CS598
Final Project
Presentation

Project Team 1149

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Project Overview

We explore the effects of transfer learning on several CNN architectures, as well as investigate more novel approaches to classify COVID-19 from non-COVID-19 X-ray images.

- Prepared a dataset of 13,200 chest X-rays
- Trained 7 CNNs for COVID-19 detection
- Documented performance metrics for each model

Agenda

1. Motivation for detecting COVID-19 on X-rays
2. Introduction to the CNN models investigated
3. Overview of data aggregation & preparation
4. Description of methods and approach
5. Presentation of experimental results
6. Discussion and reflection on findings

1.

Motivation

How can deep learning aid in the diagnosis of COVID-19?

The Prevalence of COVID-19

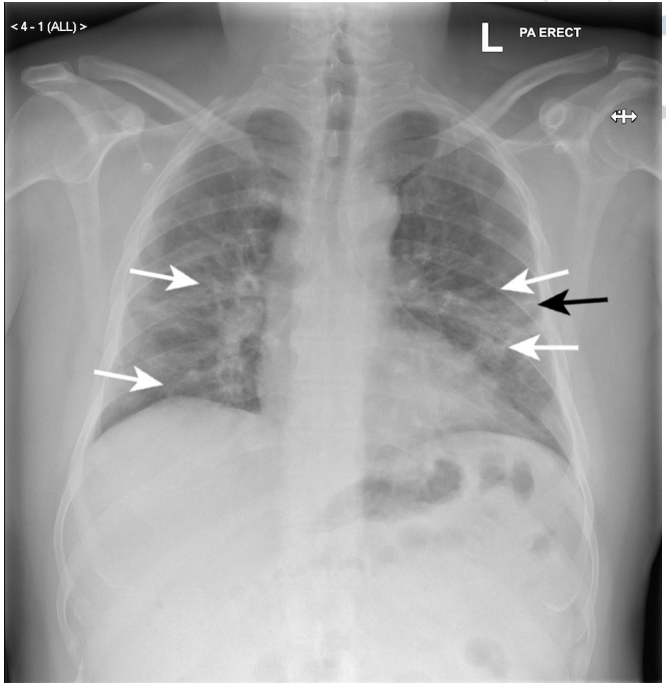
From its first public announcement in December 2019 [1], the COVID-19 pandemic has been responsible for upwards of 3.2 million deaths and 157 million reported cases [2].

Even with worldwide vaccination efforts, the detection of COVID-19 cases remains imperative for patient outcomes and public health.

Radiography as a Diagnostic Tool

Traditional PCR test results can take hours to days and may yield false negatives.

Radiography is one of the fastest, readily available diagnostics to gain insight on the progression of lung disease.



COVID-19 pneumonia may present on chest X-rays as visible regions of ground glass opacity in the lungs [5].

Deep Learning Models can Interpret X-rays

Years of education and experience are required for humans to correctly interpret X-rays.

Convolutional Neural Networks (CNN) are a class of deep learning models which are commonly used to analyze images. They provide an opportunity for fast, independent, and accurate interpretation of X-rays.

2.

CNNs

A standard for computer vision and image classification

The Deep-COVID Study

- Study with 5,000 chest X-ray dataset (100 COVID-19 images)
- Used pre-trained ImageNet models
- Results
  - 98% sensitivity
  - 90% specificity
- Recommended further studies with larger dataset

CNN Architectures

ResNet18

Comprised of 18 layers, ResNet18 uses an identity shortcut connection, making it less susceptible to the vanishing gradient problem.

ResNet50

Akin to its sibling ResNet18, ResNet 50 also utilizes the identity shortcut connections. It consists of 50 layers organized into 5 distinct stages.

SqueezeNet 1.1

A competitor to AlexNet, SqueezeNet offers similar accuracy, a reduced number of parameters, and a smaller model size to boost training efficiency.

DenseNet-121

Consisting of 121 layers, DenseNet uses the input of previous layers to address the vanishing gradient problem, reduce parameters, and strengthen feature propagation.

InceptionV3

The 3rd edition of Google's Inception CNN, Inception V3 offers factorized convolutions, regularization, dimension reduction, label smoothing and parallelized computations.

