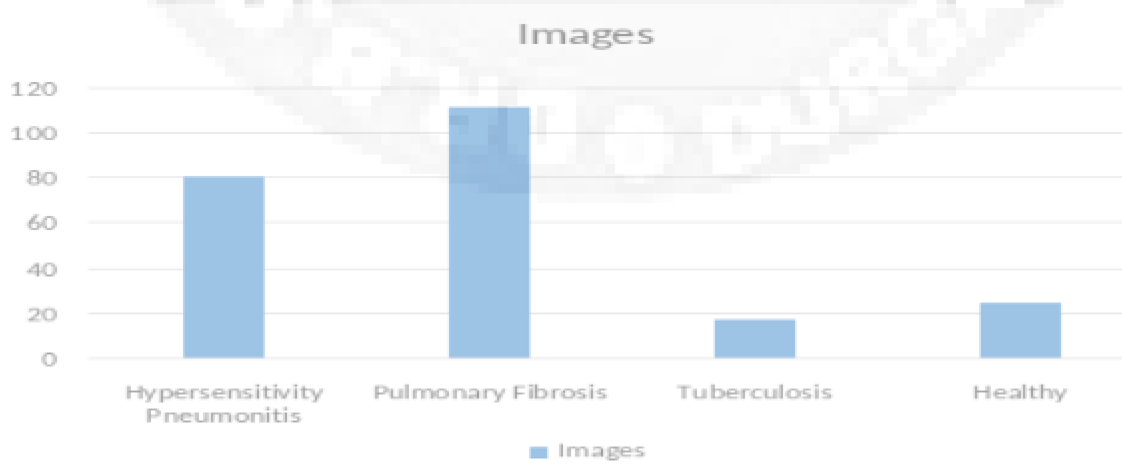
Input images for this project mainly use 235 HRCT lungs images. All of these images are taken from the MedGift data-set. It meant to be used by the researcher or engineers.These project solely focuses on interstitial lung disease detection.This data-set has 14 types of ILDs [5] and we selected 4 different types of ILDs.The total number for all of the HRCT image number with its corresponding category is shown on the below table:

No.	Category of ILD	images
a	Hypersensitivity Pneumonitis	81
b	Pulmonary Fibrosis	112
c	Tuberculosis	18
d	Healthy	25

A. Image Extraction

Our pre-trained CNN model DenseNet takes RGB images as input.So, we have to provide our input as DenseNet takes. Every image was in the shape of 512x512x1.All the images are converted in the shape of RGB.Our model performed better when it was reshaped into 224x224x3.

The ultimate dataset was created from the CT images of 4 categories with 35 patients and a total 236 images.



CHAPTER 5

EVALUATION

The performance of our CNN models could be unfavorably affected by data imbalance. Where the number of images of various classes hugely varies. To fix this data imbalance issue oversampling is used.

Validation accuracy was added with training sessions to observe our model's capability.The validation method Leave One Group Out (LOGO) was used to train our pre-trained model.Every disease is considered as a label.This assures only data specific to the disease is used for the training.

We have removed some patients from the extracted dataset so that we can assure that our model is not patient specific rather than disease specific.

After the training is finished then we will use the removed patient's photo to test the accuracy of our model regardless of any patient.

