Computer Vision Project
Prediction of Covid-19 infections with x-ray images

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Agenda

1. Motivation
2. Why use Deep Learning for Medical Image Analysis?
3. The project
4. Dataset
5. Regularization
6. Architecture
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1. Motivation

- **Idea:** Medical Image Analysis with Deep Learning
  - Help doctors to analyze, model and make sense of complex clinical data
  - Aim: Assign the patient to one of a small set of classes (Amato et al. 2013)
    - Not new: Medical Image Analysis exists since the 60s (edge and line detector filters) (Litjens et al. 2017)

- **Today:** sources from various medical procedures, such as CT, MRI, PET, and X-ray

- **Typical applications:**
  - Detections of structures (organs, body parts) (Lo et al., 1995)
  - Segmentation (cardiac and brain analyses, U-Net) (Ronneberger et al. 2015)
  - Image classification (disease is present or not with x-ray images) (Antony et al., 2016)

2. Why use Deep Learning for Medical Image Analysis?

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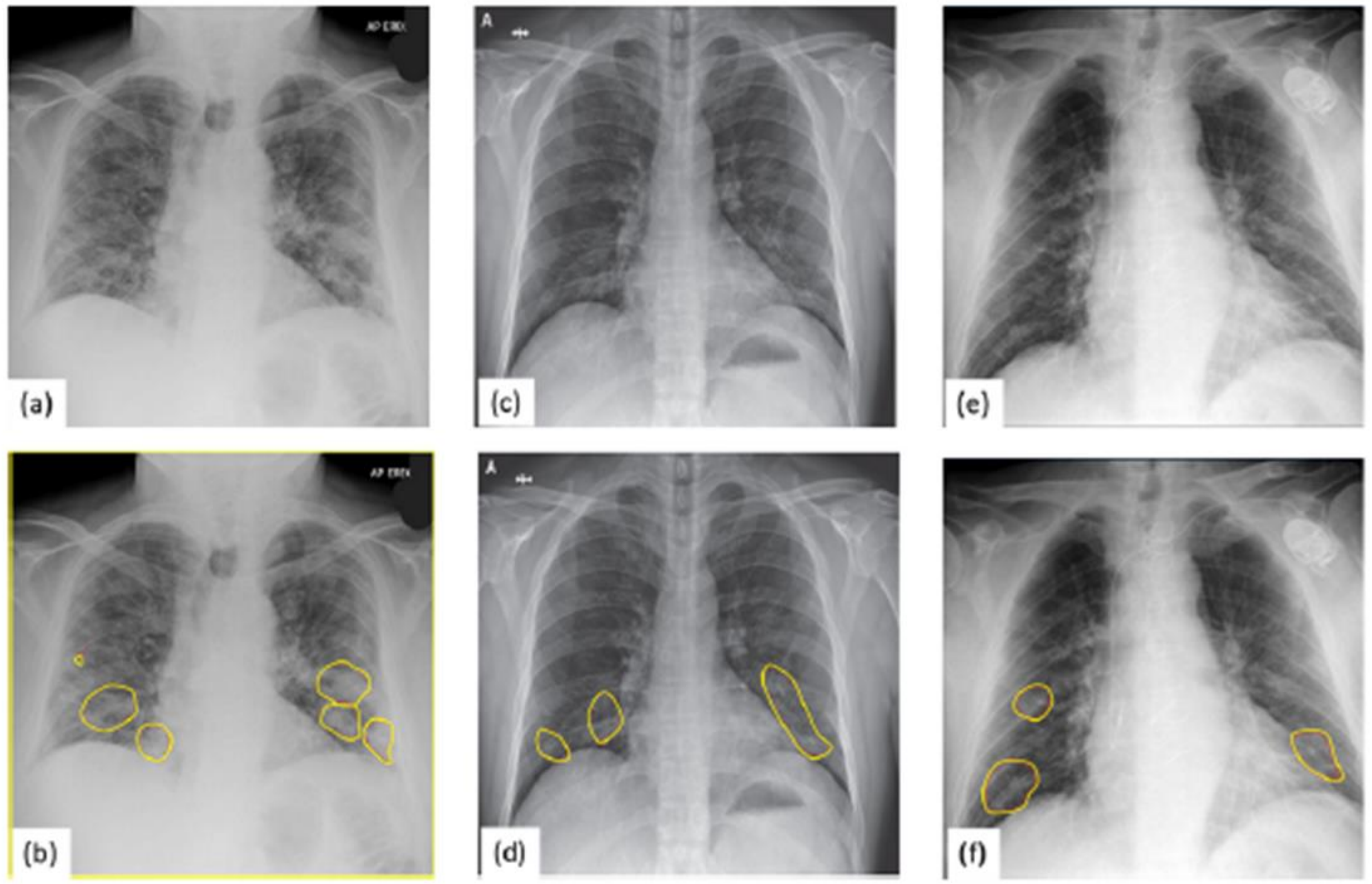
- Papers show that deep learning approaches exceed the accuracy of trained doctors:
  - Skin cancer detection, dermatologist with **66%** accuracy versus CNN with **72%** accuracy... (Esteva et al., 2017)
  - Once the neural networks are trained, debugged and fine tuned, the classification of images is a fast and easy to implement process.
  - During the COVID-19 outbreak real-time polymerase chain reaction was the standard method.
  - Problem: For ten thousands of people such an analysis cannot be carried out in a short time. Especially in countries without a good laboratory infrastructure (Zhang et al., 2020).
  - Chest X-ray is the most commonly used technique for diagnosing patients with thorax abnormalities, because it offers a fast and cheap imaging with low radiation (Self et al., 2013).

3. The Project

- Detect COVID-19 patients by classifying radiographic lung images
    - Clustering of viral pneumonia can often suggest a potential outbreak of COVID-19 infection
    - Very challenging for doctors to interpret correctly

(Joarder & Crundwell, 2009) -> distinguish between different types of pneumonia

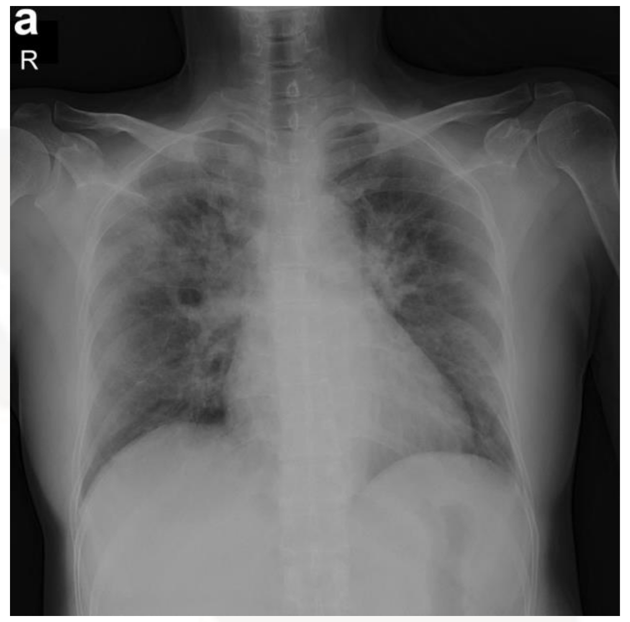
- There are approaches that have shown that the recognition of COVID-19 by X-ray images is possible and useful
(Minaee et al., 2020 ;Zhang et al., 2020)



COVID-19 images and the corresponding marked areas by radiologist (Minaee et al., 2020)
https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7372265/

