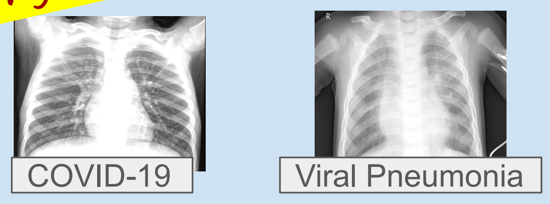
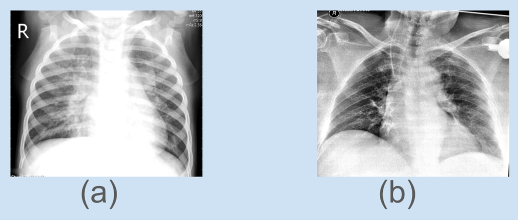
Try it yourself



Are you able to identify which of these x-rays belongs to a patient with COVID-19?



3244-2010-17

Detecting COVID-19 in Radiographic Images using Deep Learning

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1 Introduction

Motivation

The Coronavirus Disease 2019 (COVID-19) has killed over a million people globally.[1] With some experts predicting that vaccines could be widely available as late as mid 2021[2], there is an urgent need to mitigate the spread of the virus. It is essential that the infected are identified and isolated early such that the virus can be contained. One of the way to identify carriers is through chest X-ray imaging, however to be able to spot indicators of the infection require trained radiologists.

In our project, we aim to:

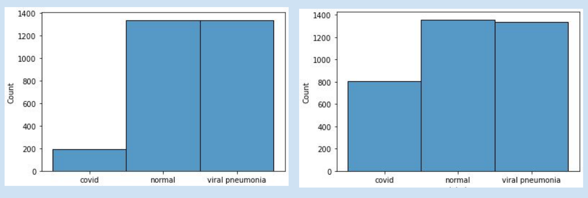
1. Develop a model which could help medical professionals identify whether a patient has COVID-19 by examining their chest X-rays.
2. Explore how deep learning can improve upon traditional machine learning techniques in diagnosing COVID-19. In particular, how deep learning can be used to identify features that distinguishes COVID-19, and how transfer learning can be used to re-train pre-existing image classification networks for this purpose.

[1] https://www.worldometers.info/coronavirus/
[2] https://www.bbc.com/news/health-51665497

2 Dataset

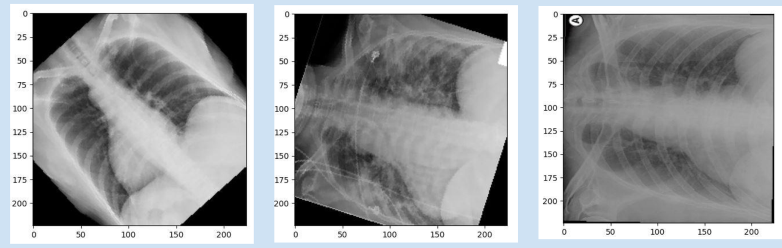
Dataset

We used the COVID-19 Radiography Database which won the community COVID-19 dataset award on kaggle. However, the dataset is unbalanced (*left*), and samples for COVID-19 under represented. To rectify this issue, we sampled more images from another dataset collected by University of Montreal. This allowed us to improve the class balance of the dataset (*right*).

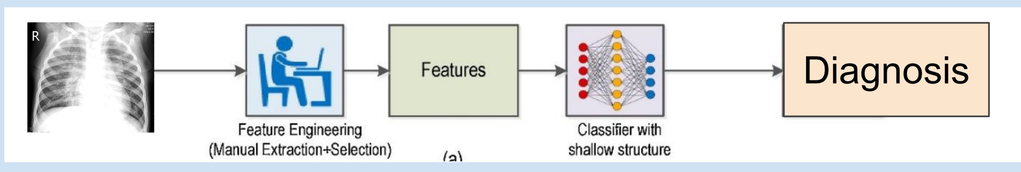


Data Augmentation

To prevent our model from overfitting data, we introduced changes to the orientation of the original training images using several augmentation techniques including horizontal flips and rotations (below). This should allow the model to generalize better to new, unseen chest X-ray scans.



