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Screening Chest X-rays for Covid-19 with Deep Learning

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Contents

Context – The Coronavirus

- 3,467,722 deaths since 31st December 2019[1].
- Predicted economic losses of up to $8.8 trillion worldwide[2].
- Market instability despite vaccination announcements.

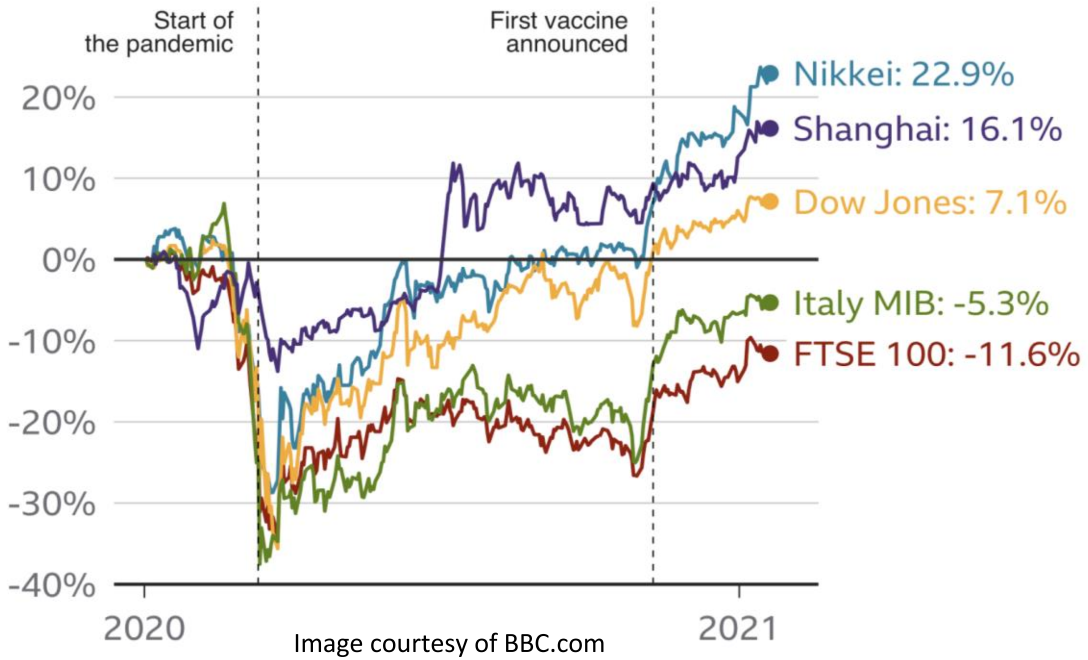


Image courtesy of BBC.com

1. European Centre for Disease Control, 2021
2. Baig et al., "Deaths, panic, lockdowns and US equity markets: The case of COVID-19 pandemic," Finance Research Letters, 2021

Context - Prevention

- Strategies generally involve detection and isolation.
- Testing with PCR and antigens tests.
- Can be expensive[1], require resources.
- Deep learning and X-rays show potential to help[2, 3, 4].

1. Neilan et al. "Clinical Impact, Costs, and Cost-effectiveness of Expanded Severe Acute Respiratory Syndrome Coronavirus 2 Testing in Massachusetts," *Clinical Infectious Diseases* 2020
2. M. E. H. Chowdhury et al., "Can AI Help in Screening Viral and COVID-19 Pneumonia?," *IEEE Access* 2020
3. S. Minaee et al., "Deep-COVID: Predicting COVID-19 from chest X-ray images using deep transfer learning," *Medical Image Analysis* 2020
4. P. Kedia et al., "CoVNet-19: A Deep Learning model for the detection and analysis of COVID-19 patients," *Applied Soft Computing* 2020

Objectives

- Use deep learning to classify images of lungs into one of three classes: Covid-19, Normal or Viral Pneumonia.
- Investigate Convolutional Neural Networks and techniques to increase performance and compare results with baseline results found in literature.
- Investigate feasibility of applying deep learning to this kind of medical screening.
- Compare results obtained with results from a pretrained model using transfer-learning to fine-tune its parameters.