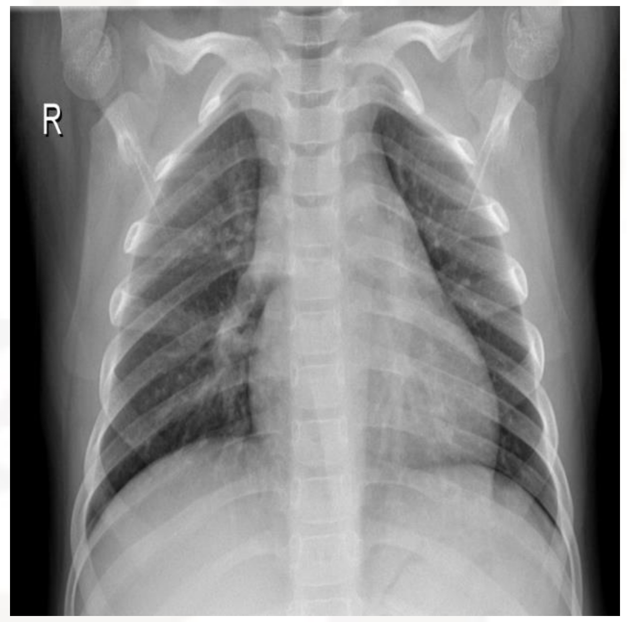
4. Dataset

- Initial Dataset:
  - https://www.kaggle.com/tawsifurrahman/covid19-radiography-database (version 1)
  - 219 COVID-19 positive images, 1341 normal images and 1345 viral pneumonia images
  - Cons: Low amount of covid images. Highly unbalanced dataset.