COVID-Net

- Introduced as open source in May 2020 [4]
- 13,975 chest X-ray images used, 358 labelled as COVID-19
- Tailored model for COVID-19 detection using deep residual learning and projection-expansion-projection design (PEPX)
- Results:
  - 93.3% accuracy, 91.0% sensitivity, positive predictive value 98.9%

COVID-Net

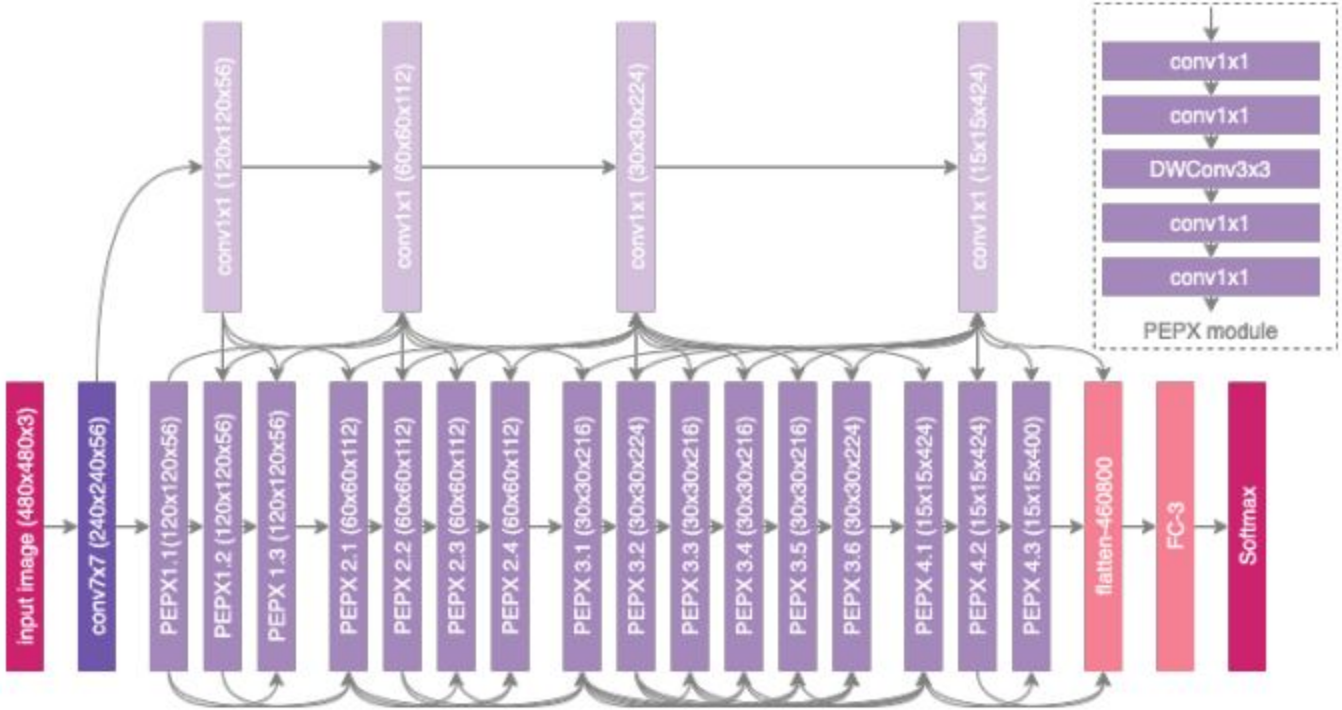


Figure 1. COVID-Net Architecture [4]

COVID-Net + LSTM

- With a baseline of COVID-Net, we combined it with a long short-term memory network.
- After the series of PEPX layers, we added a LSTM in hopes of utilizing memory for the final classification layers.
- LSTM addresses the vanishing or exploding gradient issue typically found in traditional recurrent neural networks.