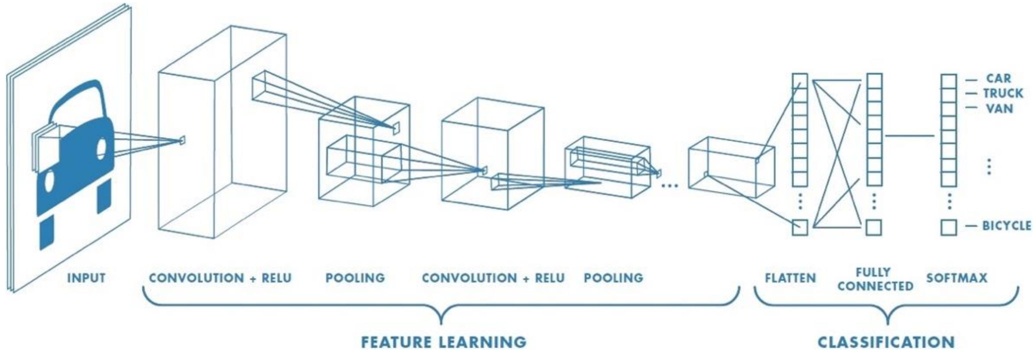
Medical Context

- Medical imaging heavily used in diagnosis.
- Chest x-rays (CXR) considerably cheaper than alternatives[1].
- Pneumonia detected in CXR with deep learning (DL)[2, 3].
- Several papers succeed in detecting Covid-19 in CXR with DL[4, 5, 6].

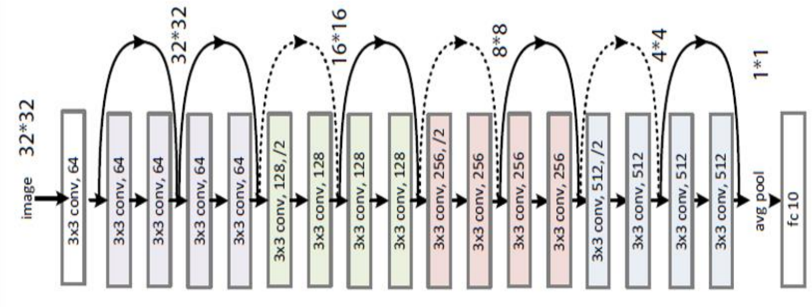
1. Wielputz et.al., *Deutsches Arzteblatt International*, 2014.
2. N. M. Elshennawy et.al. Deep-Pneumonia Framework Using Deep Learning Models Based on Chest X-Ray Images," *Diagnostics 2020*
3. T. Rahman et al., "Transfer learning with deep Convolutional Neural Network (CNN) for pneumonia detection using chest X-ray," *Applied Sciences (Switzerland)*, 2020
4. M. E. H. Chowdhury et al., "Can AI Help in Screening Viral and COVID-19 Pneumonia?," *IEEE Access* 2020
5. S. Minaee et al., "Deep-COVID: Predicting COVID-19 from chest X-ray images using deep transfer learning," *Medical Image Analysis* 2020
6. P. Kedia et al., "CoVNet-19: A Deep Learning model for the detection and analysis of COVID-19 patients," *Applied Soft Computing* 2020

Techniques employed

- Convolutional Neural Network (CNN).
- Data Augmentation.
- Batch Normalization.
- L2 Regularization.
- Dropout.
- Transfer learning.