COVID

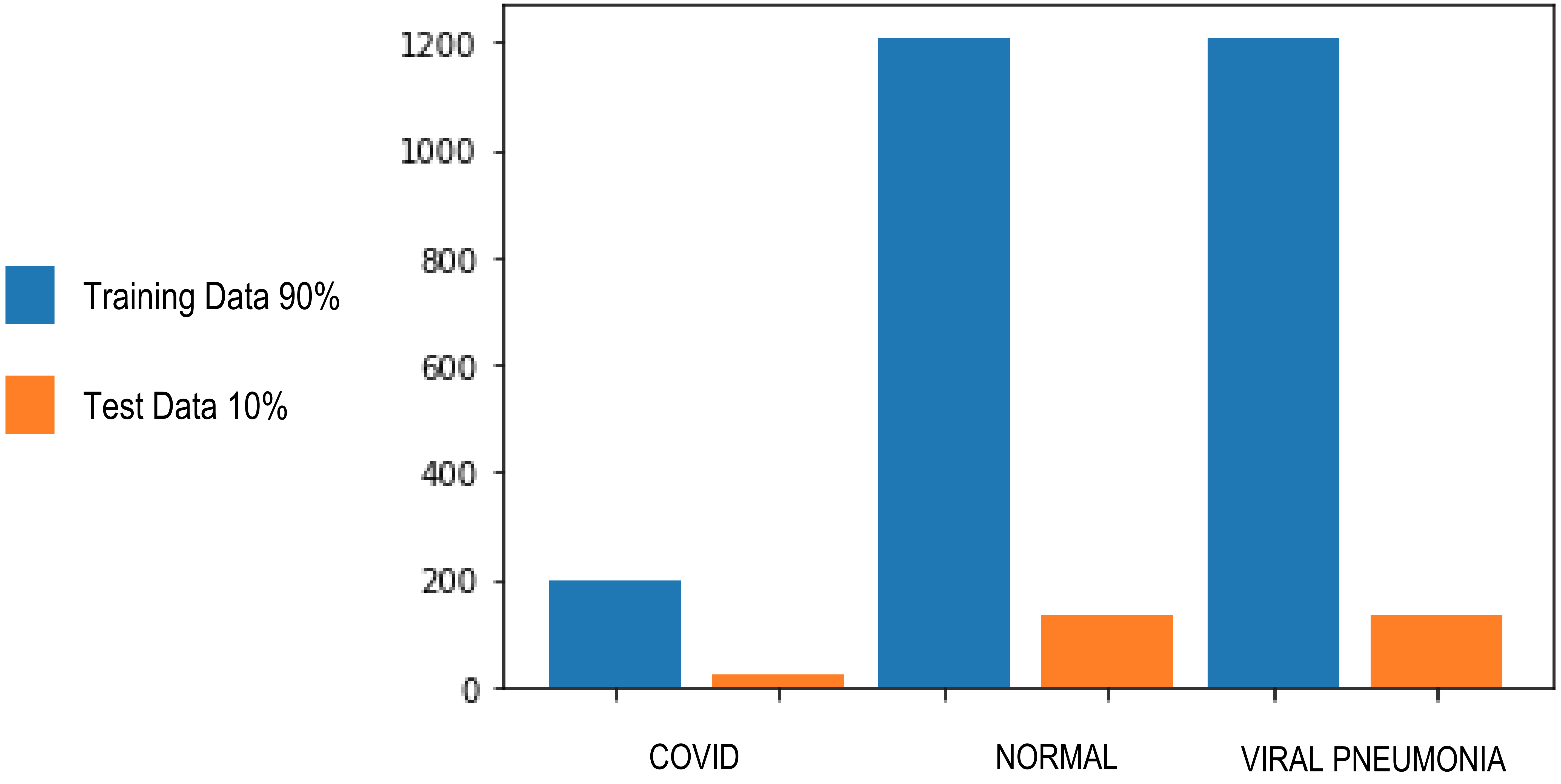
VIRAL PNEUMONIA



NORMAL

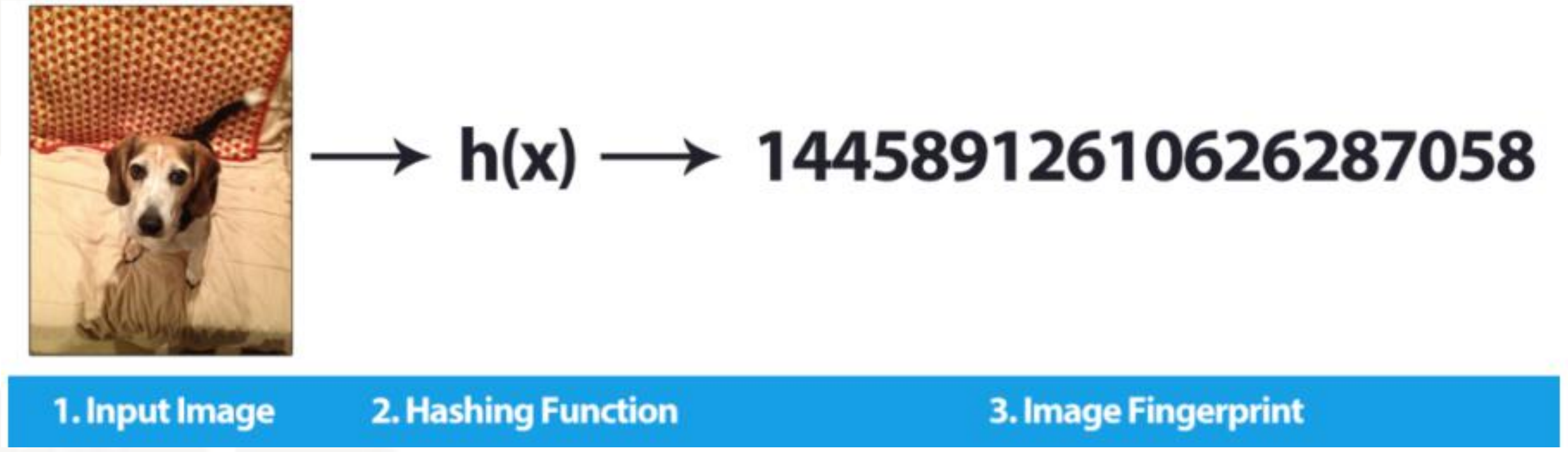
SIDE IMAGES

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



4. Dataset

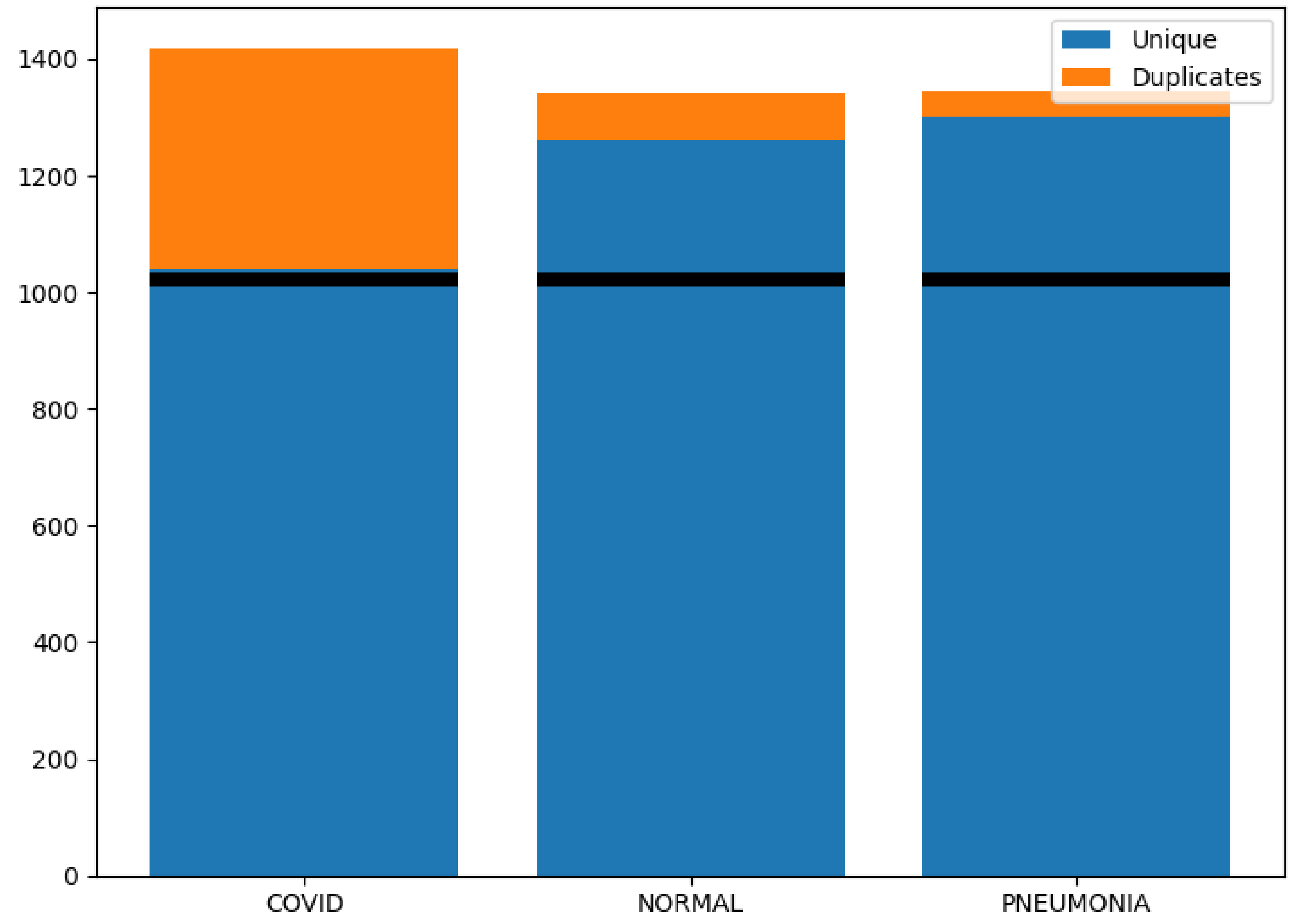
- Current Dataset:
  - https://www.kaggle.com/tawsifurrahman/covid19-radiography-database (version 3)
  - 1200 COVID-19 positive images, 1341 normal images and 1345 viral pneumonia images
  - removed duplicates: image-hash comparison
  - removed side photos
  - balanced the dataset : uniform distribution -> 1028 images from each category



