Title: Predictive Modeling of Covid-19 with Chest X-rays

Machine Learning: Deep Learning
Spring, 2020

BACKGROUND

Covid-19 is an extremely distressing ongoing pandemic that has negatively impacted the lives of all people globally. One significant issue surrounding the virus is difficulty in getting a diagnosis for the virus, especially in poorer countries without any medical resources. We wish to create an algorithm that will quickly determine whether an individual has been infected by the Covid-19 virus with only an chest X-ray.

METHODS

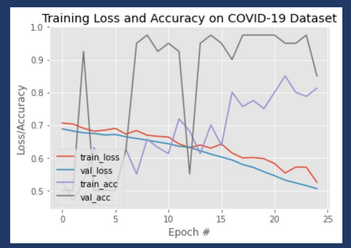
We worked specifically with frontal chest X-rays. Therefore images were visualized and filtered for consistency to train. We had three different sets of data for training. The first set contained only healthy(100) and covid-19(100) images. The second set contained healthy (75), covid-19 (75), and pneumonia images (75). The last set contained healthy (75), covid-19 (75), viral (75), and bacteria (75) images. The viral and bacteria specifically refer to lung diseases that involve viral or bacteria infections. For each data set we trained a self-constructed CNN, and transfer learning on VGG and ResNet models trained on imagenet. The self-constructed CNN contains 3 convolutional layers, dropout, and max pooling. We performed hyperparameter tuning while training each model to try and see which models produced the highest accuracy. Data augmentation by rotating the image. The hyperparameters we specifically tuned were batch size, learning rate, loss function, optimizer. In addition , our self constructed CNN was optimized as well as we tuned how many layers ,channels, and activation function to obtain the best accuracy. We performed an 80/20 split to train and test the model as well as a 5-fold cross validation due to our lack of data.

Performance of neural networks for classifying chest X-rays **varies** with respect to **architecture** and **number of classes** in data.

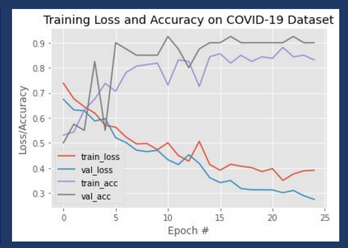
Model	Description	80/20 Train Test Accuracy	Cross-Validation Accuracy
ResNet 101 (transfer learning)	100 normal :100 covid	90%	89.5%
VGG 16 (transfer learning)	100 normal :100 covid	97.5%	97.5%
CNN	100 normal :100 covid	100%	95.0%
ResNet 101 (transfer learning)	75 normal :75 covid : 75 other pneumonia	65%	63.1%
VGG 16 (transfer learning)	75 normal :75 covid : 75 other pneumonia	93%	93.3%
CNN	75 normal :75 covid : 75 other pneumonia	91%	87.1%
ResNet 101 (transfer learning)	75 normal :75 covid : 75 other bacterial : 75 other viral	65%	48.7%
VGG 16 (transfer learning)	75 normal :75 covid : 75 other bacterial : 75 other viral	79%	80.3%
CNN	75 normal :75 covid : 75 other bacterial : 75 other viral	73%	80.3%

2 classes

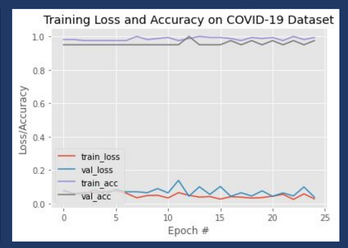
ResNet 101, 2 classes



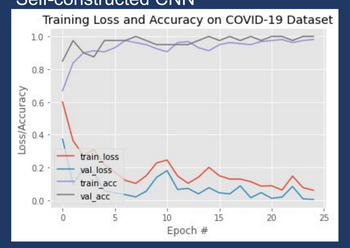
ResNet 101 + transfer learning



VGG16 + transfer learning

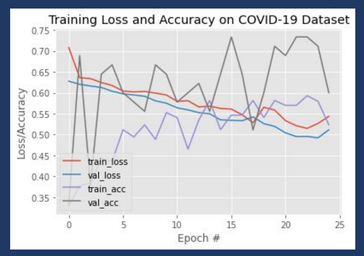


Self-constructed CNN

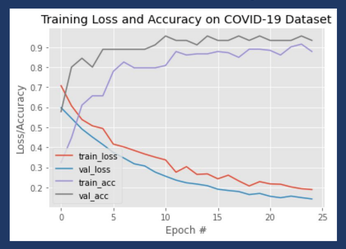


3 classes

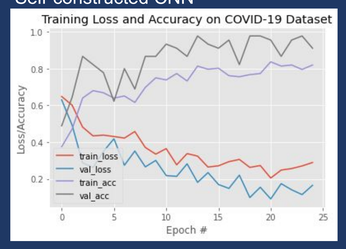
ResNet 101 + transfer learning



VGG16 + transfer learning

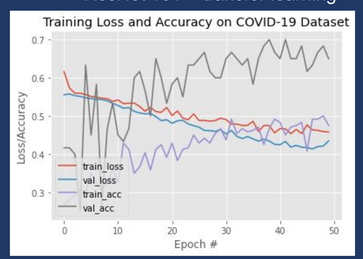


Self-constructed CNN

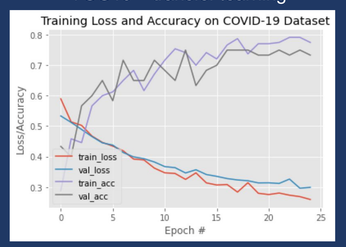


4 classes

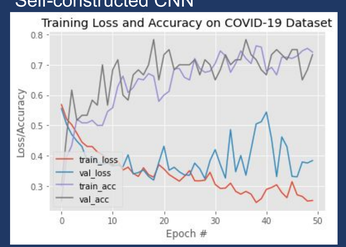
ResNet 101 + transfer learning



VGG16 + transfer learning



Self-constructed CNN



RESULTS

The results from out 80/20 train test split displayed results much higher than originally expected. In the two class case, all architectures performed quite well with high accuracy (>90%). When adding more classes for the architectures to train on, accuracies dropped accross the board. Out of all three architectures, ResNet 101 consistently performed the worst out of all three classes. VGG 16 and our self-constructed CNN had very similar accuracies. Our cross-validation runs showed that accuracies stayed consistent. Sometimes the accuracy would increase while other times accuracy would decrease compared to our 80/20 runs. These trends should be apparent in the ablation study. The graphs are for the 80/20 split runs.

LIMITATION AND FUTURE IMPROVEMENTS

The first main limitation was that our models had too little data to train on. More data would be necessary to create a more reliable model. Second is that due to covid-19 being a viral disease, certain similarities make it harder to differentiate than other viral diseases.

Data Source: Covid-19 image data collection and RSNA Pneumonia Detection Challenge

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