3 Approach / Methodology



Traditional

We attempted to classify the images using a couple of different traditional classification models such as linear regression and support vector machines, and explored how different data preprocessing techniques affected the model's ability to classify the image.

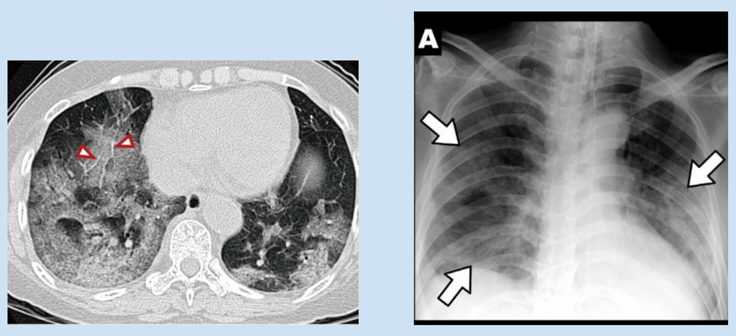
Dimensionality Reduction

X-ray images tend to be quite large, thus when using raw pixel intensity as the feature space, the dimensionality of the data tends to be very high. In order to speed up training of the model, we explored using dimensionality reduction techniques such as downsampling and principal component analysis (PCA).

Feature Extraction

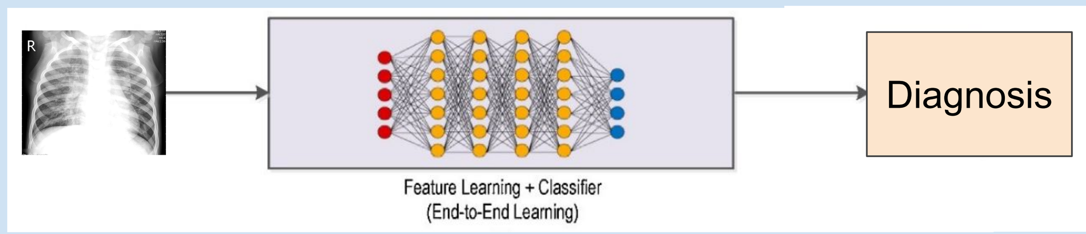
Due to how pixels are spatially related to each other in images, using raw pixel intensity may not result in proper classification as the features are not independent of each other.

Substantial extent GGO may indicate presence of COVID-19 Infection (right)



Medical research (HKCR Publication) shows that in a radiographs representative of COVID-19 infection, there tends to be regions of ground glass opacity (GGO) within the lungs, where the degree and extent of GGOs suggests the progress of the infection.

However, to be able to interpret those higher level features, the model needs to be able to interpret images. Hence, we attempted to use pre-trained visual neural networks such as VGG16 to extract these higher level features from the images for use in classification.



Deep Learning (transfer learning)

Convolutional neural networks (CNN) are used heavily in the computer vision field of machine learning due to the stacking of several convolution layers that allow it to transform low-level features into increasingly higher level features.

There are many pre-trained visual neural networks which are able to classify images, and these can be re-trained to classify images outside of the original dataset.

We started with pre-trained models and performed gradual fine-tuning by first training the head, and slowly unfreezing the rest of the models for a smoother training process. We also used weight decay and LR schedulers to avoid having our model parameters jump out of local minima at later epochs.