CHAPTER 6

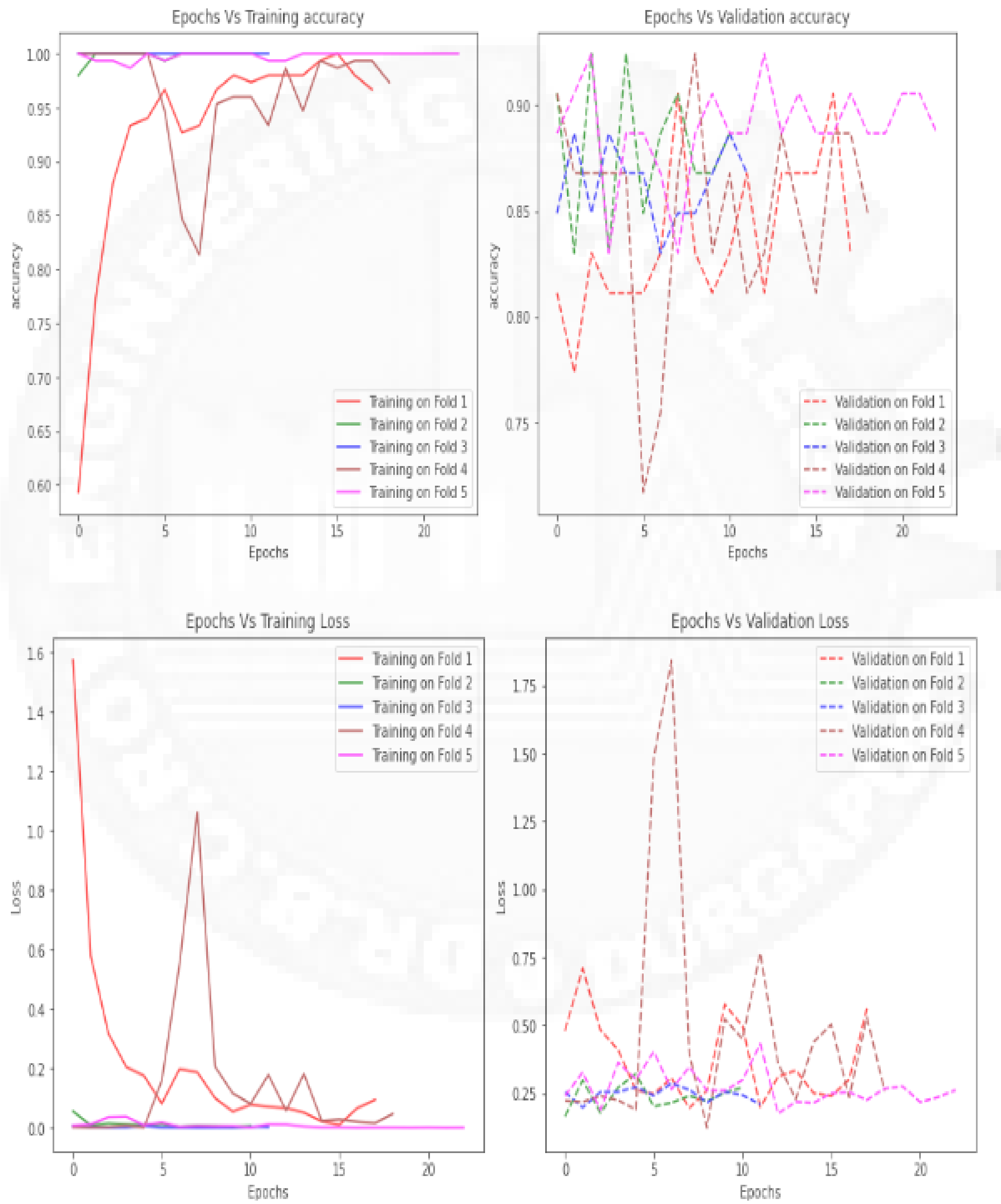
RESULTS

A. Validation Accuracy Results

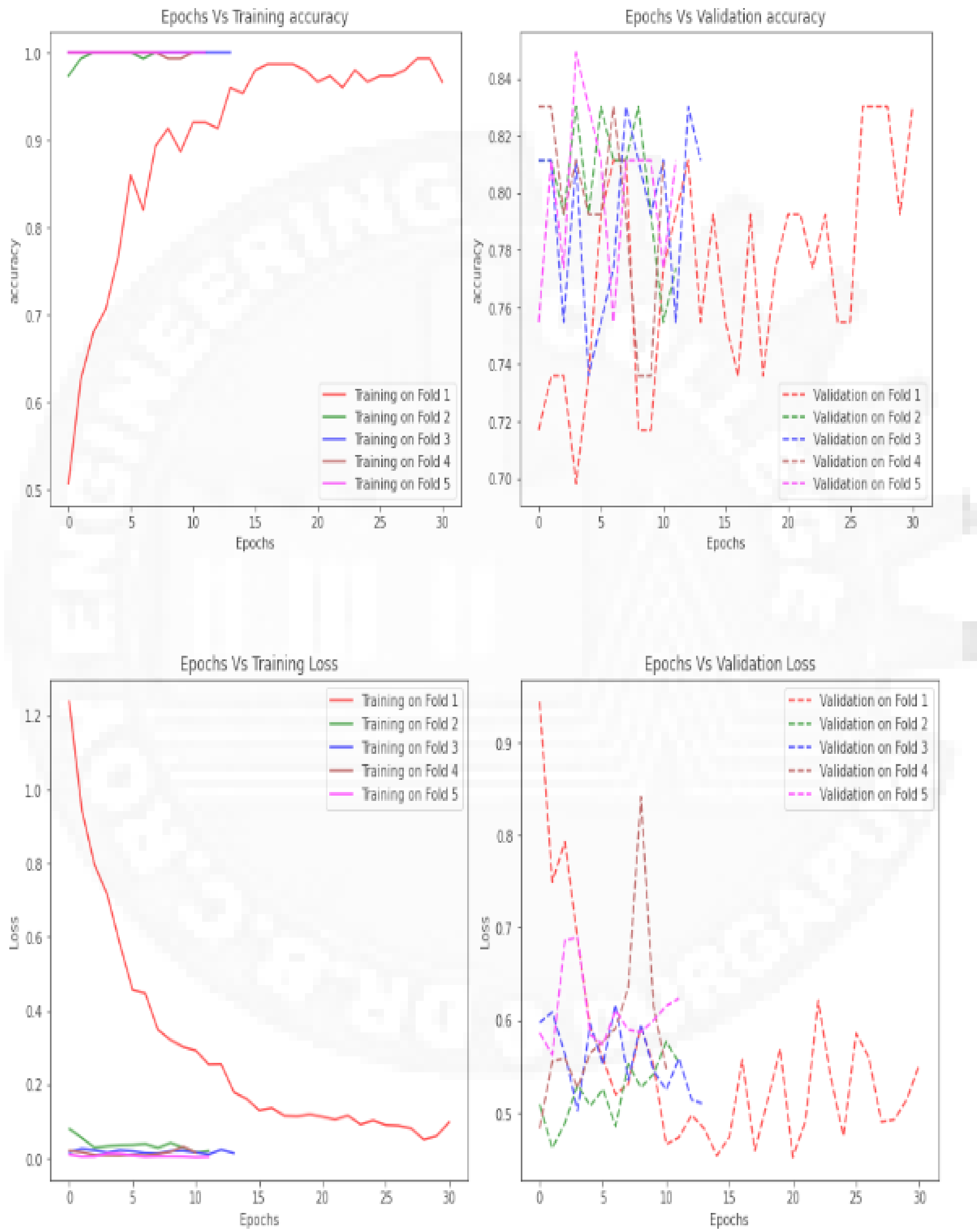
	VALIDATION ACCURACY				
	DENSENET121	VGG16	INCEPTION V3	XCEPTION	RESNET50
FOLD 1	0.83	0.83	0.79	0.86	0.49
FOLD 2	0.88	0.77	0.79	0.79	0.49
FOLD 3	0.86	0.81	0.83	0.79	0.49
FOLD 4	0.84	0.81	0.81	0.79	0.49
FOLD 5	0.88	0.81	0.79	0.75	0.49
AVERAGE	**0.85**	0.80	0.80	0.79	0.49