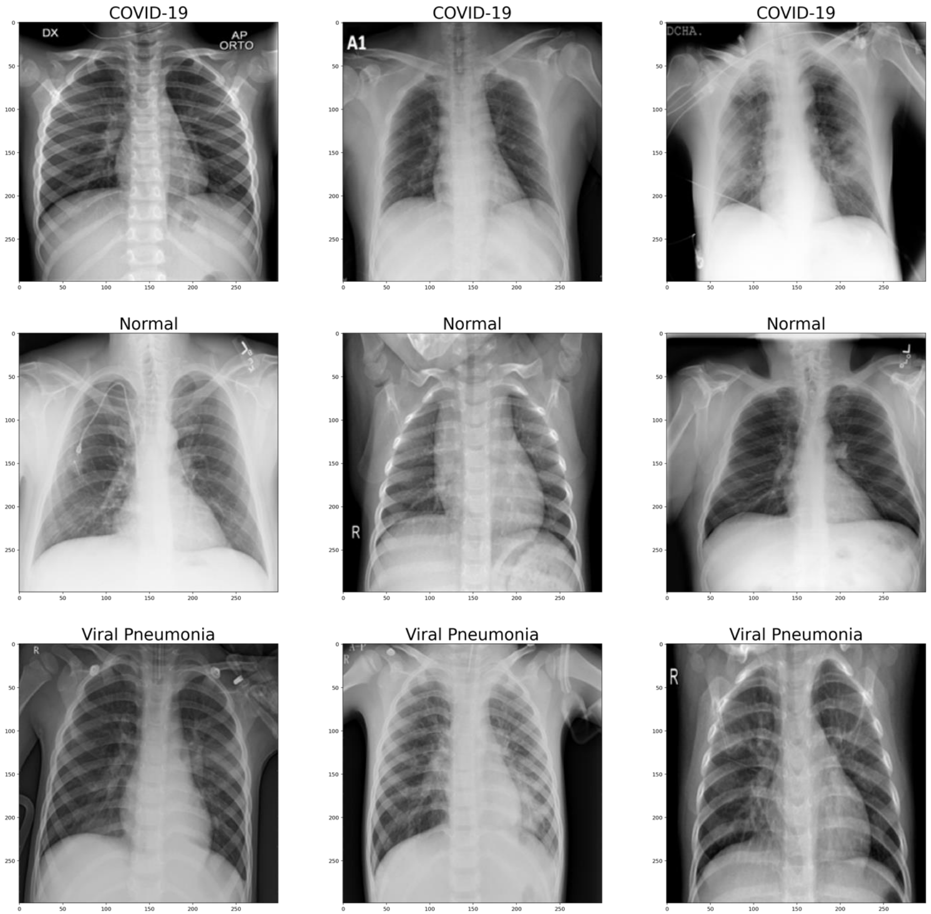


CNN Vo. 2018

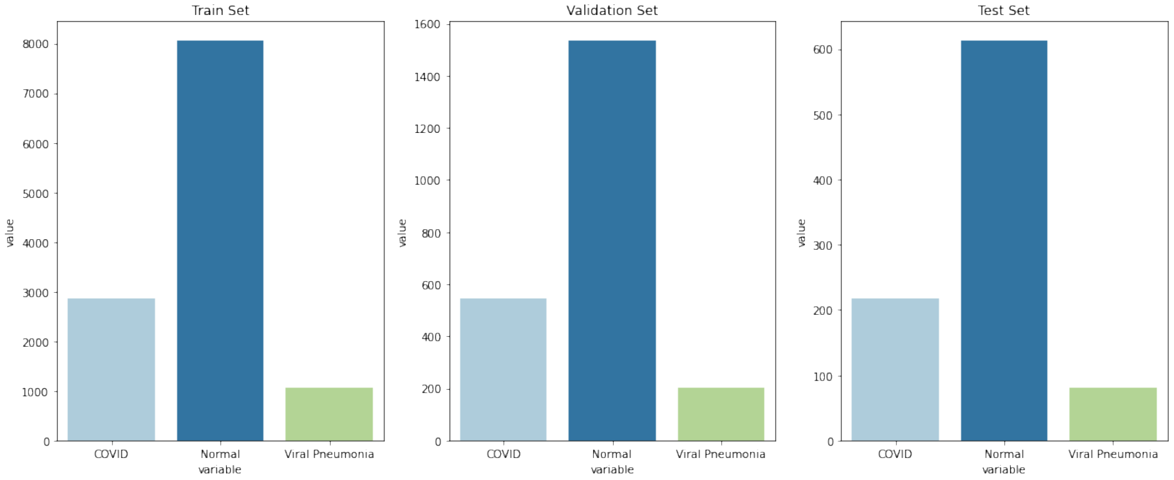


ResNet18, programmersought.com

Data



Class	Number of images	Percentage of Total
COVID-19	3,616	23.86%
Normal	10,192	67.26%
Viral Pneumonia	1,345	8.88%



Experiments - 1

Experiment 1

Layer type	Output	Kernel/Filter	Stride	Padding
Convolutional	(295,295,32)	5	1	0
ReLU	(295,295,32)	N/A	N/A	N/A
Max Pooling	(147,147,32)	2x2	1	0
Convolutional	(138,138,64)	5	1	0
ReLU	(138,138,64)	N/A	N/A	N/A
Max Pooling	(69,69,64)	2x2	1	0
Convolutional	(50,50,128)	5	1	0
ReLU	(50,50,128)	N/A	N/A	N/A
Max Pooling	(25,25,128)	2x2	1	0
Flatten	(80,000, 1)	N/A	N/A	N/A
Fully Connected	(128, 1)	N/A	N/A	N/A
Output	(3, 1)	N/A	N/A	N/A

Experiment 2

- Data Augmentation
  - Random Grayscale: 0.05p.
  - Random Vertical Flip: 0.08p.
  - Random Rotation: $\pm$ 10 degrees.

