CONVOLUTIONAL NEURAL NETWORKS FOR THE DETECTION OF COVID-19

Panakakis Stavros
2018108

Sophia Tsivoula
2018130

Description

Pandemic in March 2020

Appearance

- Wuhan, China
- December 2019
- Seefood Market

Form

- RNA positive-strand virus
- Infects the respiratory system

Zhu, Na, et al.
A novel coronavirus from patients with pneumonia in China, 2019.
New England Journal of Medicine (2020).

Li, Bo, et al.
Prevalence and impact of cardiovascular metabolic diseases on COVID-19 in China.
Clinical Research in Cardiology 109.5 (2020): 531-538.

Abdulamir, Ahmed S, Rand R. Hafidh.
The Possible Immunological Pathways for the Variable Immunopathogenesis of COVID--19 Infections among Healthy Adults, Elderly and Children.
Electronic Journal of General Medicine 17.4 (2020).

Description

Pandemic in March 2020

Common symptoms

- Fever
- Cough
- Fatigue
- Expectoration
- Shortness of breath

Critical Patients

- Elderly
- Weak immune system
- Suffering from other diseases

Li, Long-quan, et al.
COVID-19 patients' clinical characteristics, discharge rate, and fatality rate of meta-analysis.
Journal of medical virology 92.6 (2020): 577-583.

Huang, Chaolin, et al.
Clinical features of patients infected with 2019 novel coronavirus in Wuhan, China.
The lancet 395.10223 (2020): 497-506.

Cases

COVID-19 Cases Worldwide

Worldwide

Total: 90.4m

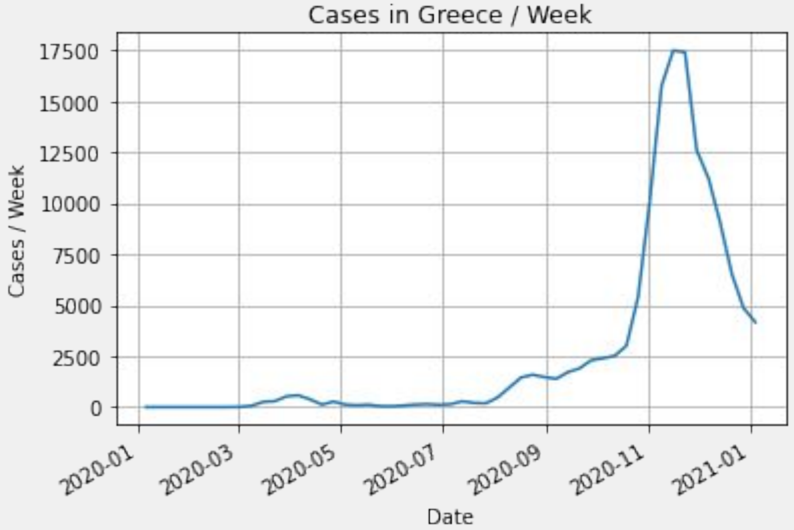
Recovered: 50.1m

Deaths: 1.94m

European Centre for Disease Prevention and Control
http://data.europa.eu/88u/dataset/covid-19-coronavirus-data
10.2906/101099100099/1

Cases

COVID-19 Cases in Greece



Greece

Total: 145k

Recovered: 93,764

Deaths: 5,263

European Centre for Disease Prevention and Control
http://data.europa.eu/88u/dataset/covid-19-coronavirus-data
10.2906/101099100099/1

Cost

Cost of COVID-19

Social

- Transfer on web
- Online classes
- Prioritization of admissions in medical centers

Financial

- 3.3 trillion $ government stimulus packages
- 4.5 trillion $ additional loans
- Central banks have reduced policy interest rates

Huang, Chaolin, et al.
Clinical features of patients infected with 2019 novel coronavirus in Wuhan, China.
The lancet 395.10223 (2020): 497-506.

Akhtaruzzaman, Md, Sabri Boubaker, and Ahmet Sensoy
Financial contagion during COVID–19 crisis.
Finance Research Letters (2020): 101604.

Need for analytics

Need for analytics for COVID-19

A.I. Benefits

- Help physicians detect diseases on patients faster and accurately
- Usage in remote areas where there is a lack of specialized physicians
- Mimimize the mean time that takes to diagnose a patient
- Avoid interaction between physicians and patients

Chest x-ray images

Used by Convolutional Neural Networks

Healthy

Pneumonia

COVID-19

Paul Mooney. Chest X-Ray Images (Pneumonia); 2017
Kaggle.
Available from: https://www.kaggle.com/paultimothymooney/chest-xray-pneumonia.

