Chest X-ray Classification for Covid-19 detection

Group 19
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Background

- Covid-19 pandemic has caused millions of deaths worldwide
- Covid-19 is contagious
- No efficient way to detect Covid-19
- A chest x-ray cannot accurately distinguish between Covid-19 and other respiratory infections

Cases	Deaths
171,944,492	3,576,062

Literature survey

- Transfer learning and fine-tuning with VGG16

Accuracy: 95%, Classes: Covid-19, Pneumonia, Normal

- Image augmentation and transfer learning with Densenet201

Accuracy: 97%, Classes: Covid-19, Viral Pneumonia, Normal

- Normalization and transfer learning with Resnet50

Accuracy: 96%, Classes: Covid-19, Other pneumonia, Normal

Dataset

- Public data from Kaggle
- 4000 chest X-ray images
- Image dimension is 299*299*3
- 4 Classes: Covid-19, Lung Opacity, Normal, Viral Pneumonia

	Training	Validation	Testing
Normal	800	100	100
Covid-19	800	100	100
Lung Opacity	800	100	100
Viral Pneumonia	800	100	100

Dataset

Covid-19

Lung Opacity

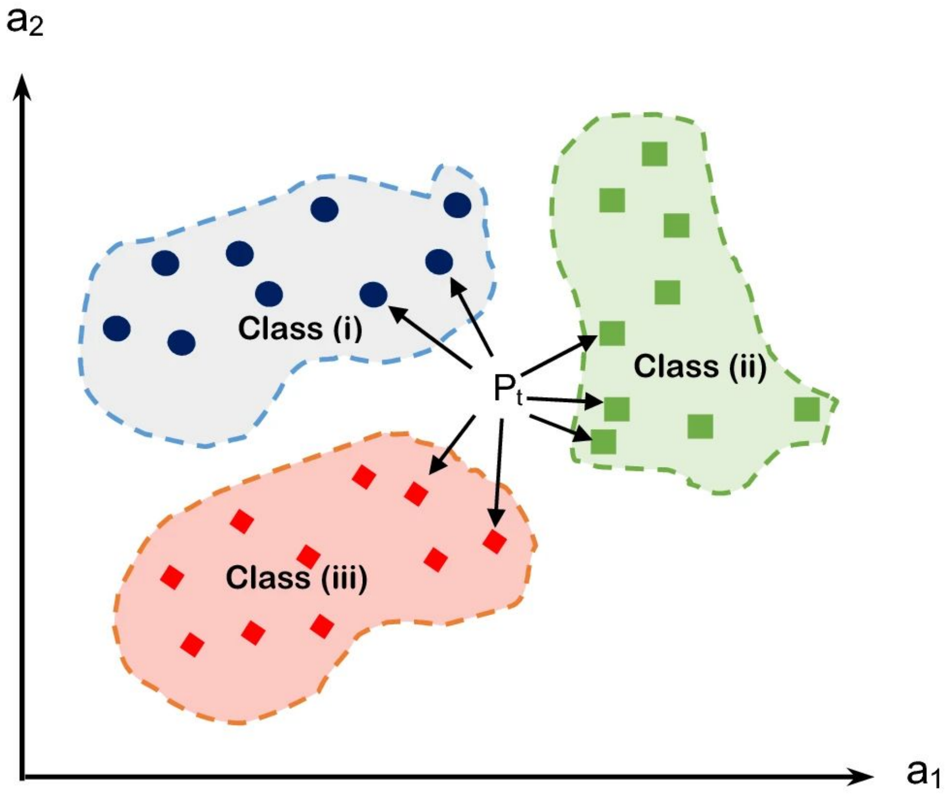
Normal

Viral Pneumonia

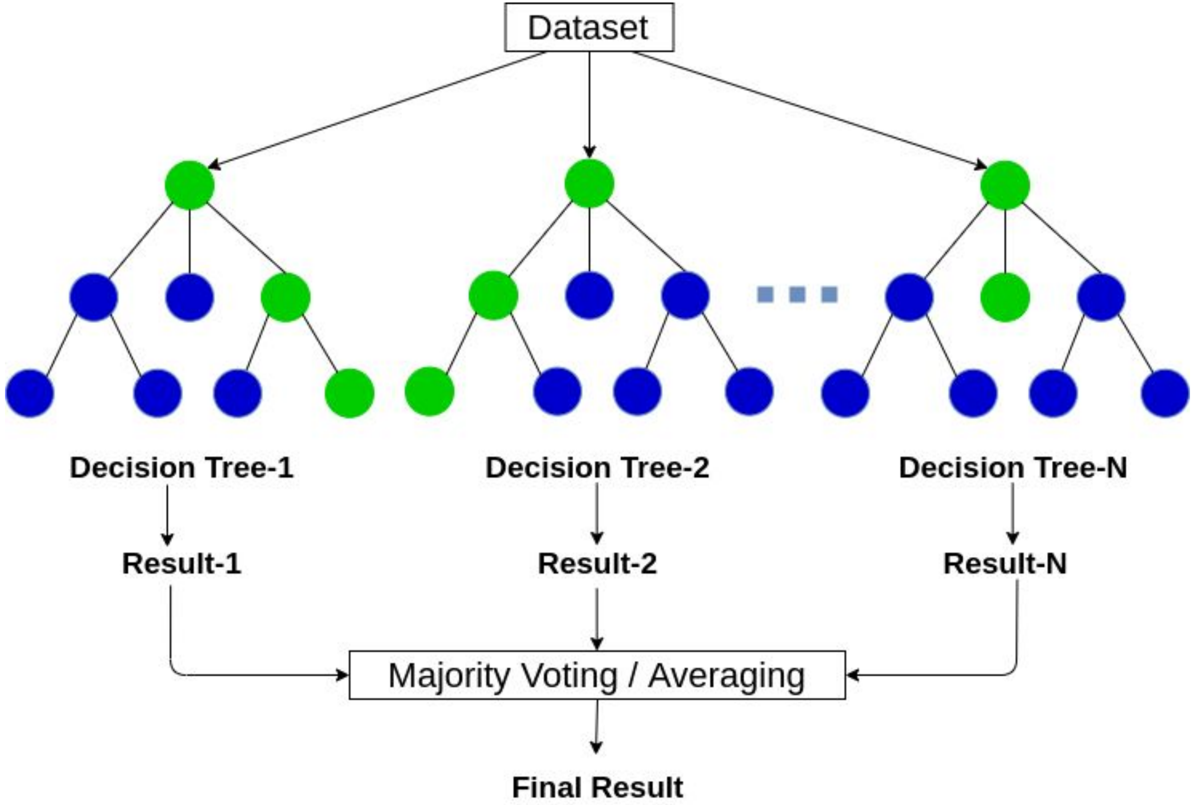
Details on the model used

- ML
  - K Nearest Neighbor
  - Random forest
- DL
  - VGG19
  - ResNet50
  - DenseNet121
  - InceptionV3
  - Xception

