# Summer Project

Ashutosh Kaushik (ICM2017002), Arya Krishnan (ICM2017501), Priyal Gupta (IHM2017004)

Under the guidance of: Prof. Pavan Chakraborty

**Lung Inflammation Detection**

## Problem statement :

Lung inflammation Detection using different Convolutional neural network architectures and a comparison of their performances. Presenting a qualitative analysis of the limitations and advantages of each of them in the field of medical imaging.

## Background :

Recently deep learning and AI have had widespread popularity in the field of medical diagnostics and research.

In the paper by Giang et al.[4], they discuss the drawbacks of manual examination of CT scans by a radiologist, then they discussed how CADs (computer-aided diagnosis system) work to classify nodules as benign and malignant. The advantages of CNN and its success in object detection is discussed. Their main objective is to boost the performance of CADs using a new 2D CNN architecture with the focal loss. They have also shown why CNN with focal loss is better for nodule detection and will help in the improvement of CADs.They are using the LIDC-IDRI data set, to classify nodules in the CT image. They have used three metrics that are sensitivity, accuracy, and specificity. LIDC dataset changes frequently still they got better sensitivity with above-average accuracy and specificity. Finally, they concluded that using 2D CNN with focal loss can improve the quality of CADs classification.

In the paper [5] the authors use four variations of a 3D CNN on a subset of the LIDC-IDRI dataset to classify detected nodules as benign or malignant. The subset they use contains only 147 scans so they use transfer learning. This is a common way to improve the performance of a network on a smaller dataset by using a pre-trained network on a similar but often larger dataset in this case the LIDC-IDRI. They also observe that dense connections or fully connected layers among convolutional layers benefit optimization. They achieve an accuracy of up to 86.84% directly working on 3D images which they argue yields better results for the lung nodule classification problem.

This paper [6] proposes a novel deep learning-based model with different strategies for the proper detection of benign and malignant lung nodules. The model consists of two three dimensional customized mixed link network architectures for detection and classification. RCNN was used for performing detection of lung nodules and the classification was done by a gradient boosting machine(GBM) on the features learned from the mixed link network. Also, false positives and misdiagnosis were reduced by considering physiological symptoms for the final decision. The dataset used was the LIDC-IDRI dataset and an accuracy of about 88.79% was achieved while working on the mixed network.

## Motivation :

Pneumonia is a life-threatening lung inflammation disease caused by viral or bacterial infection of the lungs. Early diagnosis is vital for efficient treatment. When detecting Lung Inflammation, CT scans are analyzed. The CT screening of millions of people puts a huge burden on radiologists and manual detection may be faulty. Hence recent efforts are to come up with an algorithm to automatically detect risks with professional accuracy.

AI has the potential to review an immense amount of images and diagnose cases difficult for human experts. Since deep learning models are always data-hungry, one way is to use the technique of transfer learning, especially when faced with a lack of labeled data in the given domain. Instead of training from scratch, the model can use the findings from a similar domain as initialization for further fine-tuning.

## Objectives :

In this study, we will try to get a CNN to achieve the same level of performance on a small dataset that it would on a large dataset. We will employ the method of transfer learning using pre-trained architectures on ImageNet along with also trying different optimizers, initialization techniques, and addition of dropout and batch normalization layers to achieve optimal learning. We will use five different models and analyze their relative and absolute performances.

## Methodology :

We will be using the Kaggle dataset Chest X-Ray Images (Pneumonia). The dataset is organized into 3 folders (train, test, val) and contains subfolders for each image category (Pneumonia/Normal). There are over 5,000 X-Ray images (JPEG) and 2 categories (Pneumonia/Normal).The training set: Images we're going to train the neural network on. The validation set: Images we're going to use to check if the model is underfitting or overfitting. The test set: These are images we're going to use to check how good our neural network is with data it has not seen before.

- 5216 images belonging to 2 classes in the training set.
- 16 images belonging to 2 classes in the validation set.
- 624 images belonging to 2 classes in the test set.

Preprocessing and data augmentation have been performed. For our train, validation, and test sets, we will zoom the image randomly by a factor of 0.2, Rescale pixel values to 0 to 1, randomly flip half the images horizontally and vertically, and apply shear based transformations randomly. We will run all models for 326 steps per epoch (number of batches per epoch) with a batch size of 16. The networks are evaluated on their Accuracy measure and Binary Cross-Entropy loss.

In the first experiment, we train a Simple CNN with Default initialization, No Padding, No Dropout, and No Batch Normalization for 10 epochs.

In the second experiment, we train the simple CNN modified with He initialization, Padding added of size 1 on each side, Adam optimizer, Dropout, and Batch Normalization. Since dropout allows training for more epochs without overfitting we run the training for 16 epochs. resnet50,InceptionV3 and VGG16 are often used in Transfer Learning in the medical field, pretrained on ImageNet as a feature extractor.

In the third, fourth and fifth experiments, we fine-tune the pretrained ResNet50 architecture [1], InceptionV3 architecture [2] and the VGG16 architecture [3]. We will run each for 16 epochs. The optimizer used is the Stochastic Gradient Descent optimiser with a learning rate of 1e-4. Each is then fine-tuned using the SGD optimizer to fit the given data distribution. We have also added a Global Pooling, Dense and sigmoid activation layer for the purpose of binary classification to each of the networks.

## References:

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