B.GRAPH RESULTS

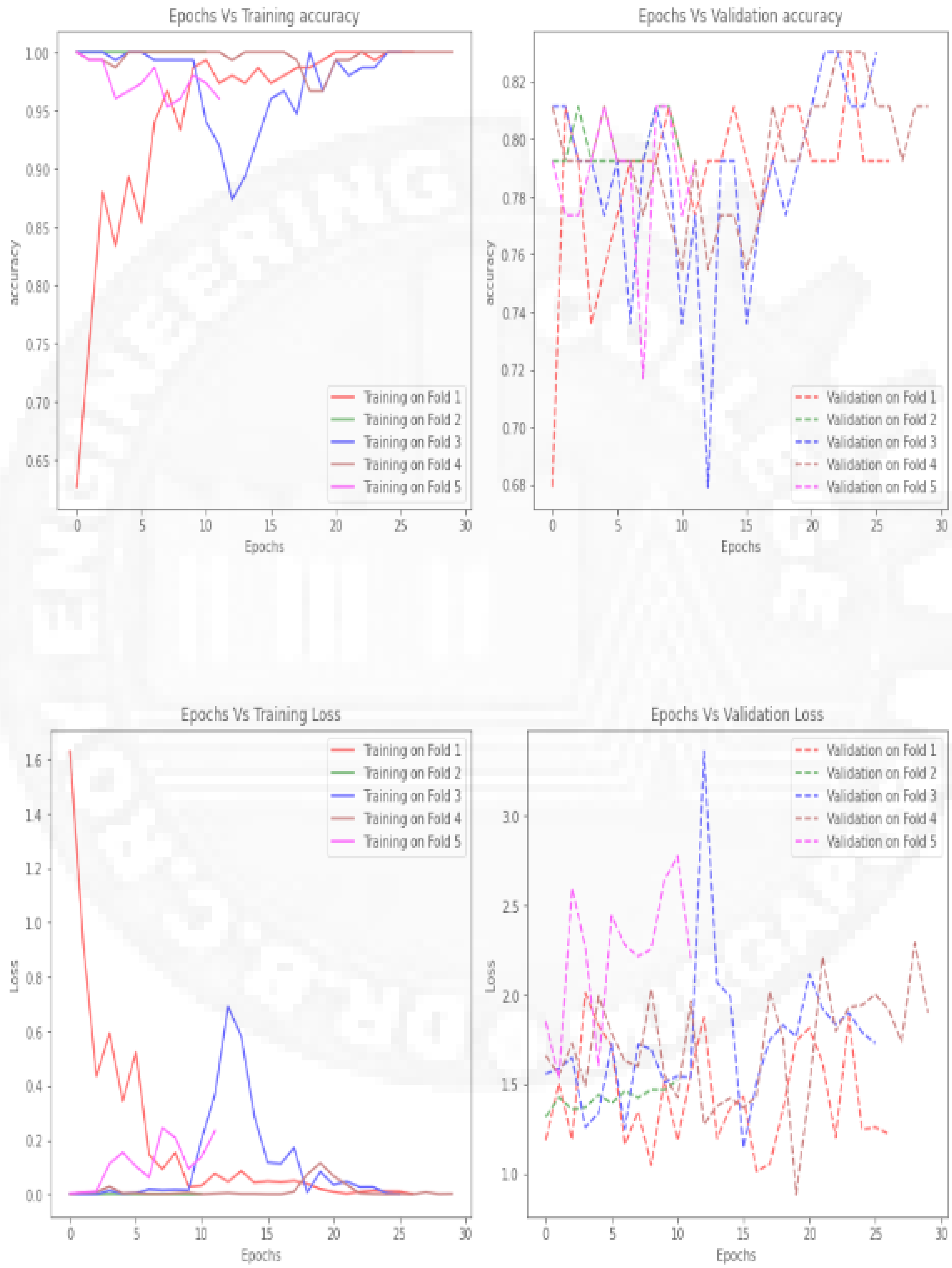
- **DenseNet121 Graph Result**



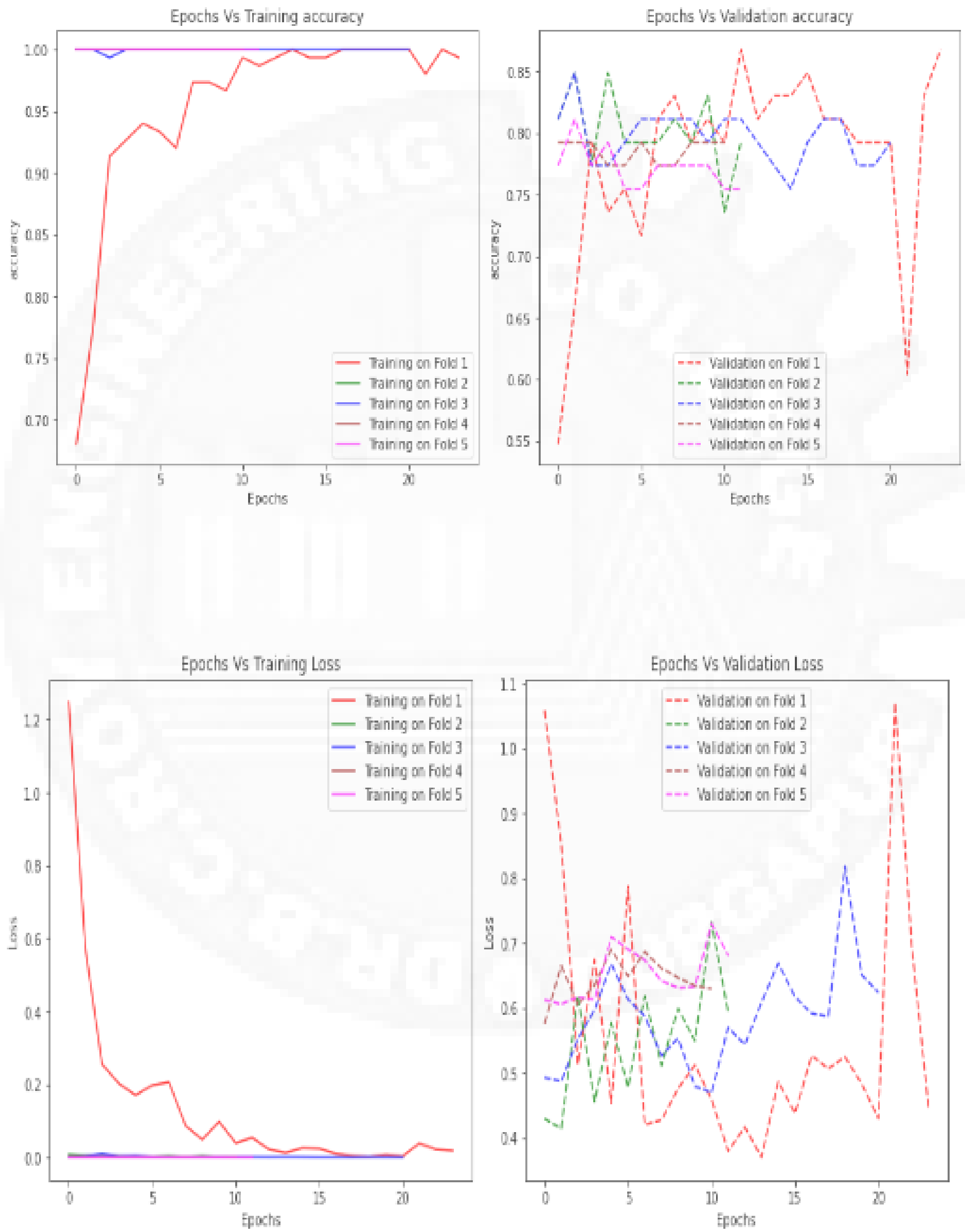
- ## VGG 16 Graph Results



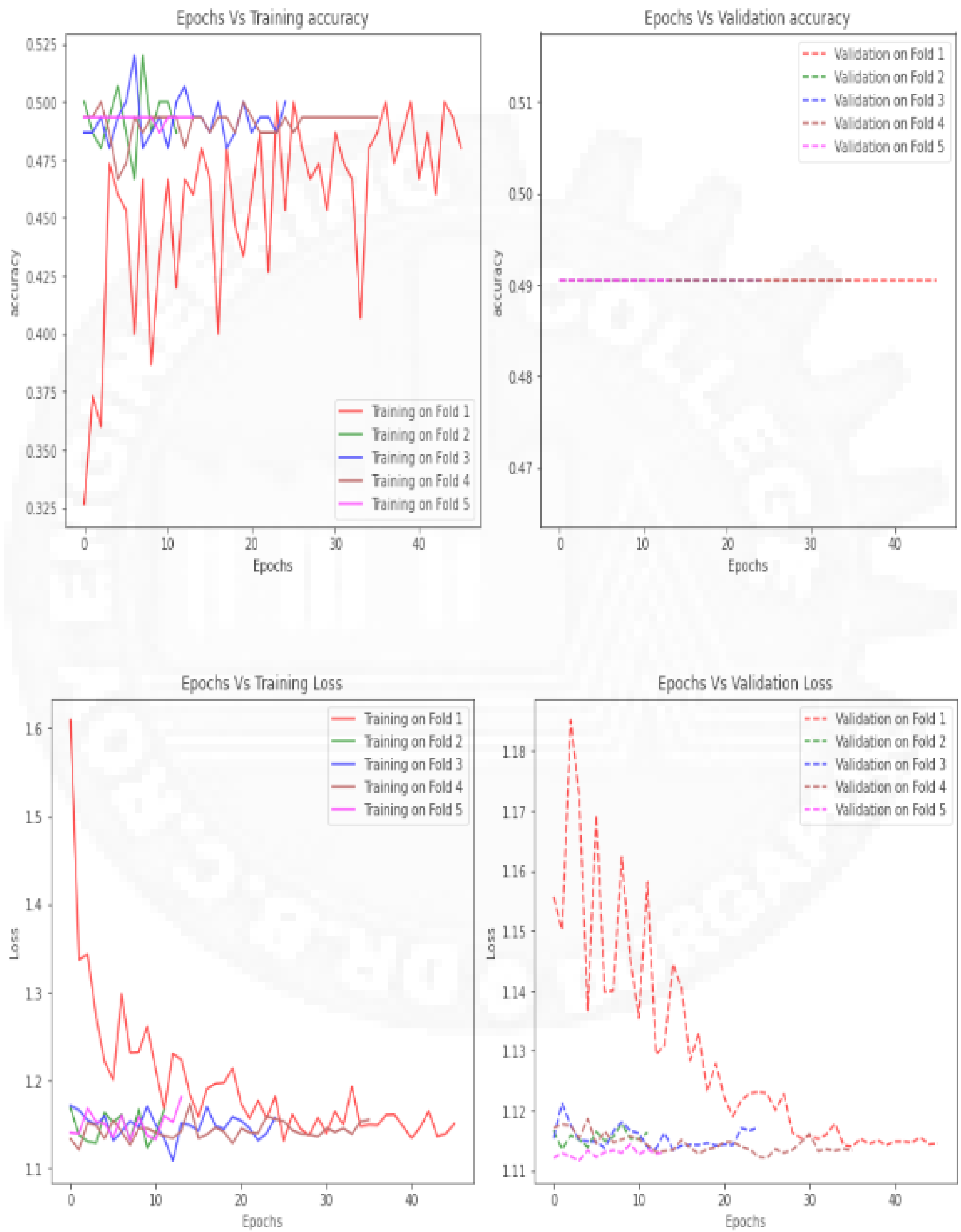
- **Inception V3 Graph Results**



- **Xception Graph Results**



- **ResNet Graph Results**



C.Test Results

	ACCURACY	SENSITIVITY	SPECIFICITY
DENSE NET	**0.82**	**0.71**	**1.0**
VGG16	0.75	0.57	1.0
INCEPTION V3	0.68	0.42	0.70
XCEPTION	0.65	0.0	1.0
RESNET50	0.34	nan	nan

D.Confusion Matrix

CONFUSION MATRIX

H = Healthy; PF = Hypersensitivity Pneumonitis;