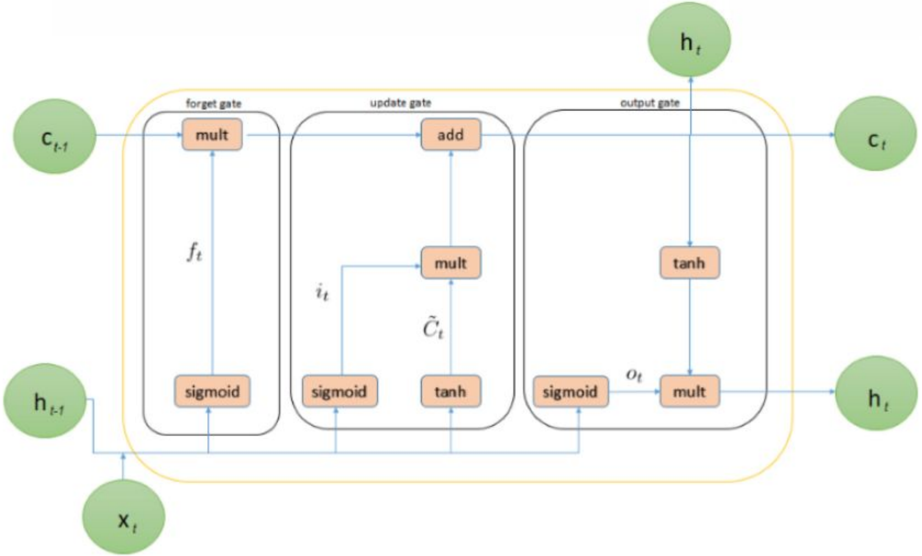


Figure 2. LSTM structure [6]

COVID-Net + LSTM

- LSTM with input gate, forget gate, and output gate [6]
  - x_t is current input, c_t and c_{t-1} are new and previous cell states, h_t and h_{t-1} are current and previous outputs
  - $f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right)$ *Forget gate* - sigmoid layer decides which info to remove from the cell state
  - $i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] + b_i\right)$ *Input gate* - sigmoid layer decides which new info to store in the cell state
  - $\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C)$ *Input gate* - tanh layer creates a vector of new info to store in the cell state
  - $C_t = f_t * C_{t-1} + i_t * \tilde{C}_t$ *Input gate* - old info is replaced with the new info
  - $o_t = \sigma\left(W_o \left[h_{t-1}, x_t\right] + b_o\right)$ *Output gate* - sigmoid layer decides which info to output
  - $h_t = o_t * \tanh\left(C_t\right)$ *Output gate* - cell state is passed through tanh layer and multiplied with output of sigmoid layer to produce the desired info as output

3.

Data Preparation

Creating a dataset of 13,200 chest X-rays

Data Acquisition

Chest X-ray images originated from the [COVID-19 Radiography Database] hosted on Kaggle curated by Rahman, Chowdhury, and Khandakar [3].

The composition of the chest X-rays are as follows:

- 10,192 normal
- 6,012 non-COVID lung infections
- 1,345 viral pneumonia
- 3,616 COVID-19

Data Breakdown

Split	COVID	Non-COVID
Train	1440 (2880 augmented)	4800 - 2079 Normal - 642 Viral pneumonia - 2079 Other lung disease
Validation	580	1199 - 519 Normal - 161 Viral pneumonia - 519 Other lung disease
Test	1200	3999 - 1732 Normal - 535 Viral pneumonia - 1732 Other lung disease

60/40 split on training and test
80/20 split on test and validation

4.

Approach

Experimental methods and model evaluation

Experimental Methods

We investigated both the pre-trained and non-pretrained versions of 7 CNN models: ResNet18, ResNet50, DenseNet-121, SqueezeNet 1.1, Inception V3, COVID-Net, and COVID-Net + LSTM:

- For the pre-trained models, we only updated features on the last fully-connected layer

During training, the following hyperparameters were used:

- Learning rate of 0.004
- 50 epochs
- Momentum of 0.9
- Batch size of 32

The resulting performance of the machine learning models was then assessed.

Model Evaluation Metrics

Accuracy

$$\frac{TP + TN}{TP + TN + FP + FN}$$

Precision

$$\frac{TP}{TP + FP}$$

Sensitivity

$$\frac{TP}{TP + FN}$$

Specificity

$$\frac{TN}{TN + FP}$$

F1-Score

$$\frac{2 * Precision * Sensitivity}{Precision + Sensitivity}$$

Goal

Achieve a score of 95% or above for all 5 metrics.