Wang et al.
COVID-Net: a tailored deep convolutional neural network design for
detection of COVID-19 cases from chest X-ray images
2020, https://doi.org/10.1038/s41598-020-76550-z

Computer-aided detection of COVID-19 from X-ray images using multi-CNN and Bayesnet classifier

Abraham, Bejoy et al.
Computer-aided detection of COVID-19 from X-ray images using multi-CNN and Bayesnet classifier.
Biocybernetics and biomedical engineering 40.4 (2020): 1436-1445.

Review

Multi-CNN & Bayesnet Classifier

Networks

- Shufflenet
- Darknet-53
- Squeezenet
- MobilenetV2
- Xception

- Feature matrix of dimension 950x5000

Zhang X et al.
Shufflenet: an extremely efficient convolutional neural network for mobile devices.
Proceedings of the IEEE Conference on Computer Visionand Pattern Recognition; 2018. p. 6848–56.

Redmon J et al.
Yolov3: an incremental improvement.
2018, arXiv preprint arXiv:1804.02767

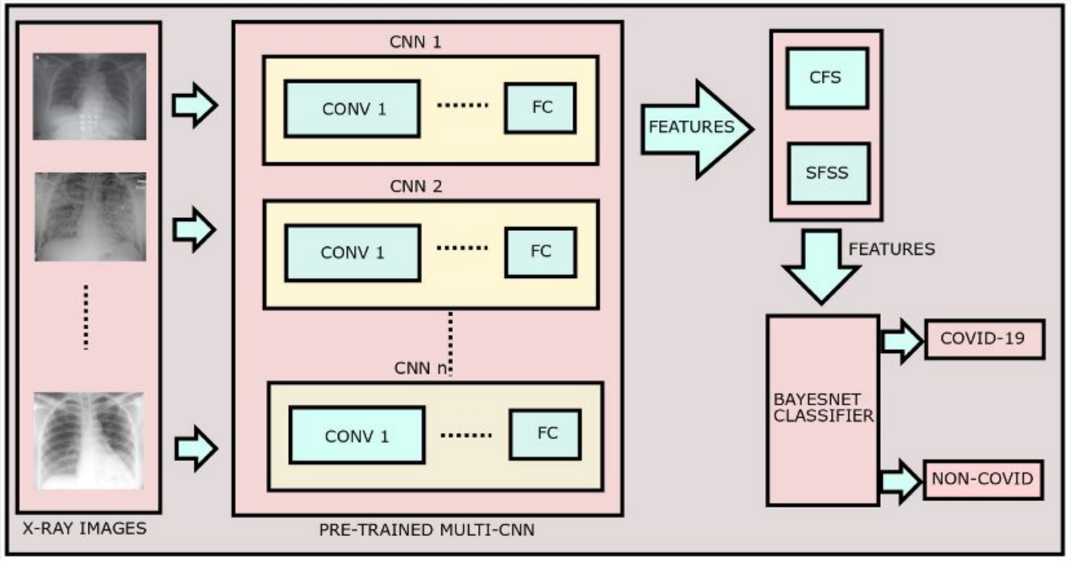
Iandola, Forrest N., et al.
SqueezeNet: AlexNet-level accuracy with 50x fewer parameters and< 0.5 MB model size.
arXiv preprint arXiv:1602.07360 (2016).

M. Sandler, A. Howard et al.
MobileNetV2: Inverted Residuals and Linear Bottlenecks
2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition, Salt Lake City, UT, 2018, pp. 4510-4520, doi: 10.1109/CVPR.2018.00474.

Chollet, François.
Xception: Deep learning with depthwise separable convolutions.
Proceedings of the IEEE conference on computer vision and pattern recognition. 2017.

Review

Feature Matrix > Bayesnet Classifier > COVID-19 vs Non-COVID-19



Abraham, Bejoy et al.
Computer-aided detection of COVID-19 from X-ray images using multi-CNN and Bayesnet classifier.
Biocybernetics and biomedical engineering 40.4 (2020): 1436-1445.

Review

Datasets used for classification

Dataset #1

- COVID-19 images: 453
- Non-COVID-19 images: 497
- Accuracy: 91.16%

Dataset #2

- COVID-19 images: 71
- Non-COVID-19 images: 7
- Accuracy: 97.44%

Kermany, et al.
Identifying medical diagnoses and treatable diseases by image-based deep learning.
Cell 172.5 (2018): 1122-1131.