https://www.pyimagesearch.com/2017/11/27/image-hashing-opencv-python/

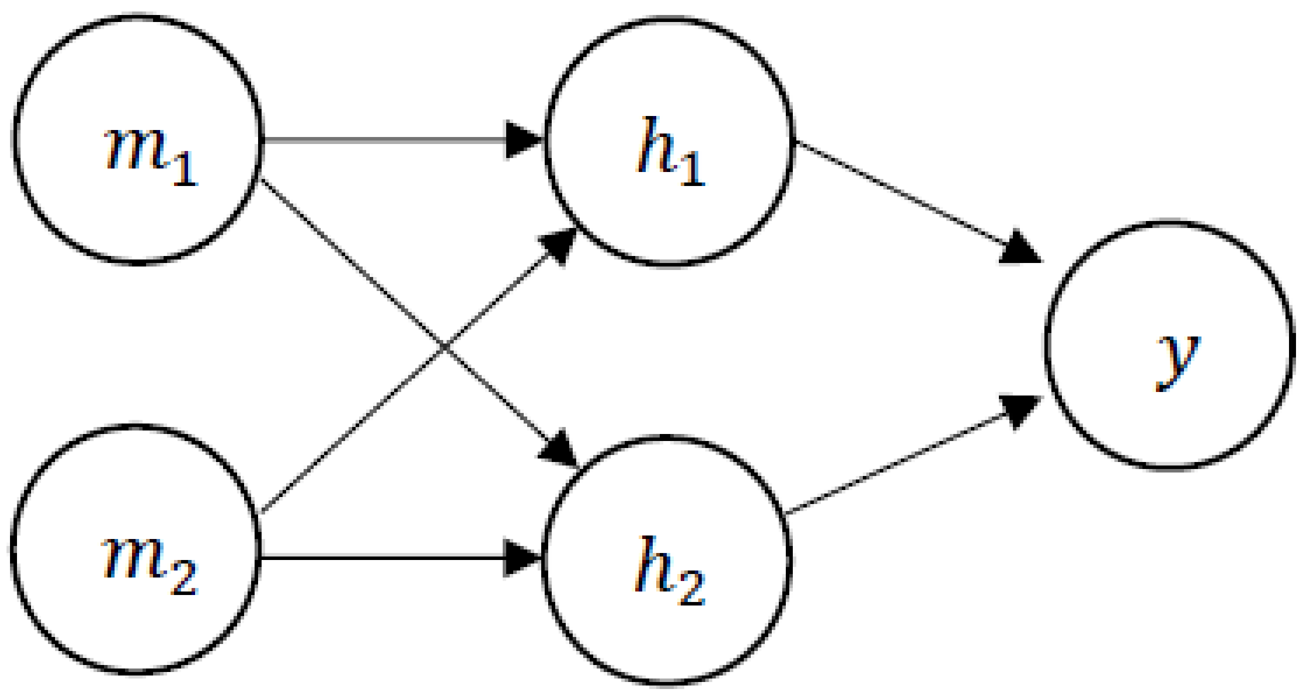
SIDE IMAGES

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

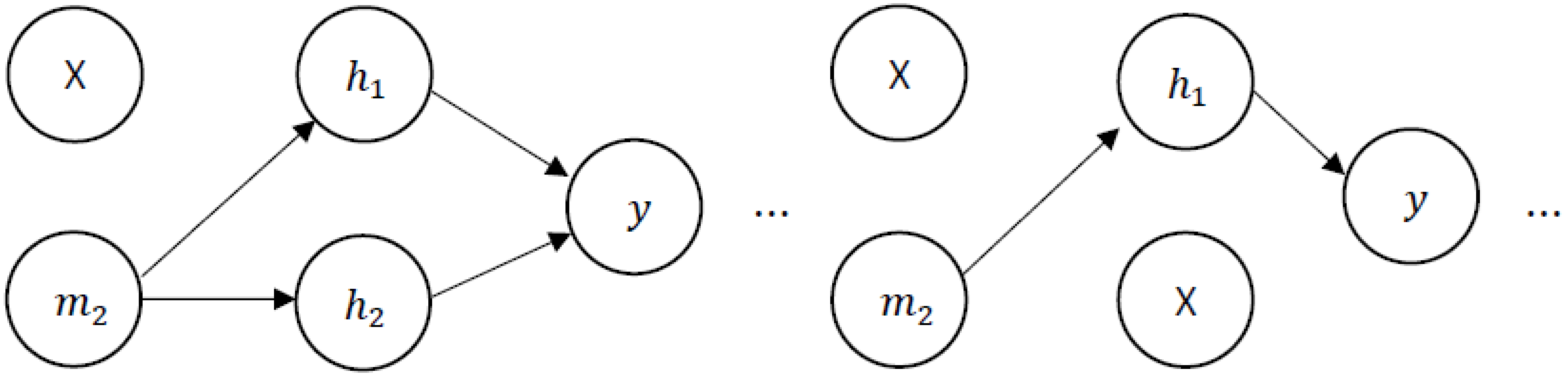


5.Regularization

5. Regularization: Dropout

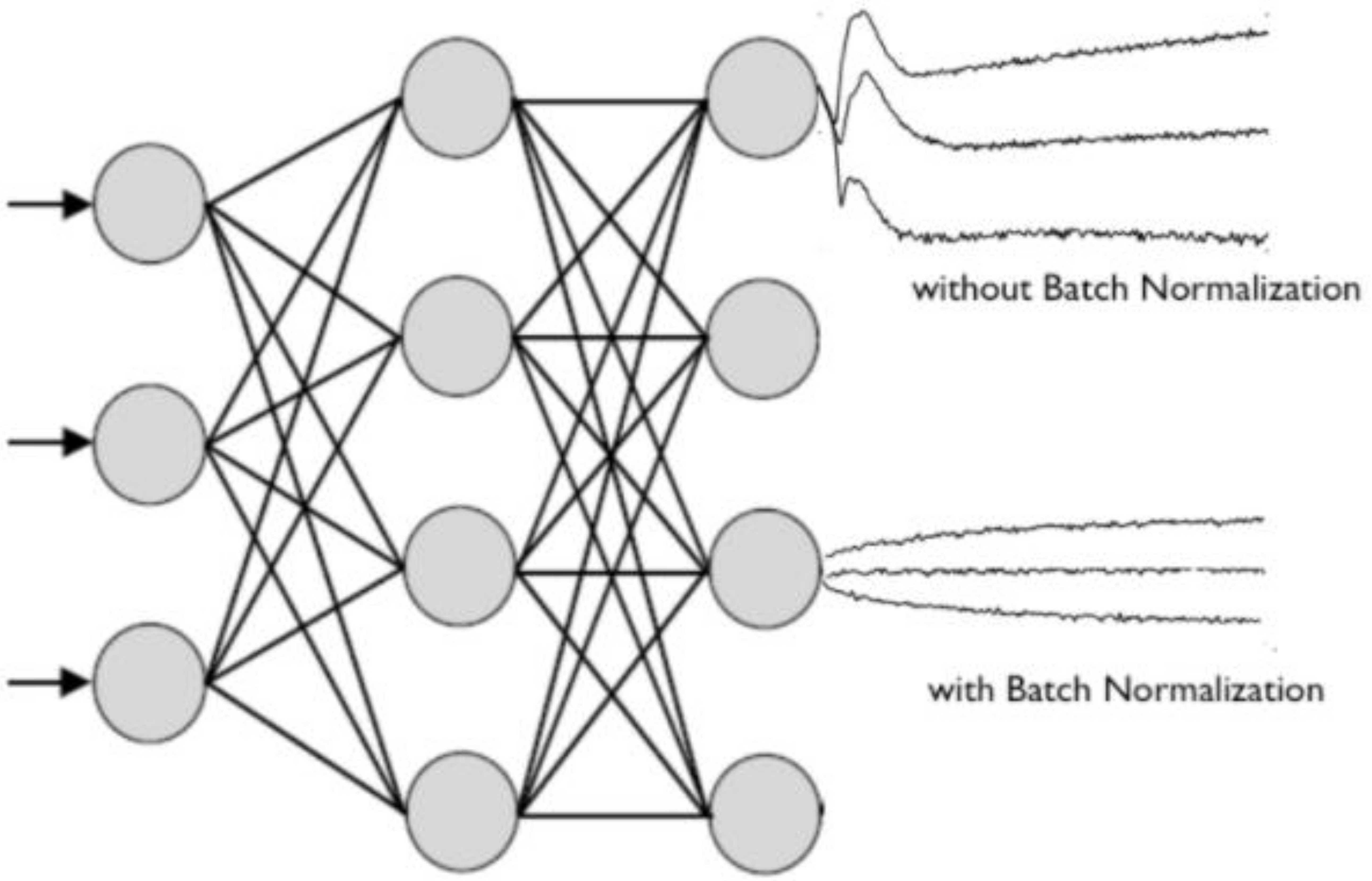


inital network



example of possible subnetworks

5. Regularization: Batch Normalization



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5. Regularization: Data Augmentation

Augmentation operations and their probability of being applied to the image

Operation	Probability
Random Brightness	25%
Flip Vertical	25%
Random Rotation	25%
Random Shear	25%
Random Erasing	25%