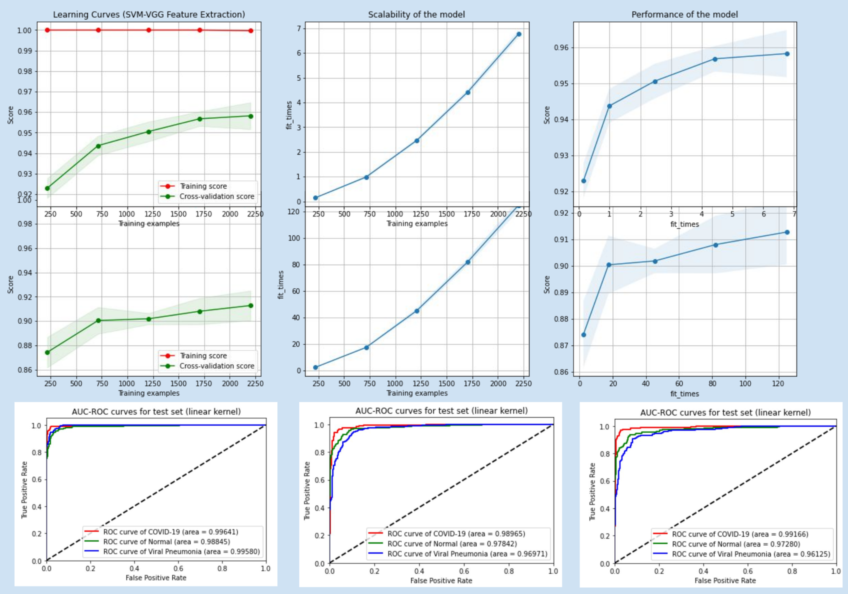
3 Results

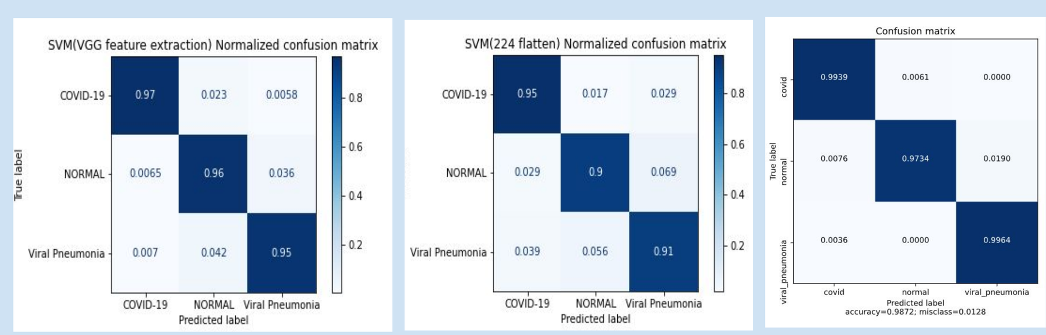
Metrics used

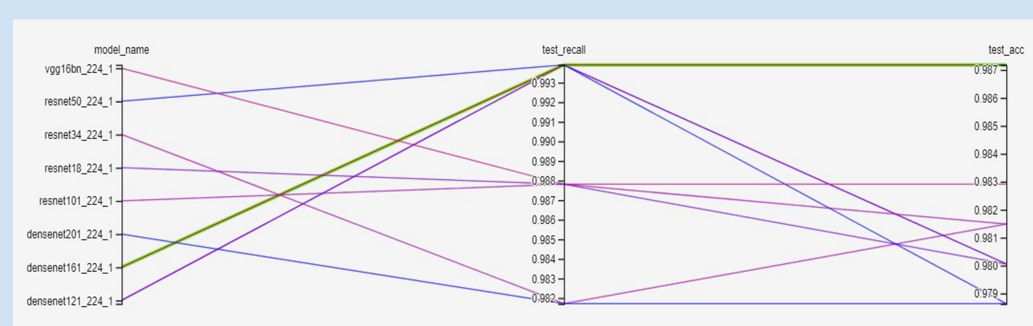
For the case of COVID-19 diagnosis, because detection is essential in order to be able to isolate potentially infection individuals, it is important to ensure that we minimise false negatives (higher recall). Additionally, it is also important that patients are not wrongly classified as COVID-19 positive so that hospital resources are not unnecessarily wasted (higher precision).

