CSE 674 ADVANCED MACHINE LEARNING PROJECT

Detection of COVID-19 from CT images using Deep Convolutional Neural Network Design

Team members:

CONTENTS

MOTIVATION

- Covid19 continues to have a significant impact on patients and healthcare systems worldwide
- CT scan, key screening method used as a complement to RT-PCR testing
- CT based screening reported abnormalities in the chest CT images
- These abnormalities may be difficult to distinguish from abnormalities caused by Covid19 and other lung conditions

AIM

To design a deep convolutional neural network architecture that is tailored to detect Covid19 cases from chest CT images using DenseNet-161 architecture that classifies the given data into three categories: 'Normal', 'Pneumonia' and 'COVID-19'.

DATASET

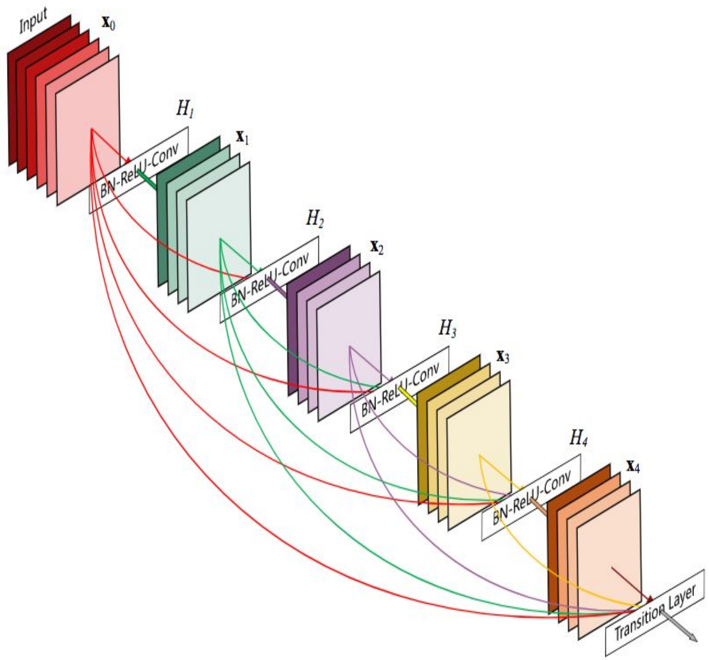
- Dataset used was **COVIDx-CT**
- Its an open-access benchmark dataset that was generated from open-source datasets
- Currently, it comprises of 104,009 CT slices from 1,489 patients
- It consists of three splits:
  - Training - 82,286
  - Validation - 35,996
  - Testing - 25,496
- The CT scans are classified into three categories: *'Normal'*, *'Pneumonia'* and *'COVID-19'*

DATA PREPARATION

- Processed the images of CT scans by performing standard normalization, gray scaling and resizing
- The training dataset was augmented with random rotation and random horizontal and vertical flipping
- The dataset needed to be resampled and balanced as the samples were not uniformly distributed in the three label categories

MODEL ARCHITECTURE

- The architecture used was DenseNet-161
- It connects each layer to every other layer in a feed-forward fashion (L(L+1)/2 direct connections).
- Traditional convolutional networks with L layers have L connections i.e one between each layer and its subsequent layer
- Input of a layer is the connection of feature maps from previous layer



DenseNet ADVANTAGES

- They alleviate the vanishing-gradient problem
- Strengthen feature propagation
- Encourage feature reuse
- Substantially reduce the number of parameters

IMPLEMENTATION DETAILS

- Hyper-parameters
  - growth_rate = 32
  - block_config = (6, 12, 24, 16)
  - num_init_features = 64
  - bn_size = 4
  - drop_rate = 0
  - epoch = 3

- Optimizer = Adam Optimizer
- Loss Function = Cross Entropy Loss
- Evaluation Metric : Confusion matrix, precision, recall, F1 score

OPTIMIZATION TECHNIQUE

- Adam optimizer was used as the optimization technique for gradient descent of DenseNet.
- It adds to the advantages of Adadelta and RMSprop.
- No need to focus on the learning rate value
- Good with sparse data.