HP = Pulmonary Fibrosis; TB = Tuberculosis

- DENSENET121

Predicted/True	H	HP	PF	TB
H	5	2	0	0
HP	0	10	0	0
PF	0	0	9	0
TB	0	3	0	0

- VGG16

Predicted/True	H	HP	PF	TB
H	4	3	0	0
HP	0	8	1	0
PF	0	0	10	0
TB	0	3	0	0

- INCEPTION V3

Predicted/True	H	HP	PF	TB
H	3	4	0	0
HP	3	7	0	0
PF	0	0	10	0
TB	1	1	0	0

- XCEPTION

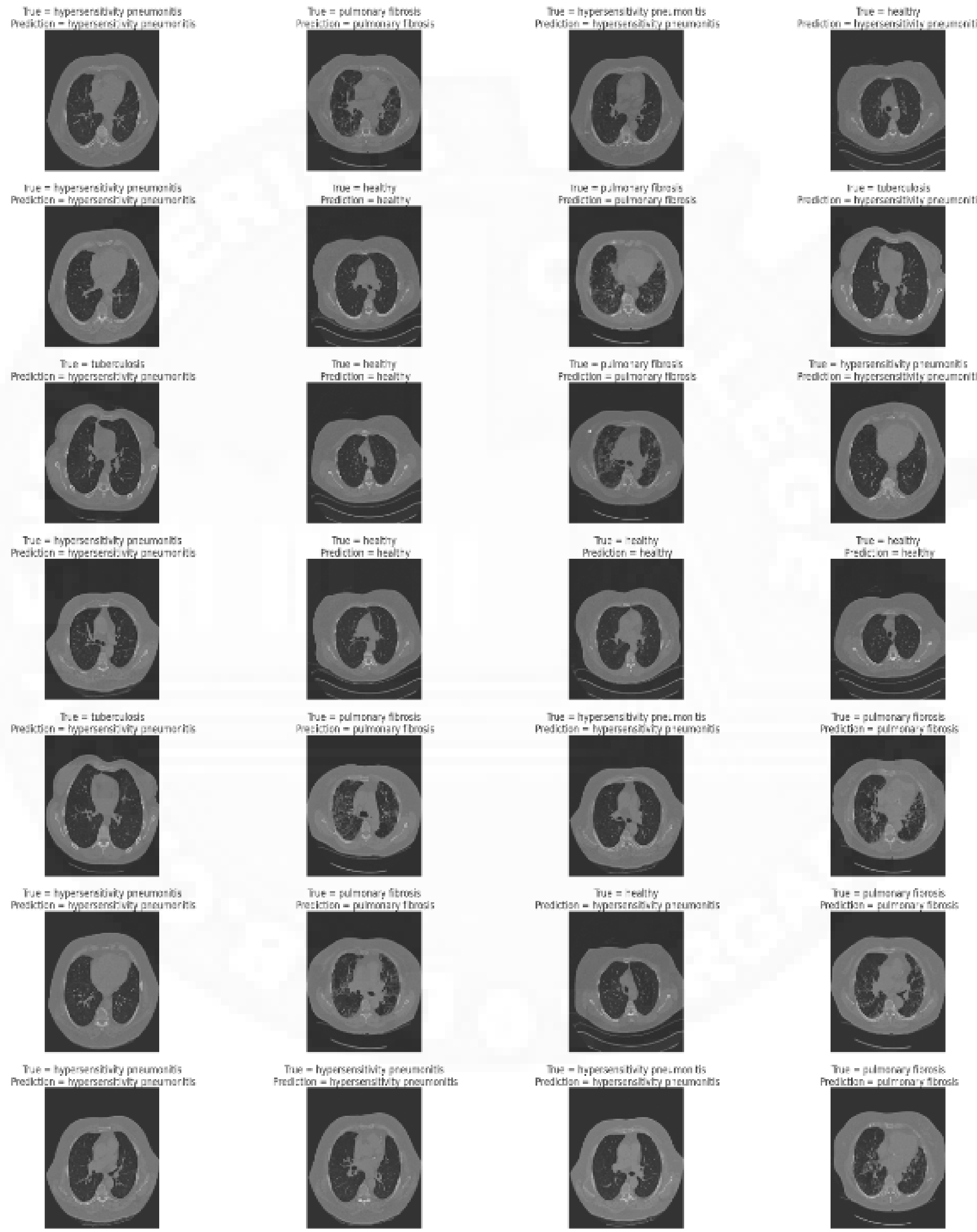
Predicted/True	H	HP	PF	TB
H	0	3	2	1
HP	0	9	1	0
PF	0	0	10	0
TB	0	3	0	0