Hence, we will use a model's F1-score, which considers both precision and recall in order to evaluate how proficient our models are.

	Acc	COVID19 Recall	Weighted Recall	Weighted F1
Raw Pixel Intensity				
Linear Regression	n/a	n/a	n/a	n/a
SVC linear	.85602	.92614	.89856	.90144
SVC rbf	.94371	.94827	.94371	.94373
SVC poly	.90445	.94886	.93262	.92842
PCA dimensionality reduction				
SVC linear	.86126	.92614	.90633	.90279
SVC rbf	.93455	.97660	.95750	.95057
SVC poly	.87434	.98148	.92944	.91365
Higher Level Features				
SVC linear	.95549	.95953	.94552	.94981
SVC rbf	.95811	.98276	.96710	.96457
SVC poly	.95811	.96711	.96710	.96457
Transfer Learning				
ResNet18	0.9800	0.9878	0.9801	0.9800
VGG16	0.9829	0.9878	0.9829	0.9828
Densenet161	**0.9872**	**0.9939**	**0.9872**	**0.9872**



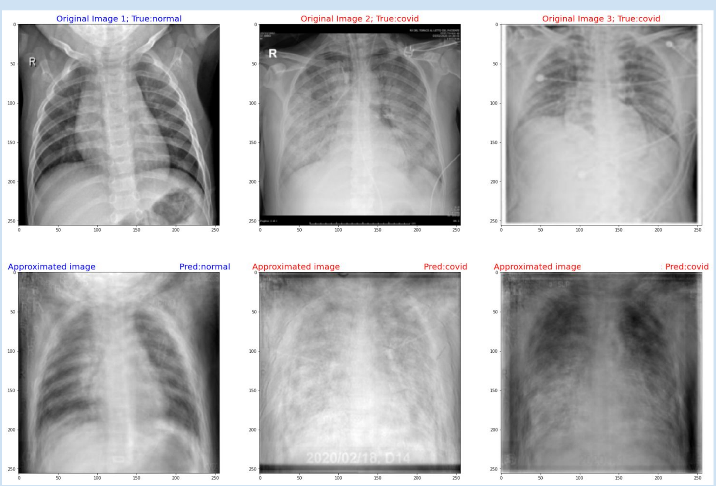




5 Analysis of results

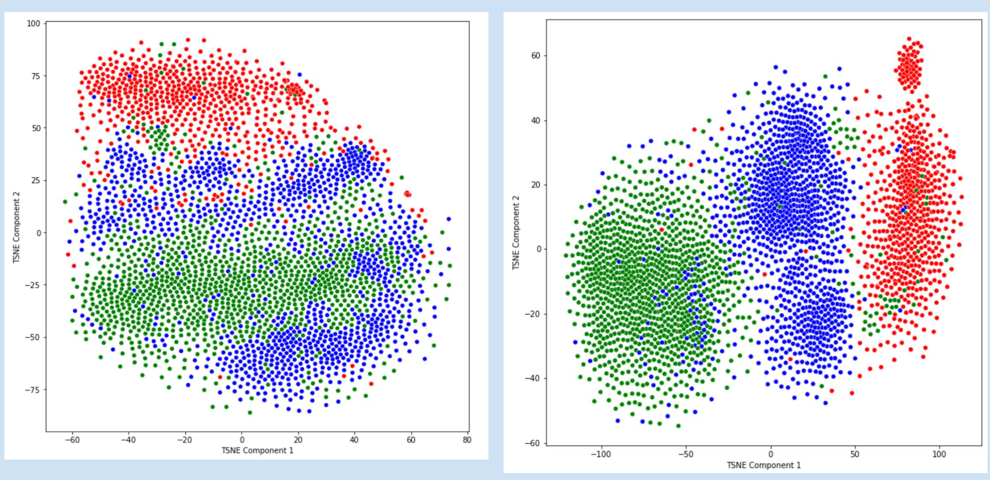
PCA reduced features may be problematic.