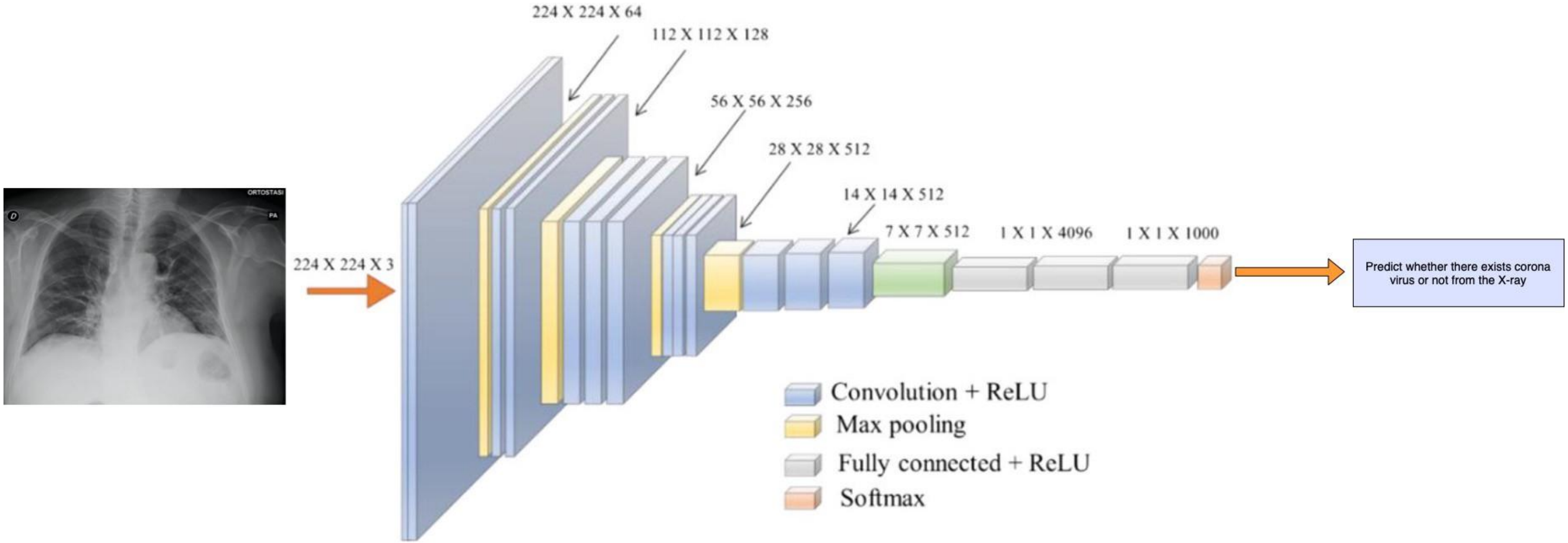
K Nearest Neighbor (k-NN)



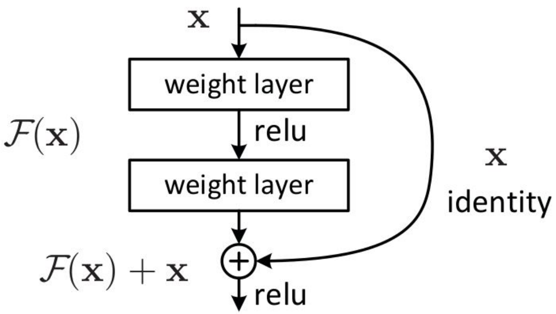
Random forest (RF)

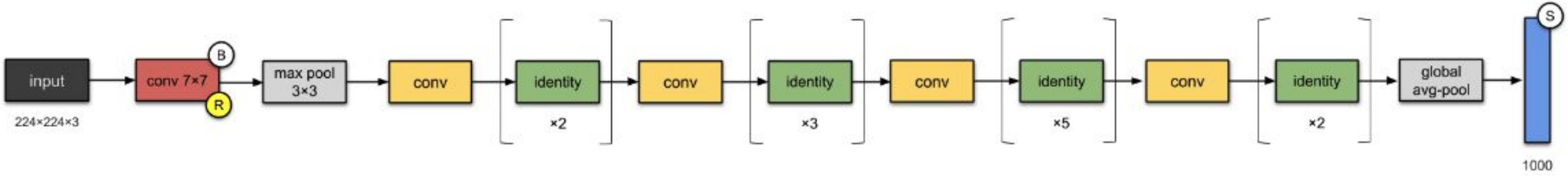


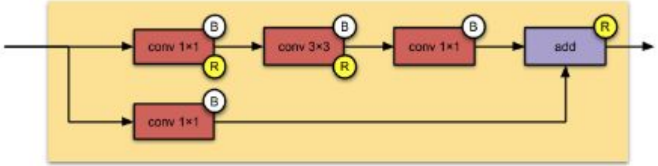
VGG19


ORTOSTASI
PA
224 X 224 X 3
224 X 224 X 64
112 X 112 X 128
56 X 56 X 256
28 X 28 X 512
14 X 14 X 512
7 X 7 X 512
1 X 1 X 4096
1 X 1 X 1000
Predict whether there exists corona virus or not from the X-ray
Convolution + ReLU
Max pooling
Fully connected + ReLU
Softmax