5. Regularization: Data Augmentation

(a) Original image

(b) Random brightness

(c) Flip vertical

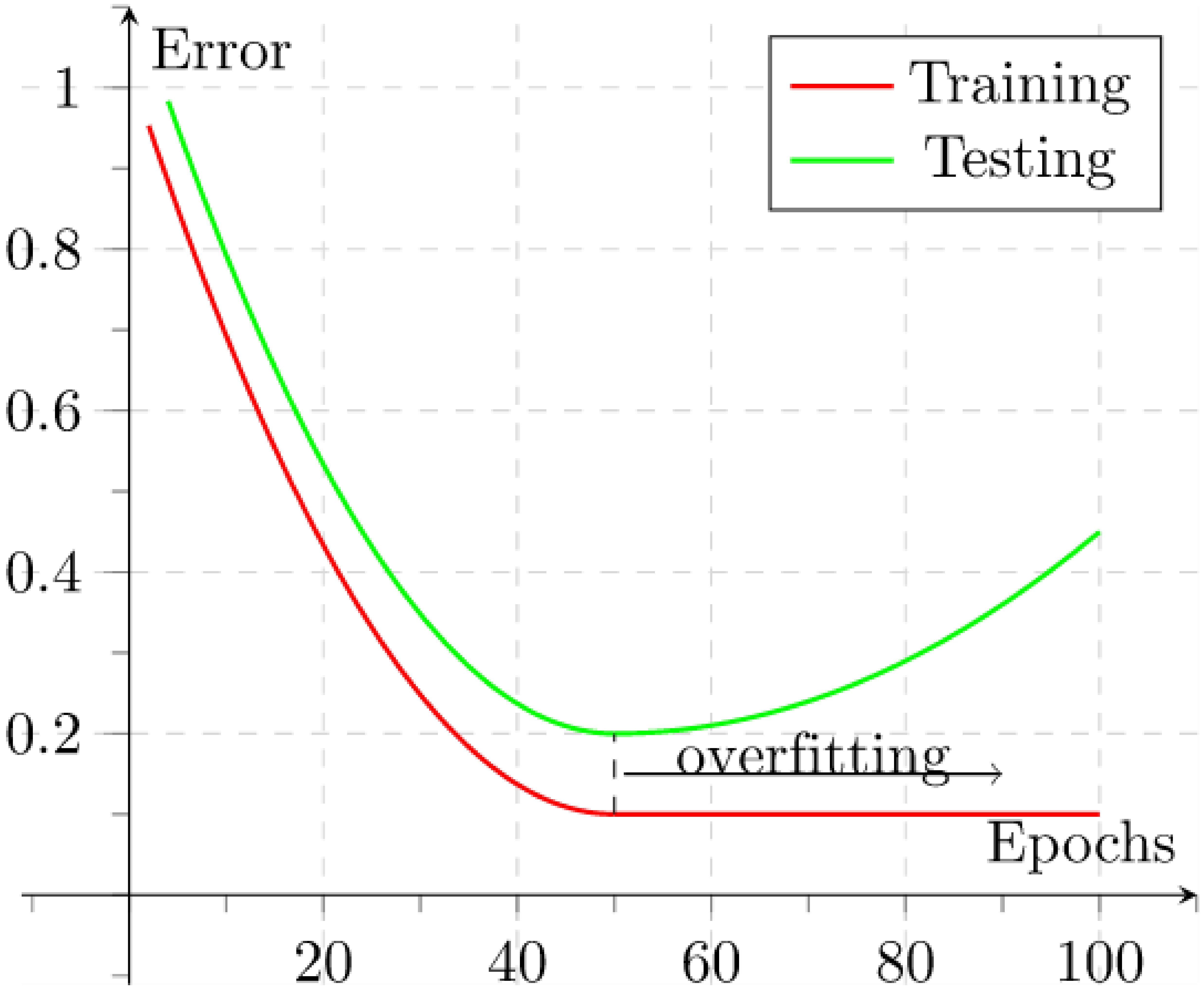
(d) Random rotation and crop

(e) Random shear and crop

(f) Random erasing

(g) Chaining multiple operations

5. Regularization: Early stopping



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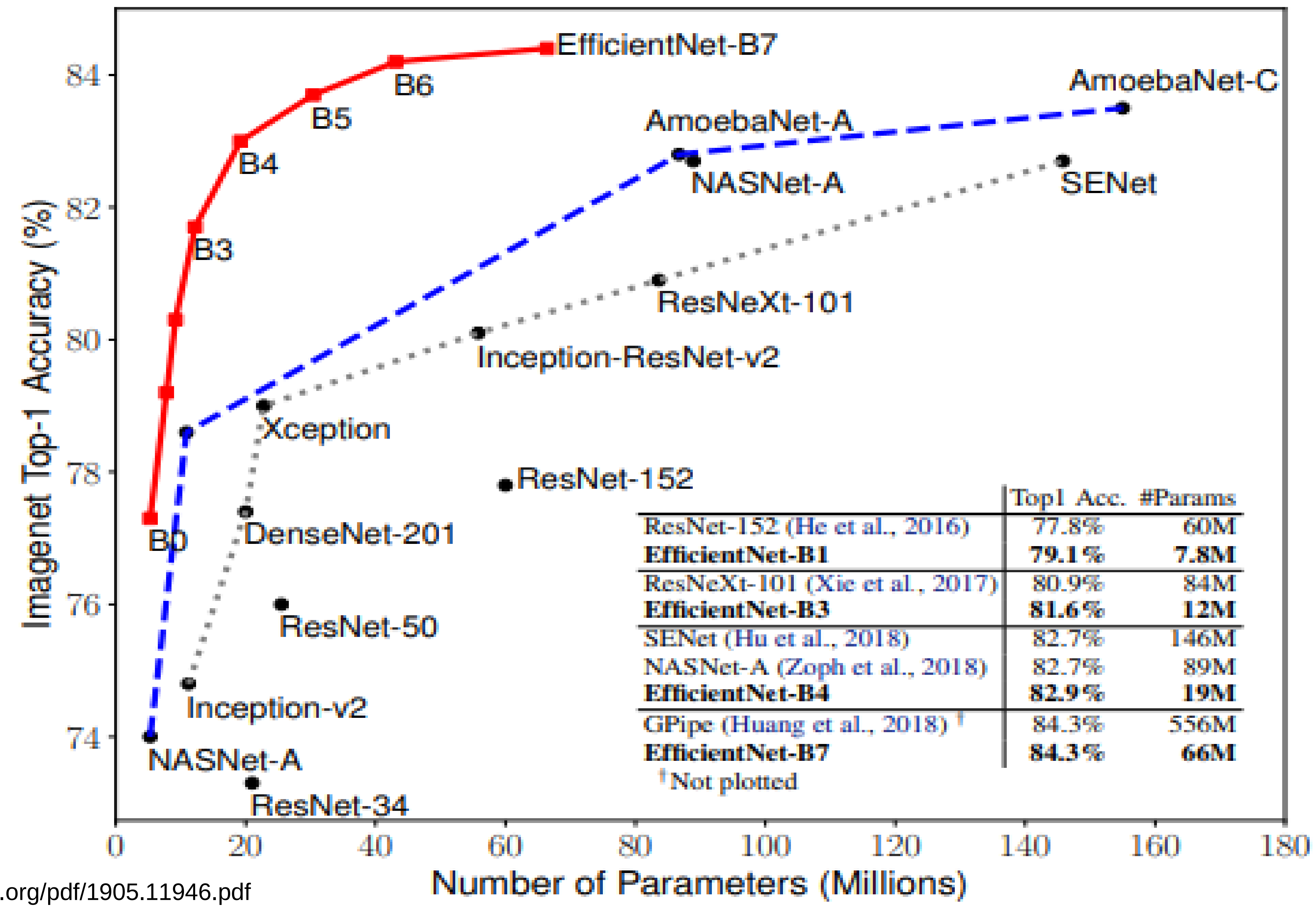
6.Architecture

6. Architecture: EfficientNet

- Presented by Tan and Le in 2019
- Their study comprises compound scaling method that efficiently scales network to achieve better performance
- Model resulted in state-of-the-art 84.4% top-1 accuracy on ImageNet while being 8.4x smaller and 6x times faster on inference than the best existing convolutional model.