Experiments - 2

Experiment 3

Layer type	Output	Kernel/Filter	Stride	Padding
Convolutional	(295,295,32)	5	1	0
BatchNorm (0.04)	(295,295,32)	N/A	N/A	N/A
ReLU	(295,295,32)	N/A	N/A	N/A
Max Pooling	(147,147,32)	2x2	1	0
Convolutional	(138,138,64)	5	1	0
BatchNorm (0.06)	(138,138,64)	N/A	N/A	N/A
ReLU	(138,138,64)	N/A	N/A	N/A
Max Pooling	(69,69,64)	2x2	1	0
Convolutional	(50,50,128)	5	1	0
BatchNorm (0.06)	(50,50,128)	N/A	N/A	N/A
ReLU	(50,50,128)	N/A	N/A	N/A
Max Pooling	(25,25,128)	2x2	1	0
Flatten	(80,000, 1)	N/A	N/A	N/A
Fully Connected	(128, 1)	N/A	N/A	N/A
Output	(3, 1)	N/A	N/A	N/A

Experiment 4

- L2 Regularization
  - Weight decay set to 1^{-6}.
- Data Augmentation
  - Random Grayscale: 0.05p.
  - Random Vertical Flip: 0.07p.
  - Random Rotation: $\pm$ 8 degrees.

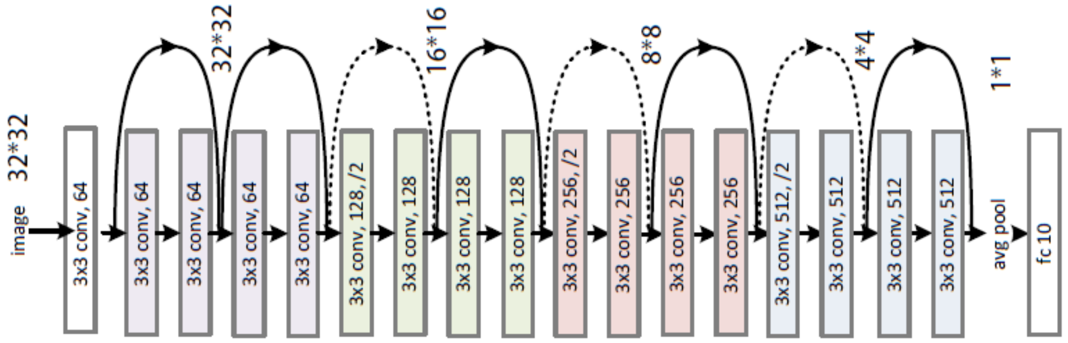
Experiments - 3

Experiment 5

Layer type	Output	Kernel/Filter	Stride	Padding
Convolutional	(295,295,32)	5	1	0
BatchNorm (0.04)	(295,295,32)	N/A	N/A	N/A
ReLU	(295,295,32)	N/A	N/A	N/A
Max Pooling	(147,147,32)	2x2	1	0
Convolutional	(138,138,64)	5	1	0
BatchNorm (0.06)	(138,138,64)	N/A	N/A	N/A
Dropout (0.08)	(138,138,64)	N/A	N/A	N/A
ReLU	(138,138,64)	N/A	N/A	N/A
Max Pooling	(69,69,64)	2x2	1	0
Convolutional	(50,50,128)	5	1	0
BatchNorm (0.06)	(50,50,128)	N/A	N/A	N/A
Dropout (0.10)	(50,50,128)	N/A	N/A	N/A
ReLU	(50,50,128)	N/A	N/A	N/A
Max Pooling	(25,25,128)	2x2	1	0
Flatten	(80,000, 1)	N/A	N/A	N/A
Fully Connected	(128, 1)	N/A	N/A	N/A
Output	(3, 1)	N/A	N/A	N/A

