Task 1- Report

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The framework used- Pytorch

Data Preprocessing

The original dataset has 930 images with around 66% of the images being covid positive. However, the dataset was not very clean and many fields were empty. After cleaning up the data (detailed explanation is given in the comments of the code), I was left with 668 images which I split into a training set (90%) and validation/testing set (10%).

Defining the model

Model 1 (Not used)

1. As a first step, I decided to use **transfer learning** as the dataset size was not big enough to train a CNN from scratch. I decided to use **VGG16** pre-trained on **ImageNet** after referring to the comparisons done in (Zebin et al., 2020].

2. To accommodate for the **2** outputs required instead of the pre-defined **1000**, I replaced the last layer with my own FC.

3. Results
   (Epochs = 100, LR = 0.01, Momentum = 0.9, SGD Optimizer, Cross-Entropy Loss):

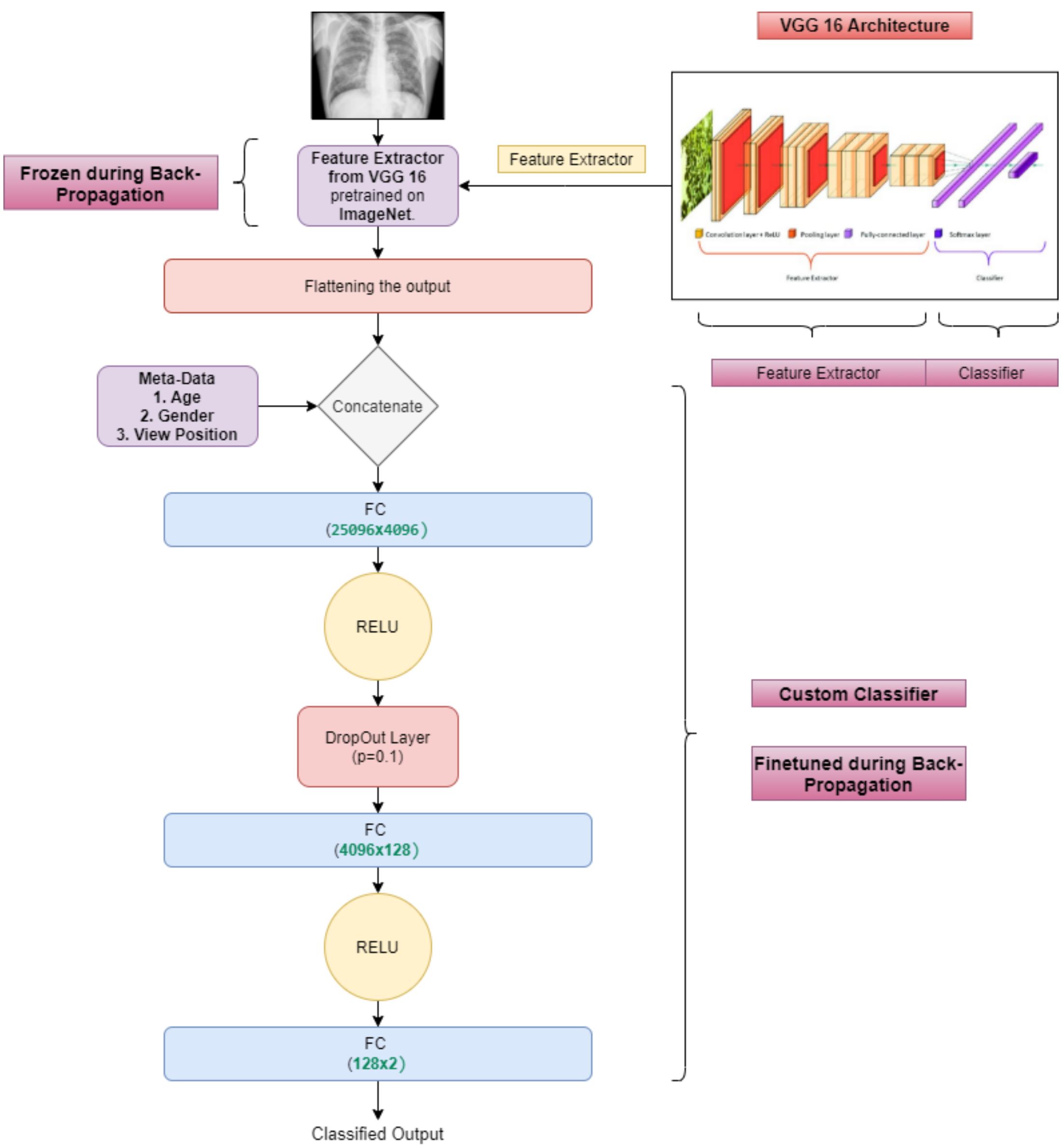
   - ❖ **Accuracy**: 0.8023
   - ❖ **Precison**: 0.68
   - ❖ **Recall**: 0.6538
   - ❖ **F1 Score**: 0.67