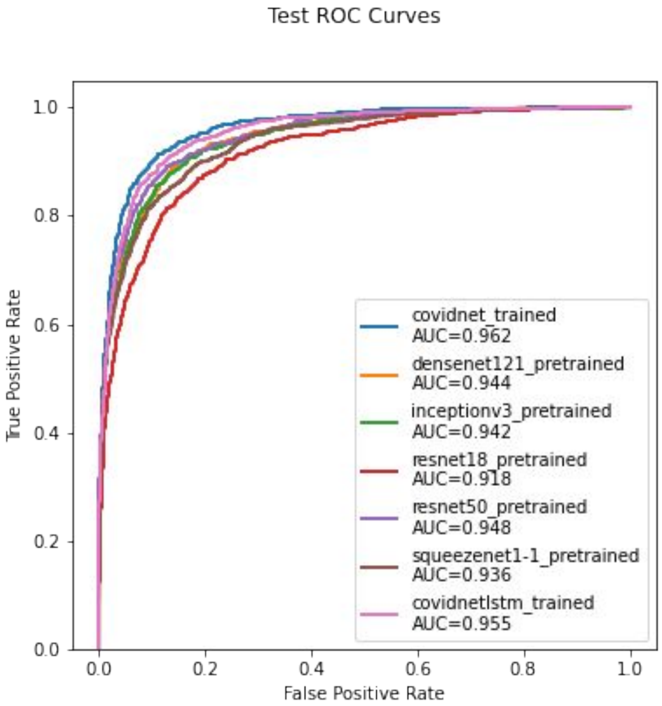
5.

Results & Discussion

Results and Metrics

	COVID-Net + LSTM	COVID-Net	ResNet18	ResNet50	SqueezeNet 1.1	DenseNet 121	InceptionV3
Sensitivity	0.852	0.852	0.81	0.891	0.911	0.898	0.862
Specificity	0.926	0.937	0.873	0.869	0.774	0.851	0.88
Accuracy	0.909	0.918	0.858	0.874	0.806	0.862	0.876
Precision	0.775	0.803	0.657	0.671	0.548	0.644	0.683
F1	0.812	0.827	0.725	0.766	0.684	0.750	0.762
AUC	0.955	0.962	0.918	0.948	0.936	0.944	0.942

ROC-AUC



Test ROC Curves
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
covidnet_trained AUC=0.962
densenet121_pretrained AUC=0.944
inceptionv3_pretrained AUC=0.942
resnet18_pretrained AUC=0.918
resnet50_pretrained AUC=0.948
squeezenet1-1_pretrained AUC=0.936
covidnetlstm_trained AUC=0.955

6.

Conclusion

Discussion

Overall, we were able to significantly improve the performance of our models through the following practices:

- Increasing the size of our dataset
- Further increasing the size of our training dataset through image augmentation
- Fine-tuned our hyperparameters
- Explored more novel approaches to classification through use of COVID-Net and the subsequent integration of an LSTM layer
- Adjusting the threshold based on the true positive and false positive rate

Reflection

The most significant of our challenges was the turn-around-time for model training. We had 7 models to see through the iterative process of training, evaluating, tuning parameters and training again.

With more time, it would have been interesting to study how the addition of LSTM, on top of our expanded dataset, affected the models from the Deep-COVID study.

With respect to the future, continued work could include updating the models to support multi-class classification.

Credits and References

[1] World Health Organization. Timeline: WHO’s COVID-19 Response.

https://www.who.int/emergencies/diseases/novel-coronavirus-2019/interactive-timeline#!

[2] Worldometer. COVID-19 Coronavirus Pandemic. https://www.worldometers.info/coronavirus/

[3] https://www.kaggle.com/tawsifurrahman/covid19-radiography-database

[4] Wang, L., Zhong Q., & Wong, A. COVID-Net: A tailored deep convolutional neural network design for detection of COVID-19 cases from chest X-ray images. arXiv:2003.09871v4;2020.

[5] Cleverley J, Piper J, Jones M M. The role of chest radiography in confirming covid-19 pneumonia *BMJ* 2020; 370 :m2426 doi:10.1136/bmj.m2426

[6] Islam, Md.Z., Islam, Md.M., & Asraf, A. A combined deep CNN-LSTM network for the detection of novel coronavirus (COVID-19) using X-ray images. *Informatics in Medicine Unlocked* 2020;20:1-11. https://doi.org/10.1016/j.imu.2020.100412

[7] Presentation deck design from https://www.slidescarnival.com