- RESNET50

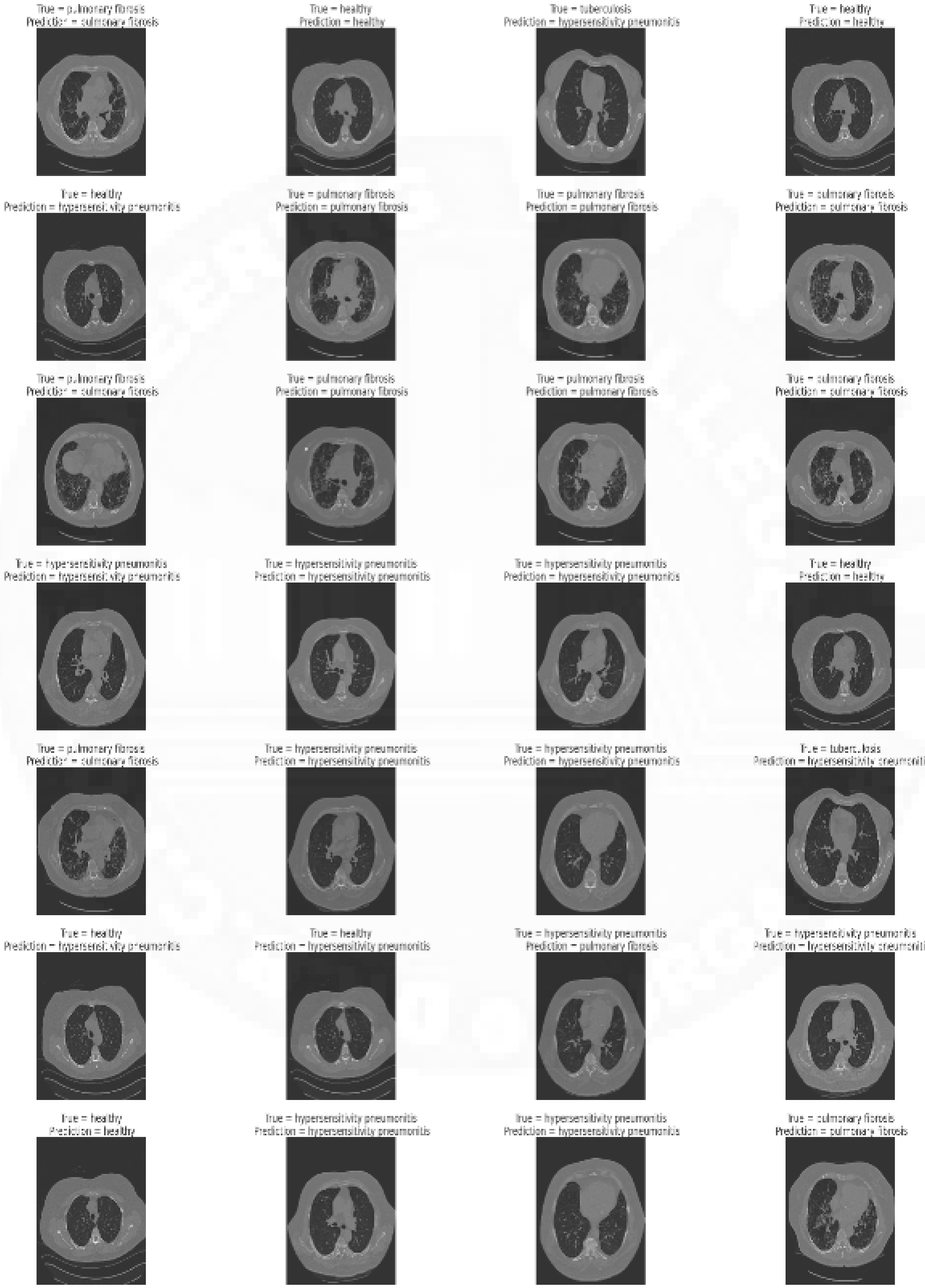
Predicted/True	H	HP	PF	TB
H	0	0	7	0
HP	0	0	9	0
PF	0	0	10	0
TB	0	0	3	0

E.Test Prediction and Grid Result Output

- DENSENET121



- VGG16


True = pulmonary fibrosis
Prediction = pulmonary fibrosis
True = healthy
Prediction = healthy
True = tuberculosis
Prediction = hypersensitivity pneumonitis
True = healthy
Prediction = healthy
True = healthy
Prediction = hypersensitivity pneumonitis
True = pulmonary fibrosis
Prediction = pulmonary fibrosis
True = pulmonary fibrosis
Prediction = pulmonary fibrosis
True = pulmonary fibrosis
Prediction = pulmonary fibrosis
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True = pulmonary fibrosis
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Prediction = hypersensitivity pneumonitis
True = pulmonary fibrosis
Prediction = pulmonary fibrosis

- INCEPTION V3

- XCEPTION


True = healthy
Prediction = hypersensitivity pneumonitis
True = hypersensitivity pneumonitis
Prediction = hypersensitivity pneumonitis
True = hypersensitivity pneumonitis
Prediction = hypersensitivity pneumonitis
True = tuberculosis
Prediction = hypersensitivity pneumonitis
True = hypersensitivity pneumonitis
Prediction = hypersensitivity pneumonitis
True = pulmonary fibrosis
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Prediction = pulmonary fibrosis

- RESNET50


True = hypersensitivity pneumonitis
Prediction = pulmonary fibrosis
True = healthy
Prediction = pulmonary fibrosis
True = healthy
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True = healthy
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True = pulmonary fibrosis
Prediction = pulmonary fibrosis
True = pulmonary fibrosis
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Prediction = pulmonary fibrosis

CHAPTER 7

CONCLUSION

In this project, we introduced a deep Convolutional Neural Network to detect various ILDs. The network consists of 1024 layers with 2X2 filters and ReLU activations, followed by average pooling,The training was performed in the loss function called sparse_categorical_crossentropy with the Adam optimizer. The introduced method gave outstanding results, well performed on a very challenging dataset of 285 CT scan images from different hospitals and scanners. All the 5 models have fluctuation of the results, for the same input, due to the random initialization of the weights. In future times, we plan to improve our models accuracy.

CHAPTER 8

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