Model 2 (Used)

1. In order to account for **meta-data** such as **age, gender, view position,** I designed my own classifier (Baltruschat et al., 2019).

2. Steps
    a. **Feature extractor** from **VGG16** ->
    b. **Flattened** the output ->
    c. **Concatenated** with the **meta-data** ->
    d. Used custom classifier.

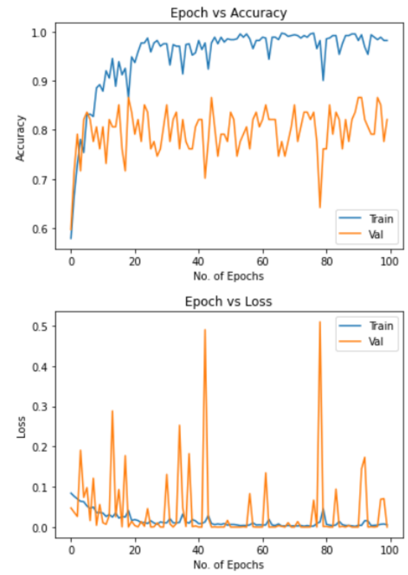
Flowchart



Results

(Epochs = 100, LR = 0.01, Momentum = 0.9, SGD Optimizer, Cross-Entropy Loss)

- **Accuracy**: 0.8657
- **Precison**: 0.8260
- **Recall**: 0.7037
- **F1 Score**: 0.76



Observations

Measures of performance	Model1	Model2
Accuracy	0.8023	0.8657
Precision	0.68	0.8260
Recall	0.6538	0.7037
F1 Score	0.67	0.76

Although straight-forward transfer learning with **VGG16** does produce satisfactory results, taking **age, gender and view position** into consideration while training the model significantly improves its performance as shown in the table above.

Future Work

1. The pre-trained weights used above were obtained from training the model on the ImageNet dataset. As we know, the ImageNet dataset does not resemble XRay scans at all. Thus, we could first train the model on standard Xrays and then use transfer learning to classify COVID XRays.

2. VGG16-T (Wang et al., 2020) is a recent network designed to identify lung cancer from CT images. Exploring the use of this network for COVID XRays seems promising.

References

Zebin, T., Rezvy, S. COVID-19 detection and disease progression visualization: Deep learning on chest X-rays for classification and coarse localization. Appl Intell (2020). https://doi.org/10.1007/s10489-020-01867-1

Wang, S., Dong, L., Wang, X., & Wang, X. (2020). Classification of Pathological Types of Lung Cancer from CT Images by Deep Residual Neural Networks with Transfer Learning Strategy. Open Medicine (Warsaw, Poland), 15, 190–197. https://doi.org/10.1515/med-2020-0028

Baltruschat, I.M., Nickisch, H., Grass, M. et al. Comparison of Deep Learning Approaches for Multi-Label Chest X-Ray Classification. Sci Rep 9, 6381 (2019). https://doi.org/10.1038/s41598-019-42294-8