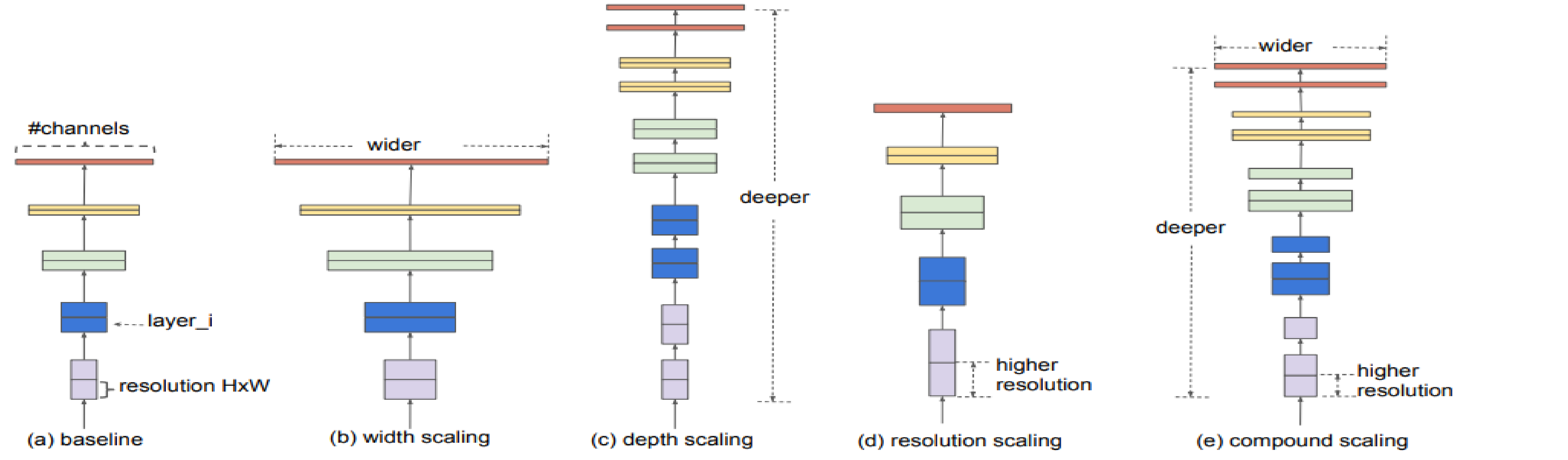


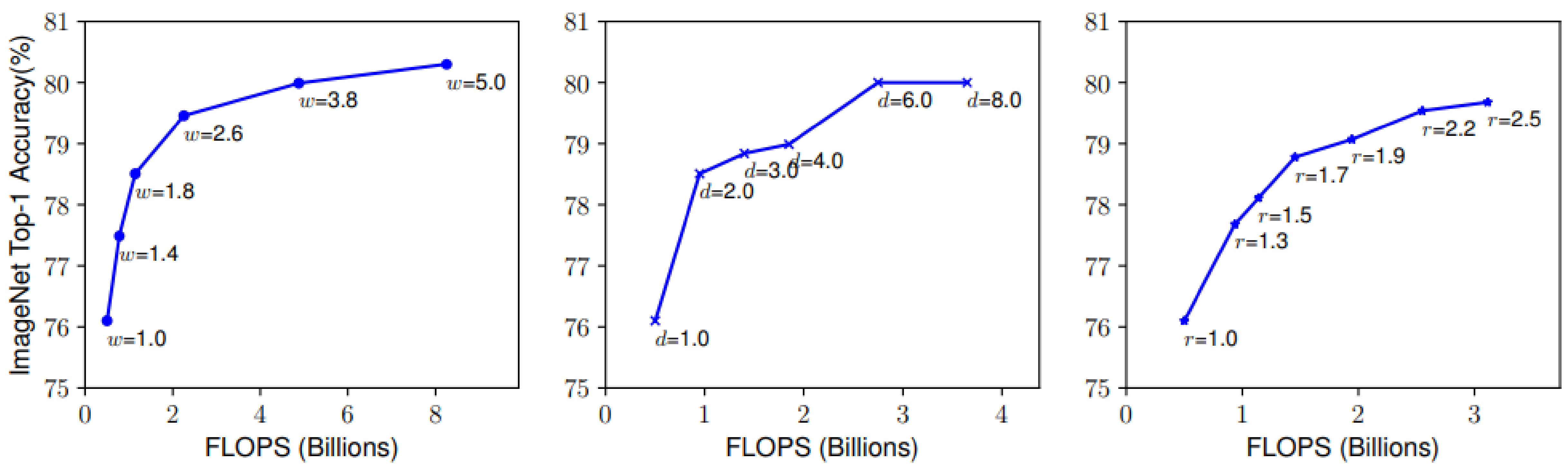
https://arxiv.org/pdf/1905.11946.pdf

6. Architecture: EfficientNet

- Conventional methods arbitrary scale either the width, depth or the resolution
- In contrast, EfficientNets scale all the factors uniformly with a set of fixed scaling coefficients
- Authors observed: scaling up any dimension of the network separately

improved accuracy, but the accuracy-gain diminished as the model increased





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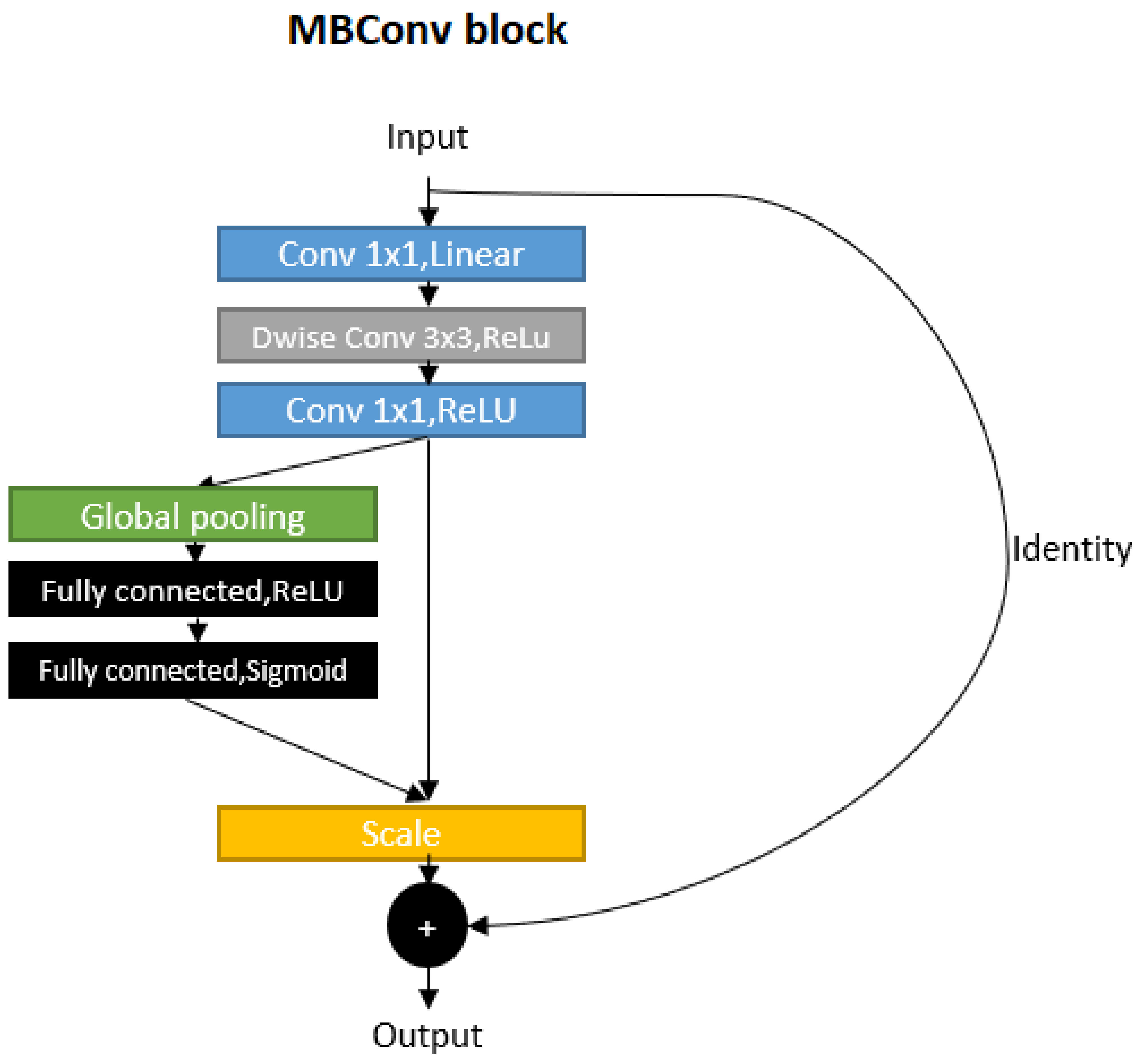
6. Architecture: EfficientNet