Dadario AMV. Covid-19 X rays; 2020.
http://dx.doi.org/10.34740/KAGGLE/DSV/101946.
Available from:https://www.kaggle.com/dsv/1019469.

Application of deep learning technique to manage COVID-19 in routine clinical practice using CT images: Results of 10 convolutional neural networks

Ardakani, Ali Abbasian, et al.
Application of deep learning technique to manage COVID-19 in routine clinical practice
using CT images: Results of 10 convolutional neural networks.
Computers in Biology and Medicine (2020): 103795.

Review

Networks used for classification

Network	Depth	Parameters	Accuracy
AlexNet	8	61	78.92
VGG-19	19	144	85.29
MobilenetV2	53	3.5	92.16
ResNet-101	101	44.6	99.51
Xception	71	22.9	99.02

- **Best Accuracy:** ResNet-101

Krizhevsky Ilya Sutskever, et al.
Imagenet classification with deep convolutional neural networks.
Advances in neural information processing systems. 2012.

Simonyan, Karen, et al.
Very deep convolutional networks for large-scale image recognition.
arXiv preprint arXiv:1409.1556 (2014).

M. Sandler, A. Howard et al.
MobileNetV2: Inverted Residuals and Linear Bottlenecks.
2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition,

K. He, X. Zhang, et al.
Deep Residual Learning for Image Recognition.
2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)

Chollet, François.
Xception: Deep learning with depthwise separable convolutions.
Proceedings of the IEEE conference on computer vision and pattern recognition. 2017.

Review

Patients COVID-19 status from clinical data

Positive

- No of patients: 108
- Age: 50.22 ± 10.85
- Female: 48
- Male: 60

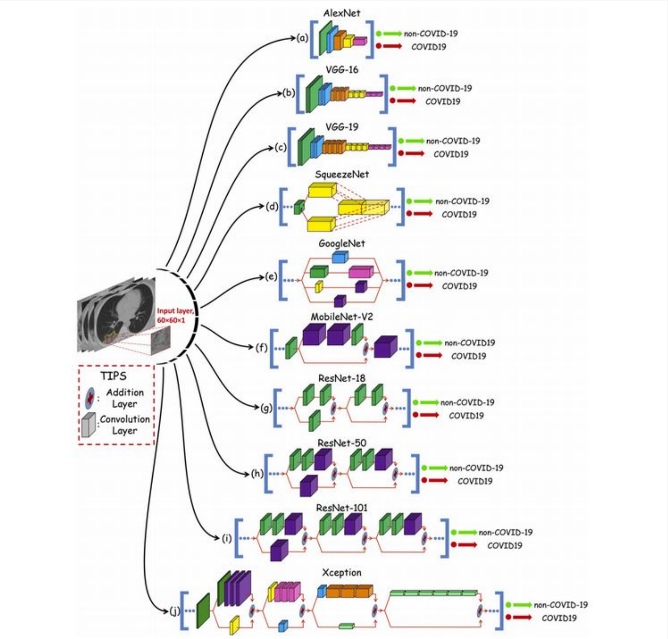
Negative

- No of patients: 86
- Age: 61.45 ± 15.04
- Female: 35
- Male: 51

Ardakani, Ali Abbasian, et al.
Application of deep learning technique to manage COVID-19 in routine clinical practice
using CT images: Results of 10 convolutional neural networks.
Computers in Biology and Medicine (2020): 103795.

Review

Architecture of the Convolutional Neural Networks



Dataset shuffled: Each epoch

Train / Validation: 80 / 20

Validation Frequency: 5

Learning Rate: 0.01

Optimizer: SGDM

Ardakani, Ali Abbasian, et al.
Application of deep learning technique to manage COVID-19 in routine clinical practice
using CT images: Results of 10 convolutional neural networks.
Computers in Biology and Medicine (2020): 103795.

COVnet-101: ResNet-101 based custom convolutional neural network

K. He, X. Zhang, et al.
Deep Residual Learning for Image Recognition.
2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Las Vegas, NV,
2016, pp. 770-778, doi: 10.1109/CVPR.2016.90.