Experiment 6

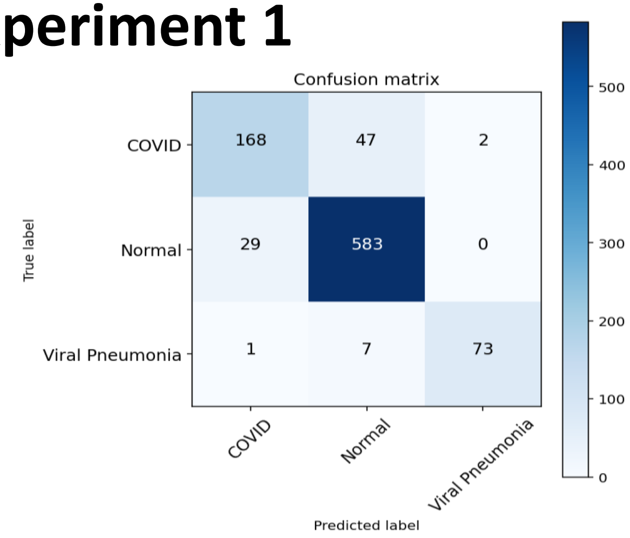
ResNet18



Courtesy of programmersought.com

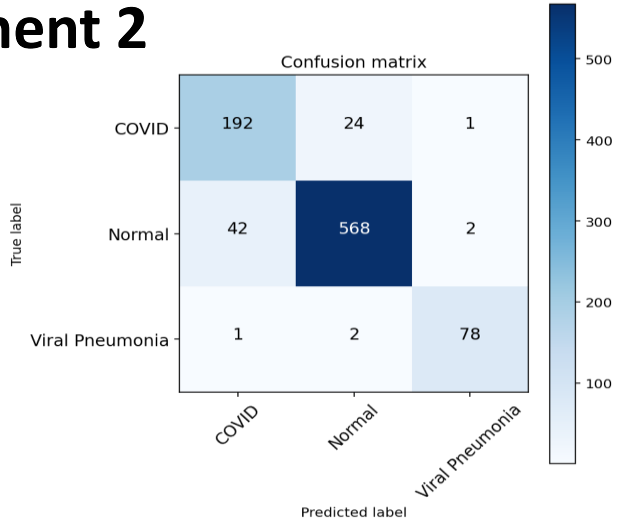
Results - 1

Experiment 1



	Precision	Recall	F1-score	Support
COVID	84.85%	77.42%	80.96%	217
Normal	91.52%	95.26%	93.35%	612
Pneumonia	97.33%	90.12%	93.59%	81
Accuracy			90.55%	910
Macro avg	91.23%	87.60%	89.30%	910
Weighted avg	90.45%	90.55%	90.42%	910

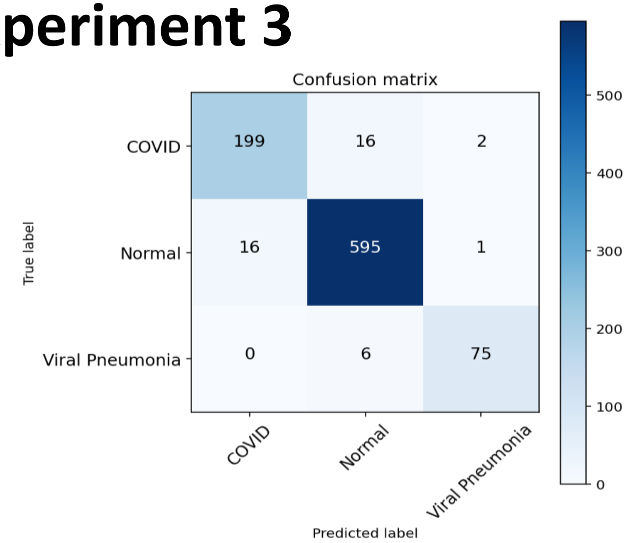
Experiment 2



	Precision	Recall	F1-score	Support
COVID	81.70%	88.48%	84.96%	217
Normal	95.62%	92.81%	94.20%	612
Pneumonia	96.30%	96.30%	96.30%	81
Accuracy			92.09%	910
Macro avg	91.21%	92.53%	91.82%	910
Weighted avg	92.36%	92.09%	92.18%	910