7.Evaluation

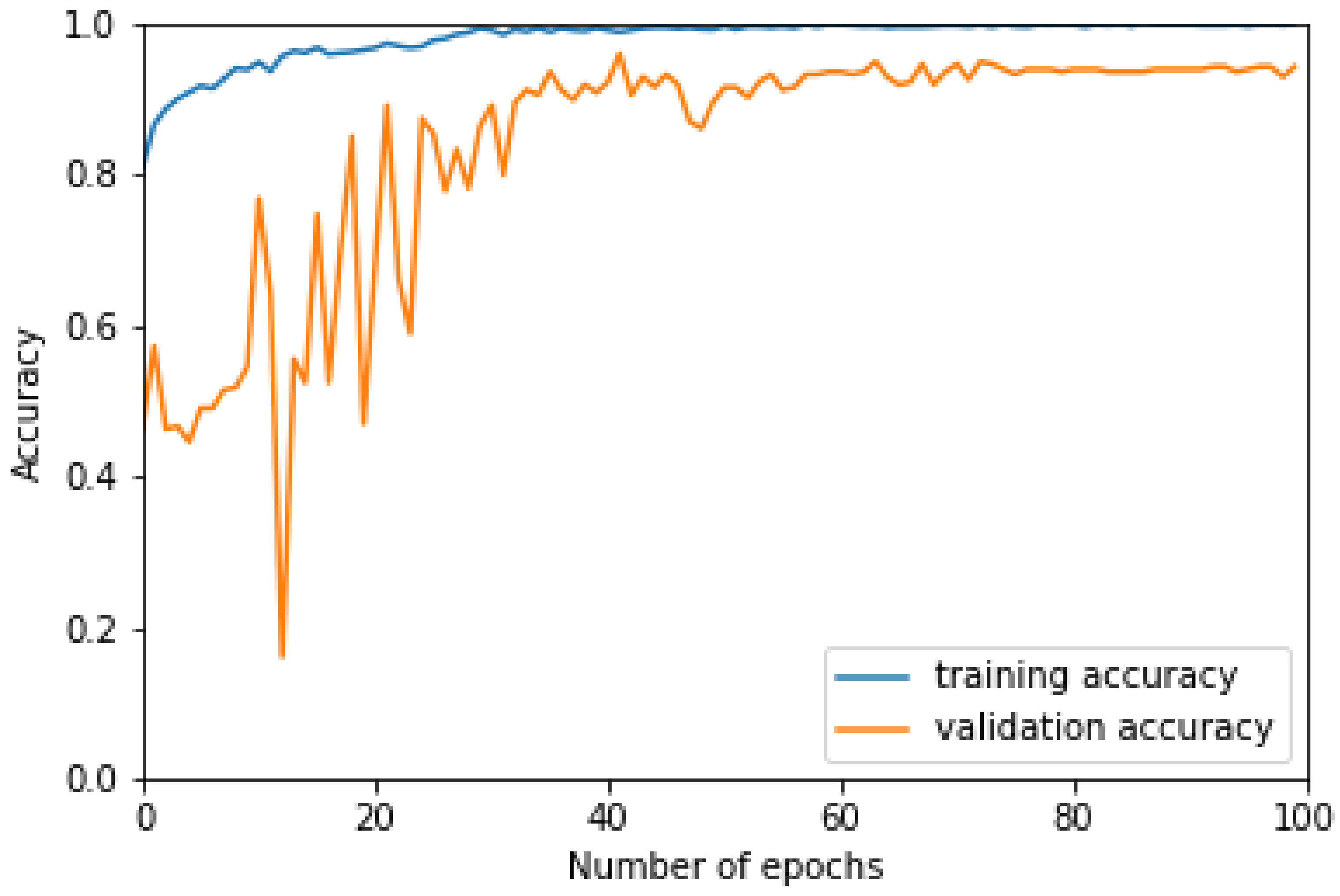
7.Evaluation: Model Summary

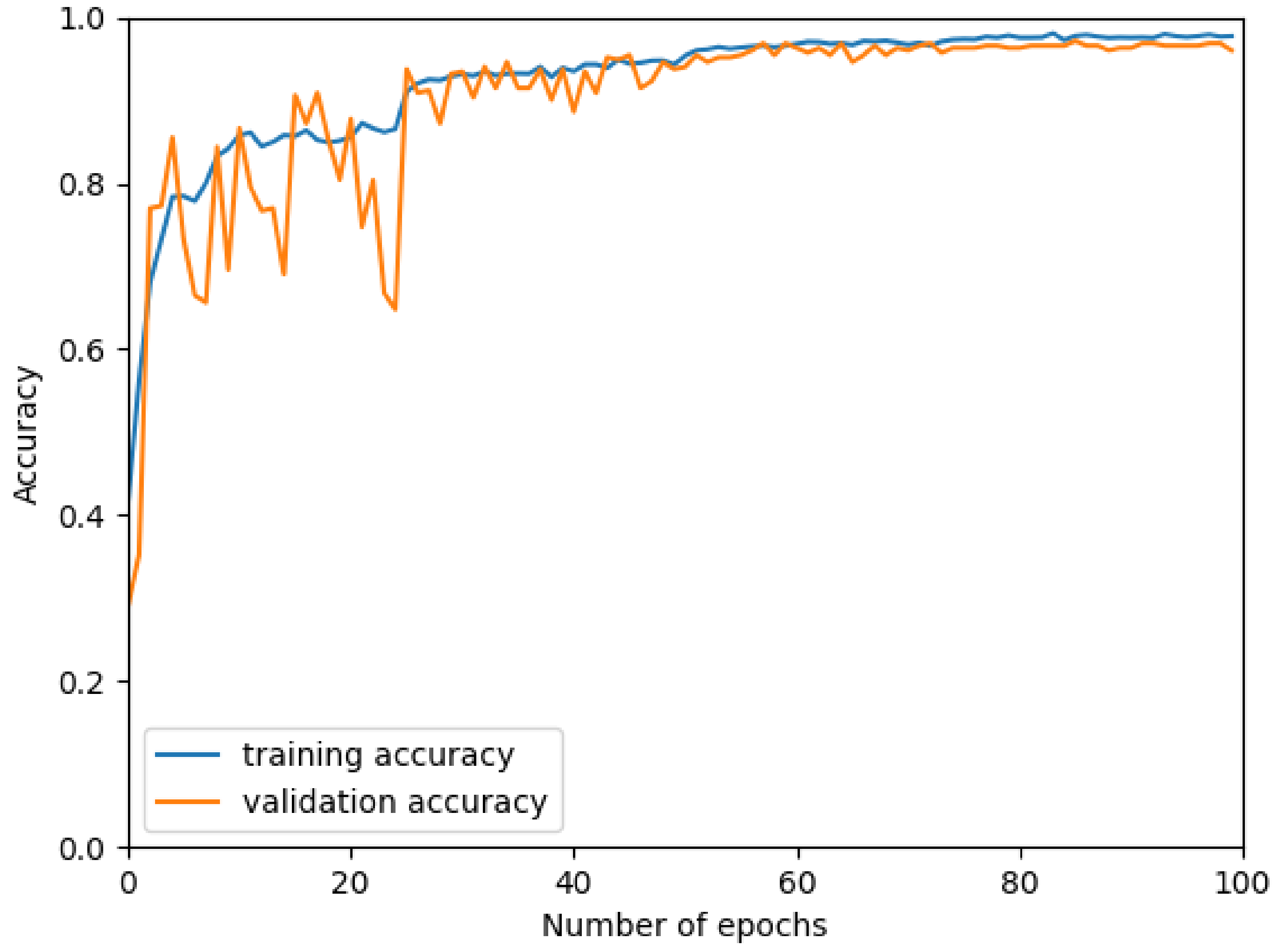
- For the experiments we trained several models for 100 epochs and measured their performance.
- All models trained with Adam optimizer and inital learning rate of 0.001.
- Varying batch-sizes & image resolutions