ResNet

Description of the Deep Convolutional Neural Network

Plain

- Philosophy of VGG
- 3x3 filters
- Global averages pooling layer
- 1000 way fully connected layer
- Softmax function
- 34 layers

Residual

- Plain based
- Shortcut Connections
- More layers

K. He, X. Zhang, et al.
Deep Residual Learning for Image Recognition.
2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Las Vegas, NV, 2016, pp. 770-778, doi: 10.1109/CVPR.2016.90.

Simonyan, Karen, et al.
Very deep convolutional networks for large-scale image recognition.
arXiv preprint arXiv:1409.1556 (2014).

ResNet-101

Dataset of the Deep Convolutional Neural Network

Dataset

- Imagenet 2012
- 1000 classes
- 1.28 million images
- 50k validation images

K. He, X. Zhang, et al.
Deep Residual Learning for Image Recognition.
2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Las Vegas, NV, 2016, pp. 770-778, doi: 10.1109/CVPR.2016.90.

Deng J et al.
Imagenet: alarge-scale hierarchical image database.
2009 IEEE Conference on Computer Vision and Pattern Recognition.IEEE; 2009. p. 248–55.

ResNet-101

Image processing of the Deep Convolutional Neural Network

Image processing

- Data augmentation
- Random samples
- Horizontally flipped
- Cropped 224x224
- Batch Normalization

K. He, X. Zhang, et al.
Deep Residual Learning for Image Recognition.
2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Las Vegas, NV, 2016, pp. 770-778, doi: 10.1109/CVPR.2016.90.

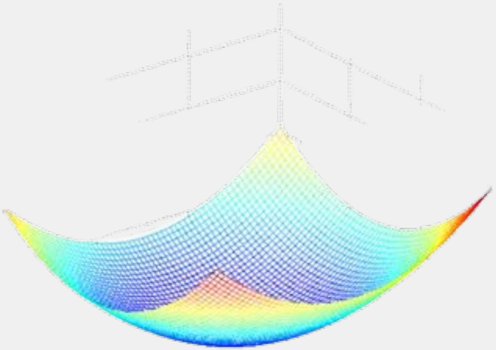
S. Ioffe and C. Szegedy.
Batch normalization: Accelerating deep network training by reducing internal covariate shift.
In ICML, 2015.

ResNet-101

Parameters of the Deep Convolutional Neural Network

Parameters

- SGD Optimizer
- 256 Batch size
- 0.1 Learning Rate
- 0.0001 Weight Decay
- 0.9 Momentum
- Dropout not uses



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Deep Residual Learning for Image Recognition.
2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Las Vegas, NV, 2016, pp. 770-778, doi: 10.1109/CVPR.2016.90.

G. E. Hinton et al.
Improving neural networks by preventing co-adaptation of feature detectors.
arXiv:1207.0580, 2012.

COVnet-101

Datasets used to train COVnet-101

Dataset #1

- No of images: 5863
- Healthy & Pneumonia Images

Dataset #2

- No of images: 569
- COVID-19 images

Paul Mooney. Chest X-Ray Images (Pneumonia); 2017
Kaggle.
Available from: https://www.kaggle.com/paultimothymooney/chest-xray-pneumonia.

Wang et al.
COVID-Net: a tailored deep convolutional neural network design for detection of COVID-19 cases from chest X-ray images
2020, https://doi.org/10.1038/s41598-020-76550-z

COVnet-101

Image processing used to COVnet-101

Image processing

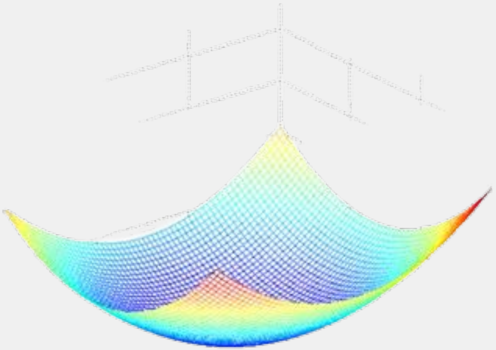
- 128x128 resize
- Shuffle images
- Divide by 255

COVnet-101

Parameters used to COVnet-101

Parameters

- Input shape (5144, 128, 128, 3)
- 16 Batch size
- Adam Optimizer
- 0.01 Learning rate
- 80 Train / 20 Validation