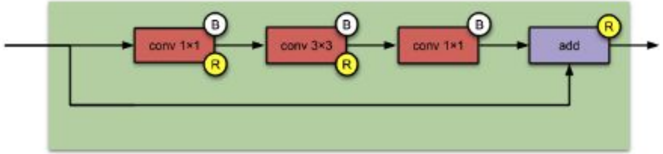
ResNet





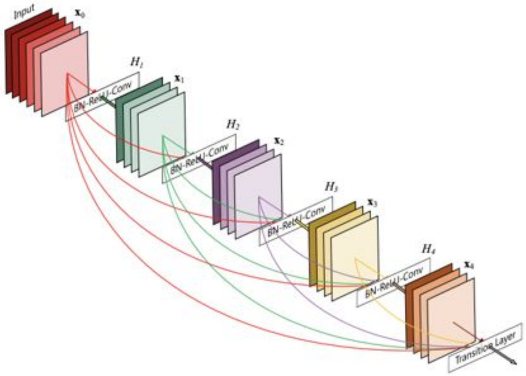


Conv block

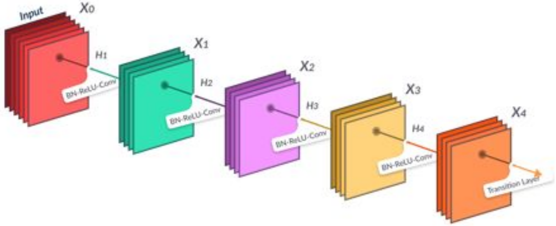


Identity block

DenseNet



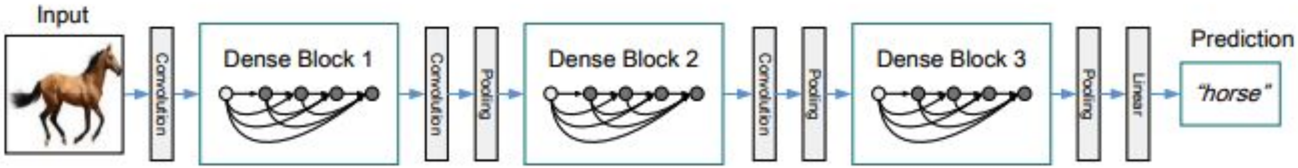
DenseNet Structure



ResNet Structure

$$a^{[l]} = g\left([a^{[0]}, a^{[1]}, a^{[2]}, \dots\dots\dots\dots, a^{[l-1]}]\right)$$

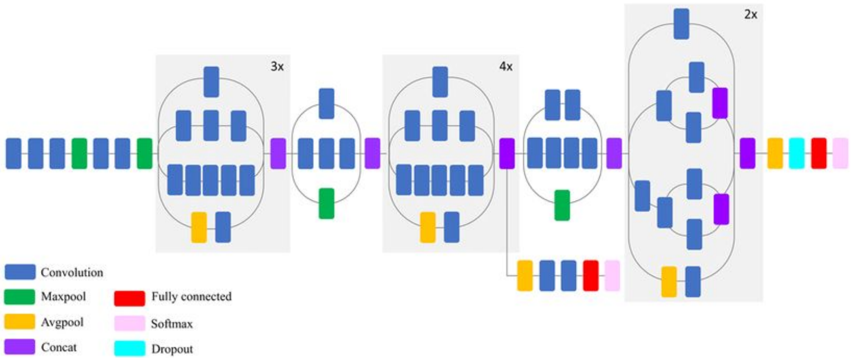
$$a^{[l]} = g\left(z^{[l+1]} + a^{[l]}\right)$$