The results of the models in which PCA was used to reduce the dimensionality of the feature space appeared to show some improvement over the raw-pixel intensity feature space. By approximating the image using the inverse transformation to the original higher dimension, we can see that there appears to be artifacts from other images used to fit the PCA transformer. This can be seen in the middle image-pair where the approximated image (bottom middle) appears to have a timestamp when the original (upper middle) did not.



Improvement in results due to the of CNNs in the models due more meaningful features.

There is some improve in results when neural networks are used to extract features, over using lower level features. Using t-distributed stochastic neighbor embedding, we can visualize the improvement in clustering of x-rays in the higher-level image descriptor feature space (right) vs. the lower level pixel intensity feature space (left).



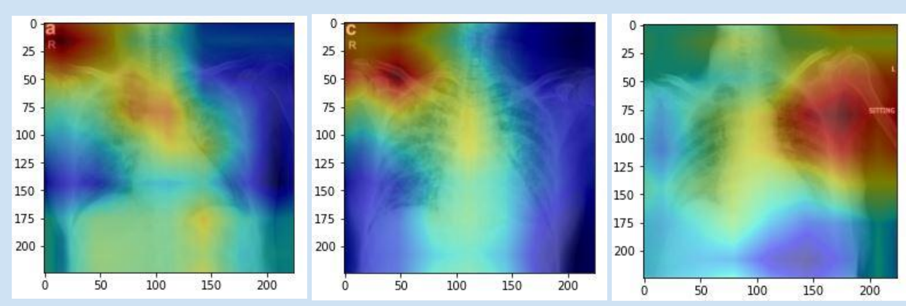
Low level features (raw pixel intensity) vs **Higher level features (extracted by neural network)**

Model is better able to focus of lungs when pre-trained image nets are re-trained on a COVID-19 x-ray dataset

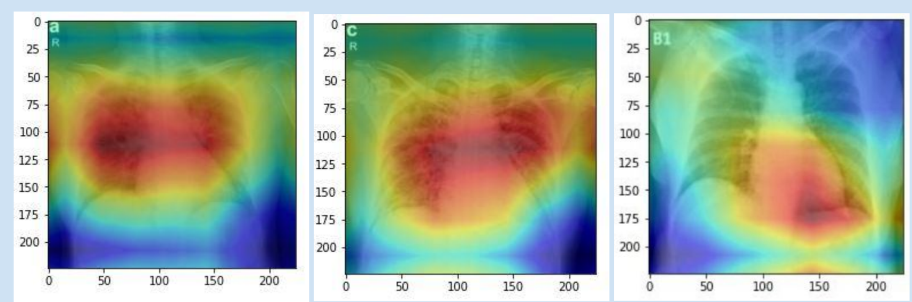
As mentioned earlier, features that suggest the presence of COVID-19 in X-ray images occur primarily around the lung area. To verify that our model picks up these signals, we made use of heatmaps to visualize regions in a chest X-ray image that our model pays the most attention to, as shown in the red regions in the heatmaps.

To demonstrate the effectiveness of retraining the network, we use the pretrained model and the retrained model to examine 3 sample images. From the heatmaps below, it is clear that the network's region of interest has moved towards the lungs after the retraining has been done.

Pre-trained model regions of interest (below):

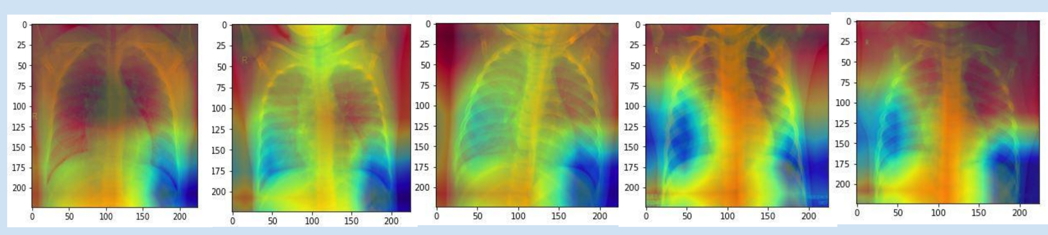


Re-trained model regions of interest (below):