Two different versions

COVnet-101

Different versions of COVnet-101

COVID-19 vs Non-COVID-19

- 2 Labels
- Binary crossentropy
- Sigmoid function
- 97,4% accuracy
- 10 epochs

$$S(x) = \frac{1}{1 + e^{-x}}$$

COVnet-101

Different versions of COVnet-101

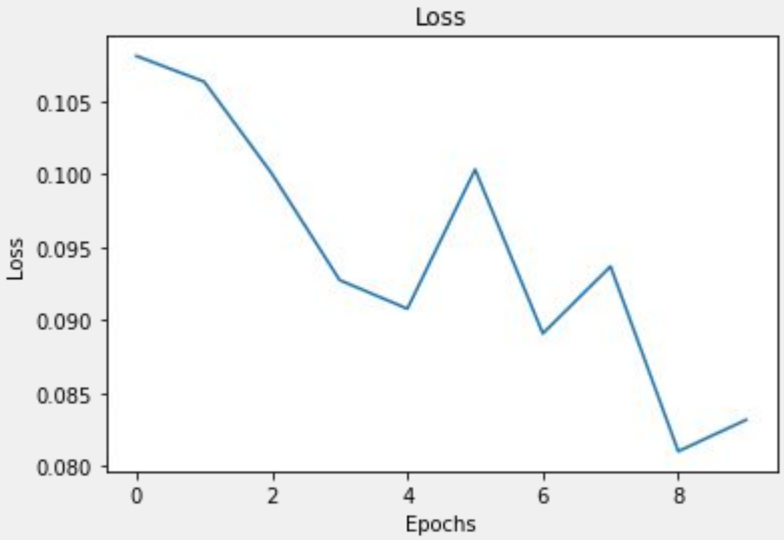
COVID-19 vs Non-COVID-19

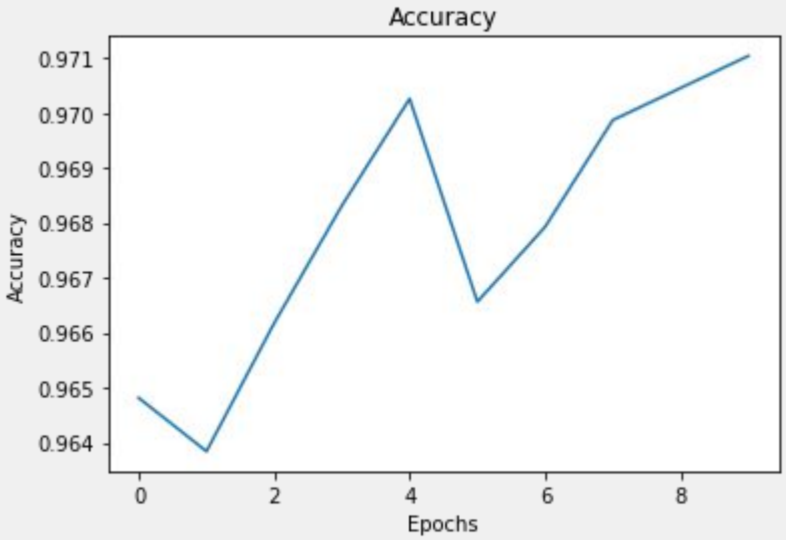
Layer (type)	Output shape	Parameters
ResNet-101	(None, 4, 4, 2048)	42658176
Flatten	(None, 32768)	0
Dense	(None, 1024)	33555456
Dropout	(None, 1024)	0
Dense	(None, 1)	1025

COVnet-101

Different versions of COVnet-101

COVID-19 vs Non-COVID-19





COVnet-101

Different versions of COVnet-101

COVID-19 vs Healthy vs Pneumonia

- 3 Labels
- Categorical crossentropy
- Softmax function
- 91,5% accuracy
- 10 epochs