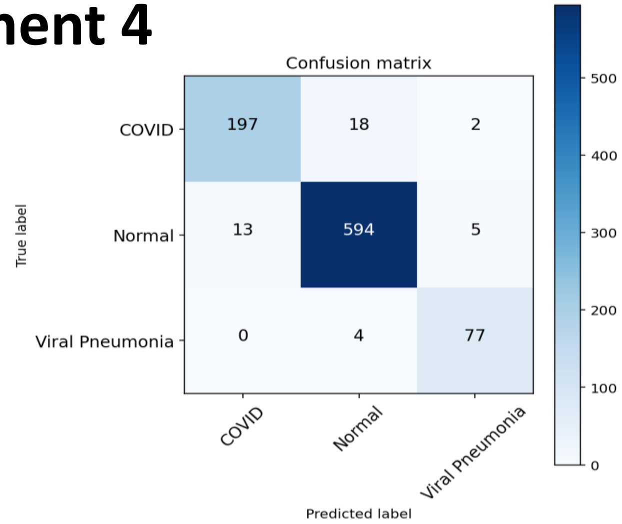
Results - 2

Experiment 3



	Precision	Recall	F1-score	Support
COVID	92.56%	91.71%	92.13%	217
Normal	96.43%	97.22%	96.83%	612
Pneumonia	96.15%	92.59%	94.34%	81
Accuracy			95.49%	910
Macro avg	95.05%	93.84%	94.43%	910
Weighted avg	95.49%	95.49%	95.49%	910

Experiment 4



	Precision	Recall	F1-score	Support
COVID	93.81%	90.78%	92.27%	217
Normal	96.43%	97.06%	96.74%	612
Pneumonia	91.67%	95.06%	93.33%	81
Accuracy			95.38%	910
Macro avg	93.97%	94.30%	94.12%	910
Weighted avg	95.38%	95.38%	95.37%	910

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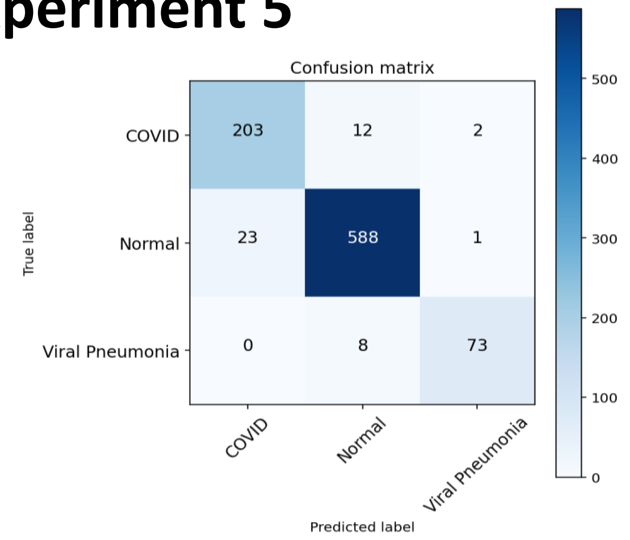
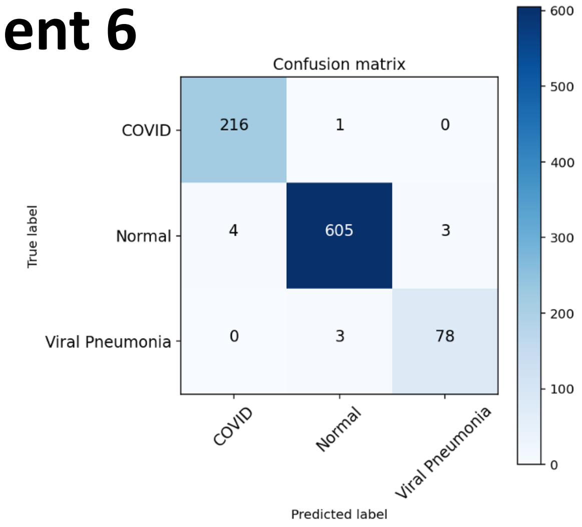
Results - 3

Experiment 5



	Precision	Recall	F1-score	Support
COVID	89.82%	93.55%	91.65%	217
Normal	96.71%	96.08%	96.39%	612
Pneumonia	96.05%	90.12%	92.99%	81
Accuracy			94.95%	910
Macro avg	94.20%	93.25%	93.68%	910
Weighted avg	95.01%	94.95%	94.96%	910

Experiment 6



	Precision	Recall	F1-score	Support
COVID	98.18%	99.54%	98.86%	217
Normal	99.34%	98.86%	99.10%	612
Pneumonia	96.30%	96.30%	96.30%	81
Accuracy			98.79%	910
Macro avg	97.94%	98.23%	98.08%	910
Weighted avg	98.80%	98.79%	98.79%	910