Model	Input resolution	Batch size	Regularization
Naive CNN with 5 layers	300x300	64	✗
EfficientNetB7	600x600	4	✓
EfficientNetB7	360x360	16	✓
EfficientNetB7	475x475	8	✓

7.Evaluation: Training/Validation Accuracy

Model	Input size	Batch size	Validation Accuracy
Naive CNN with 5 layers (left)	300x300	64	91.43% (epoch 42)
EfficientNetB7 (middle)	600x600	4	95.79% (epoch 47)
EfficientNetB7	360x360	16	96.88% (epoch 46)
EfficientNetB7 (right)	475x475	8	**97.16% (epoch 80)**





7.Evaluation: Metrics

EfficientNetB7 600x600 Batch size 4	Precision	Recall	F1-Score	Support
Normal	0.99	0.98	0.99	103
Corona	0.86	1.00	0.92	126
Pneumonia	0.98	0.83	0.90	130

EfficientNetB7 360x360 Batch size 16	Precision	Recall	F1-Score	Support
Normal	0.99	0.98	0.99	103
Corona	0.86	1.00	0.92	126
Pneumonia	0.98	0.83	0.90	130

EfficientNetB7 475x475 Batch size 8	Precision	Recall	F1-Score	Support
Normal	0.99	0.96	0.98	103
Corona	0.92	1.00	0.96	126
Pneumonia	0.98	0.92	0.94	130

COVIDNet-CXR4-A (100 Test images)

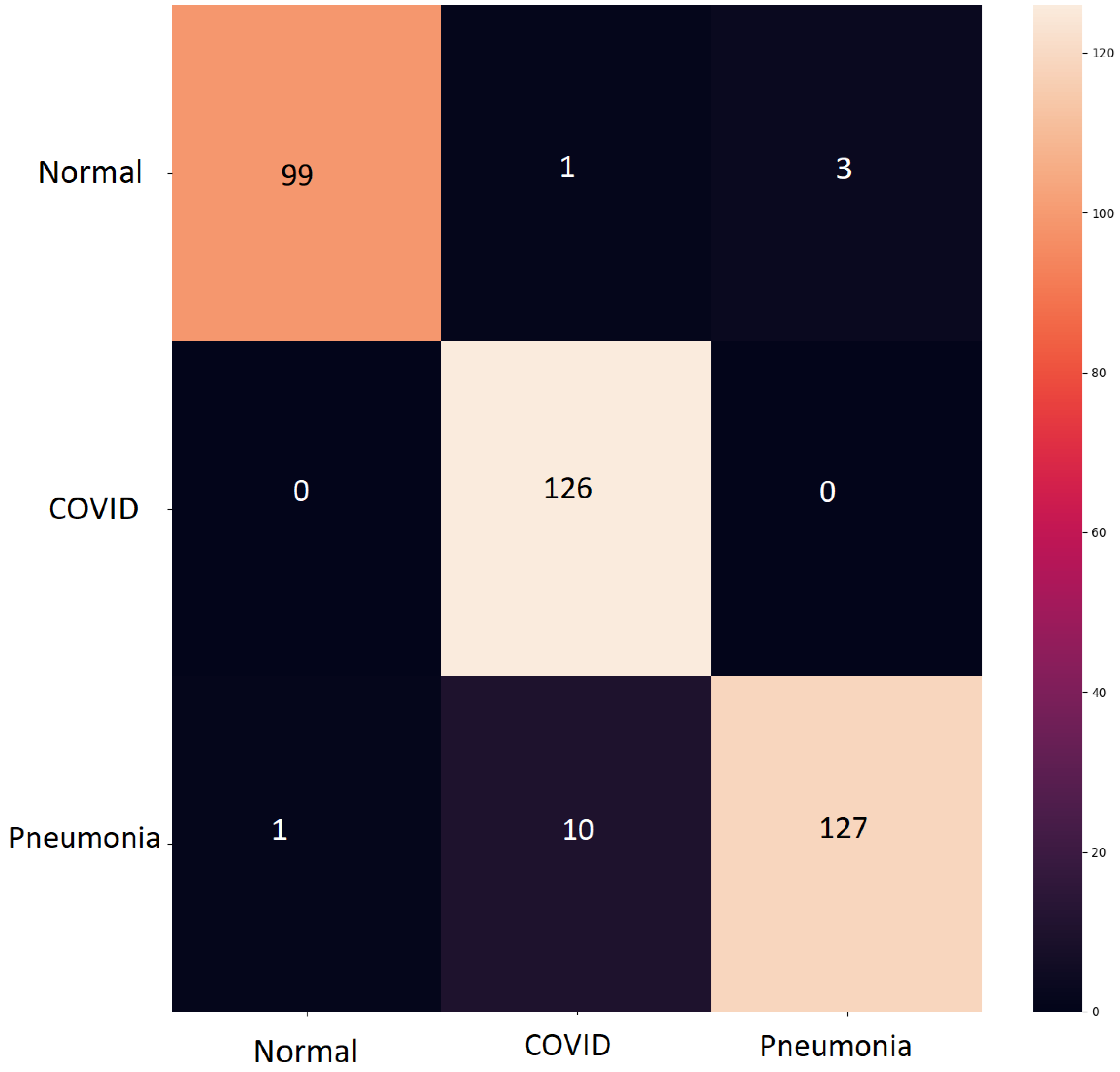
Sensitivity (%) **(=Recall)**		
Normal	Pneumonia	COVID-19
94.0	94.0	95.0

Positive Predictive Value (%) **(=Precision)**		
Normal	Pneumonia	COVID-19
91.3	93.1	99.0

https://github.com/lindawangg/COVID-Net

7.Evaluation: Confusion Matrix

EfficientNetB7 Input size 475x475 Batch size 8



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