$$\sigma(\vec{z})_i = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}}$$

COVnet-101

Different versions of COVnet-101

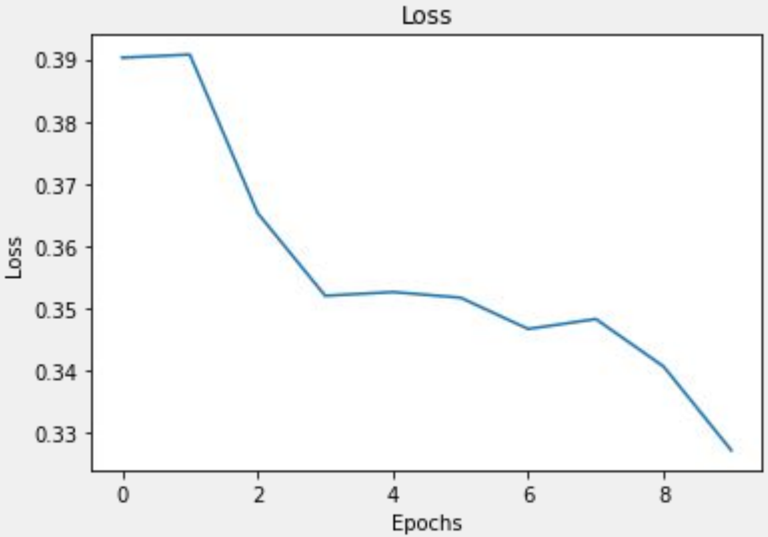
COVID-19 vs Healthy vs Pneumonia

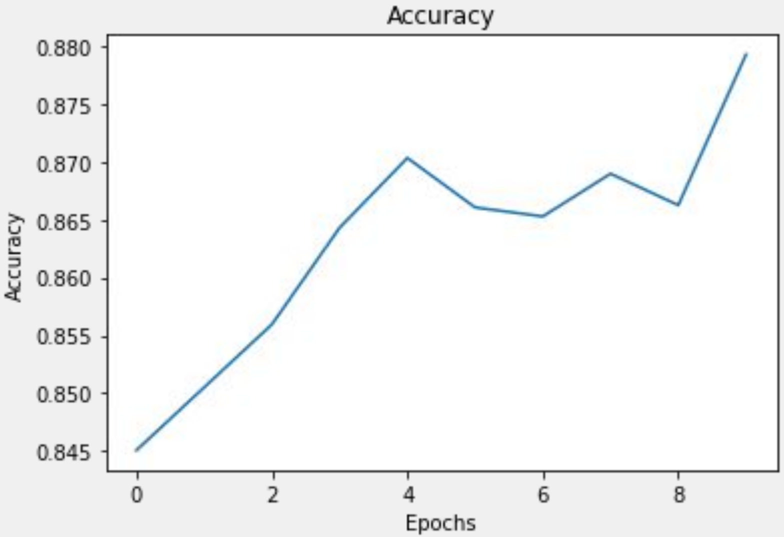
Layer (type)	Output shape	Parameters
ResNet-101	(None, 4, 4, 2048)	42658176
Flatten	(None, 32768)	0
Dense	(None, 1024)	33555456
Dropout	(None, 1024)	0
Dense	(None, 3)	3075

COVnet-101

Different versions of COVnet-101

COVID-19 vs Healthy vs Pneumonia





Results

Results from the comparison of the papers

Problem	Method	Types of data	Sample size	Accuracy
Binary classification	ResNet-101	Clinical	108 patients	99,51%
Binary classification	DarkCovidNet	Online Dataset	1127 images	98,08%
Binary classification	MultiCNN & Bayesnet	Online Dataset	78 images	97,44%
Binary classification	CovNet-101	Online Dataset	6432 images	97,40%

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2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Las Vegas, NV, 2016, pp. 770-778, doi: 10.1109/CVPR.2016.90.

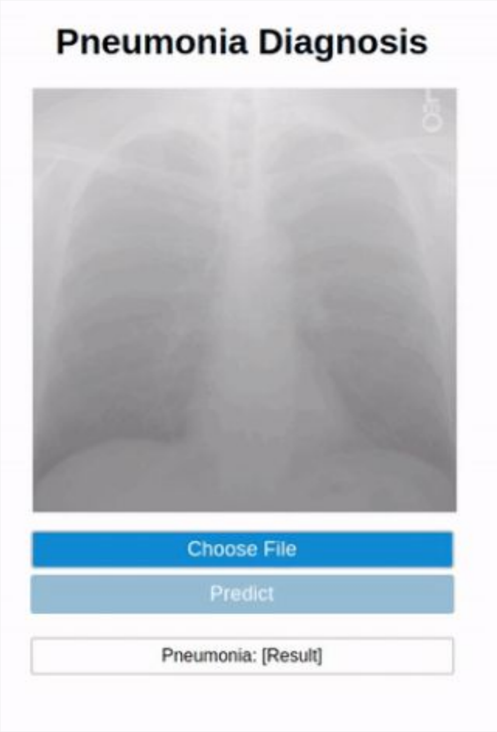
Ozturk, Tulin, et al.
Automated detection of COVID-19 cases using deep neural networks with X-ray images.
Computers in Biology and Medicine (2020): 103792.

Future work

Future work of the assignment

Informative System

- Mobile application (Scanner)
- Cloud-based
- Open Datasets
- Community



Thank you