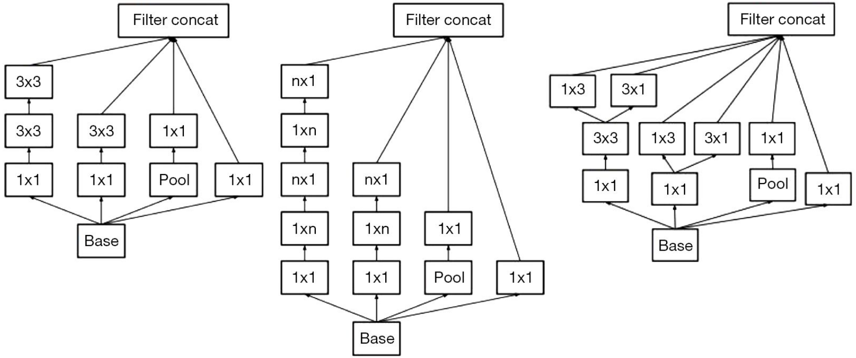


DenseNet

Layers	Output Size	DenseNet-121	DenseNet-169	DenseNet-201	DenseNet-264
Convolution	112×112	7×7 conv, stride 2			
Pooling	56×56	3×3 max pool, stride 2			
Dense Block (1)	56×56	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 6$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 6$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 6$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 6$
Transition Layer (1)	56×56	1×1 conv			
	28×28	2×2 average pool, stride 2			
Dense Block (2)	28×28	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 12$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 12$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 12$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 12$
Transition Layer (2)	28×28	1×1 conv			
	14×14	2×2 average pool, stride 2			
Dense Block (3)	14×14	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 24$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 32$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 48$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 64$
Transition Layer (3)	14×14	1×1 conv			
	7×7	2×2 average pool, stride 2			
Dense Block (4)	7×7	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 16$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 32$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 32$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 48$
Classification Layer	1×1	7×7 global average pool			
		1000D fully-connected, softmax			

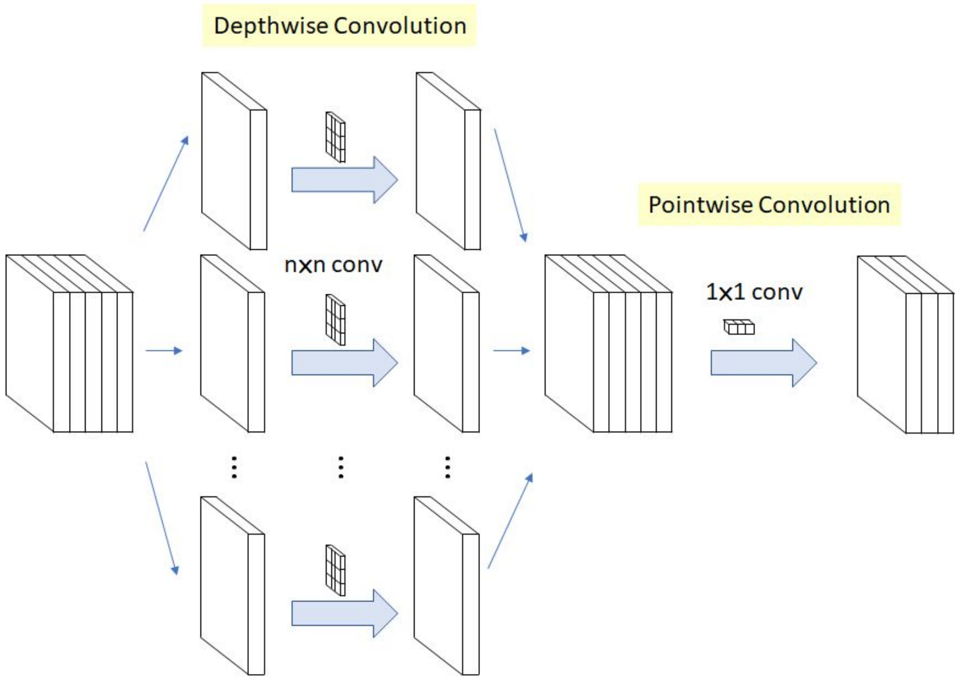
InceptionV3





Xeception

- Inception Network + Depthwise separable convolution



Result with Different Models

With 400 testing image

Model \ Accuracy	(w/o) fine-tuning	With fine-tuning
VGG19	84.25%	92.25%
ResNet50	69.50%	91.75%
DenseNet121	48.75%	91.25%
InceptionV3	51.00%	89.50%
Xception	63.00%	89.00%

Model	Accurcy
k-NN	73.25%
RF	82%

Further work to be completed

- Try some image augmentation method

- Use different models

Reference

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