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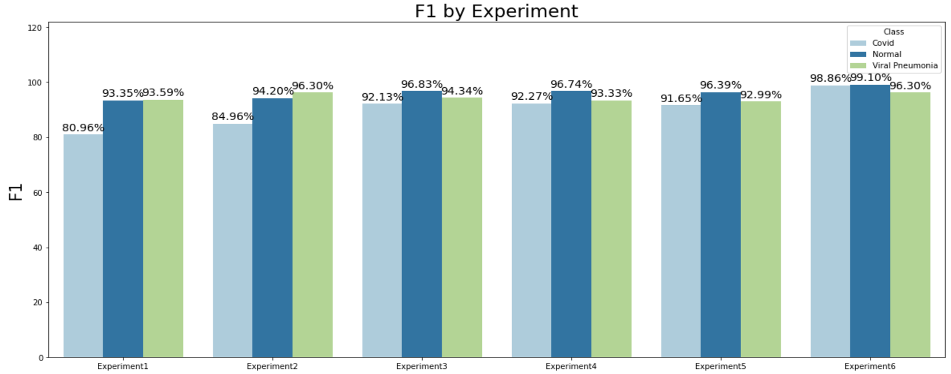
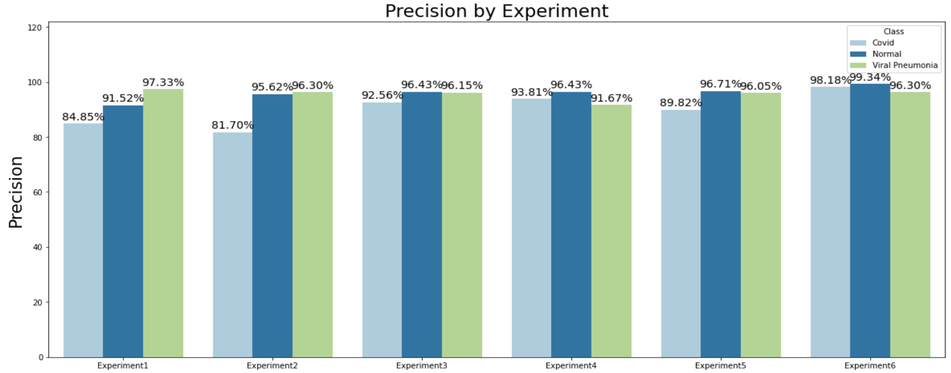
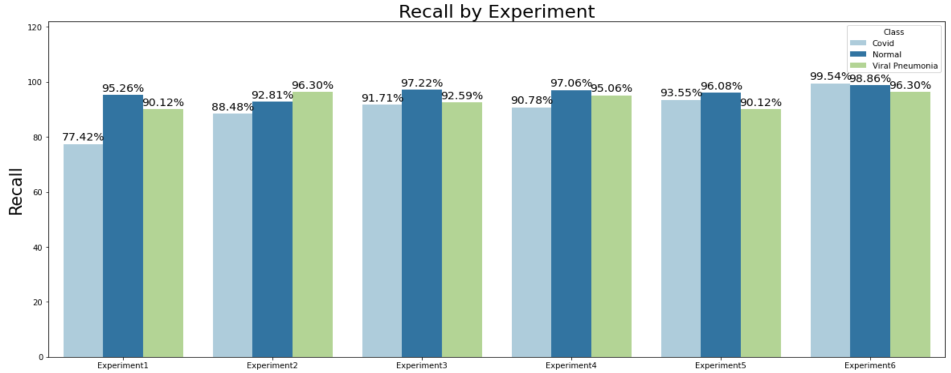
Discussion

- Data augmentation improved recall on Covid class[1, 2].
- Batch Normalization improved three metrics on Covid class.
- L2 regularization produced higher precisions in Normal and Covid classes than preceding experiments.
- Dropout produced highest recall in Covid.
- Transfer Learning shows high potential[1].







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2. P. Kedia et al., “CoVNet-19: A Deep Learning model for the detection and analysis of COVID-19 patients,” *Applied Soft Computing* 2020

Conclusions

- Compelling results suport hypothesis.
- High recall achieved for Covid and Viral Pneumonia.
- X-rays cheap, massively available.
- Further studies with more data are feasible.
- Transfer learning appears key.

Thank you for your time