RESULTS

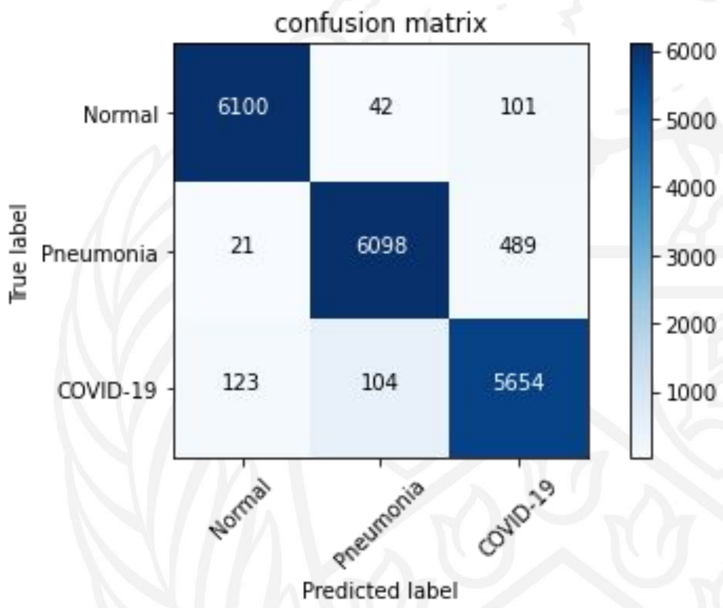
Validation total :

- Loss: 0.1855
- Accuracy : 95.30%
- All prediction accuracy : 95.3%

	Precision	Recall	F1-score
Normal	97.71	97.69	97.7
Pneumonia	92.28	97.66	94.89
Covid-19	96.14	90.5	93.26

MACRO-averaged:

- prediction= 95.38 %,recall= 95.3 %,f1= 95.34



ARCHITECTURE COMPARISON

- **Vgg16(Visual geometry group)**

	Precision	Recall	F1-score
Normal	91.82	94.14	92.97
Pneumonia	85.29	95.85	90.26
COVID-19	93.66	79.69	86.11

Best Accuracy:89%

- **Vgg19**

	Precision	Recall	F1-score
Normal	86.94	97.73	92.02
Pneumonia	83	95.84	88.96
COVID-19	97.73	70.48	81.9

Best Accuracy: 88%

ARCHITECTURE COMPARISON

- **Resnet101(Residual Neural Network)**

	Precision	Recall	F1-score
Normal	79.48	86.98	83.06
Pneumonia	74.17	89.81	81.24
COVID-19	91.31	91.31	63.44

Best Accuracy: 80%

- **Resnet152**

	Precision	Recall	F1-score
Normal	64.84	90.71	75.62
Pneumonia	71.27	74.89	73.04
COVID-19	86	47.31	61.04

Best Accuracy: 72%

ARCHITECTURE COMPARISON

- **Densenet161 (Dense Convolution neural network)**

	Precision	Recall	F1-score
Normal	97.71	97.69	97.7
Pneumonia	92.28	97.66	94.89
COVID-19	96.14	90.5	93.26

Best Accuracy: 95%

- **Densenet201**

	Precision	Recall	F1-score
Normal	86.94	97.73	92.02
Pneumonia	83	95.84	88.96
COVID-19	97.73	70.48	81.9

Best Accuracy: 91%

DISCUSSION

- In this study, we have introduced COVIDx-CT dataset using a deep convolutional neural network architecture tailored for detection of COVID-19 cases from chest CT images via densenet architecture.
- Furthermore, we analyzed the predictions of COVIDx-CT and classified into 3 categories to better understand the CT image features associated with COVID-19 infection, which may aid clinicians in CT-based screening.
- We have also compared with the existing modern architectures suited for image predictions.

FUTURE SCOPE

- While the proposed model is not yet suitable for clinical use, we aim to increase accuracy, so that it can be used by clinicians.
- The efficiency of model can be improved by increasing the amount of data. Also, the disease can be classified on the gender-based such that we can get information about whether male are affected more or females.
- More feature engineering can be performed for better results with the same deep learning approach.

REFERENCES

- Ai T, Yang Z, Hou H, Zhan C, Chen C, Lv W, et al. Correlation of chest CT and RT-PCR testing for coronavirus disease 2019 (COVID-19) in China: a report of 1014 cases. *Radiology*. (2020) 296:E32–40. doi: 10.1148/radiol.2020200642.
- Fang Y, Zhang H, Xie J, Lin M, Ying L, Pang P, et al. Sensitivity of chest CT for COVID-19: comparison to RT-PCR. *Radiology*. (2020) 296:E115–7. doi: 10.1148/radiol.2020200432.

THANK YOU