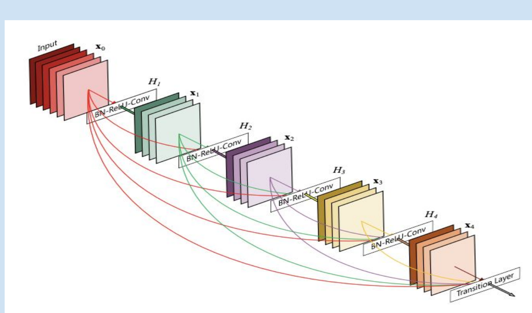


Causes for validation loss

The following images show the regions of interest within the top 5 highest loss images (Highest loss on the left). It can be seen that the red regions are not centered around the lungs, suggesting that our model is also looking at regions outside of the lung for some images. One possible way to improve the model is to do segmentation and generate lung masks to apply to the images so that regions outside the lung are ignored.

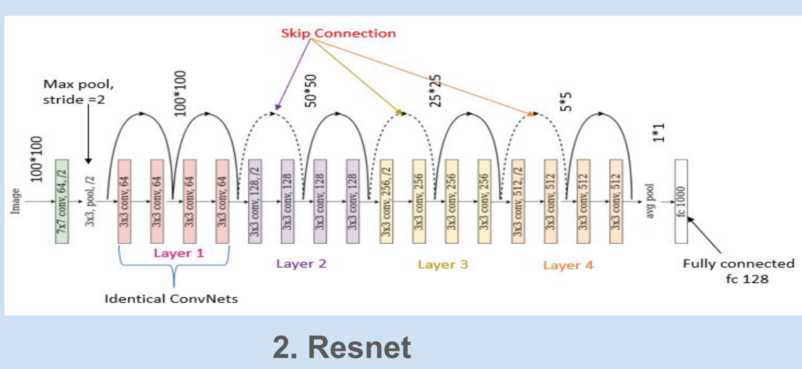


Comparison of results between different vision architectures



1. **Densenet**

Densenets connect a layer to every subsequent layer in a feed-forward fashion. This reduces the number of parameters by having all features learnt by preceding layers accessible in subsequent layers. Concatenating features maps of previous layers could also help to increase with variation in the input of subsequent layers and improve generalizability.



2. **Resnet**

Resnets were pioneered to address the issue of vanishing gradients by having skip connections that allow gradients to flow directly through them. This is so as these are identity connections which allow the gradient of previous layers to pass. y = x + F(x), who's loss when differentiated with respect to x gives 1 + F'(x) * gradient(loss(y)). This thus allows us to stack much deeper layers than before and with the universal approximation theorem essentially allow us to approximate any function.

4 Key Findings

- Linear Regression failed as the data is not linearly separable
- Using PCA to reduce dimensionality of raw pixel intensity feature space significantly reduces time to fit SVM models, but has minimal improvement in ability to classify.
- Using features extracted by neural networks significantly improves accuracy, recall, F1 score
  There is some improvement when using featured transformed using PCA. However, the most significant improvement in performance is when the model uses features extracted by a the upper layers of a neural network.
- Retraining the neural network on x-ray images significantly improves accuracy, recall, F1 score
- Overall, deep learning results in much better performance with than other models, with the best performing architecture being densenet161.
- Simple measures like Learning Rate stepping to decay by a factor of 0.1 every 2 epochs with weight decay of 0.1 to keep weights of the architecture smaller were sufficient to prevent overfitting and achieving great generalizability.
- We recognize this from the not only the high validation accuracy and recall rates but also that of the test accuracy and recall rates

6 References

HKCR Publication - An overview of COVID-19, with emphasis on radiological features, 27 March 2020