



Chest X-Ray Images for Pneumonia Classification

By Yuyue Zhou and Isabel Zhou

Motivation & Related Work

- Covid-19
- Chest X ray: critical to pneumonia detection (*Lynch, 2010*)
- Previous study : (*Kermay, 2018*)

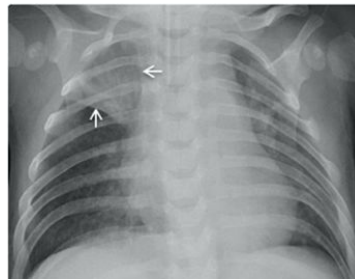
Task	Test Acc	Test AUROC
Normal vs Pneu	0.928	0.968
Bacterial vs Viral	0.907	0.940

- Our goal: to improve different CNN model performances and extend to 3-class classification

Normal



Bacterial Pneumonia



Viral Pneumonia





Data

- From retrospective cohorts of 1 to 5 years old children (*Kermany, 2018*)
- Original dataset: contains training set and testing test only
- Our split based on patient:

		Training	Validation	Testing
Normal		1349	120	114
Pneumonia	Virus	1345	80	68
	Bacteria	2538	114	128



Evaluation Metrics

- F1: precision and recall, important in medicine
- AUROC: good for imbalanced data and has all threshold levels of F scores
- Accuracy



Methods

- Trained models and performed hyperparameter tuning on 2 and 3 classes classification ResNet152 (He, 2016), Densenet161 (Huang, 2017), GoogLeNet (Szegedy, 2015) Learning rate = 0.001, optimizer = Adam
- Evaluate on validation and deploy on the test set
- Classification activation map

Task: Normal/Pneu.

Results and Discussion

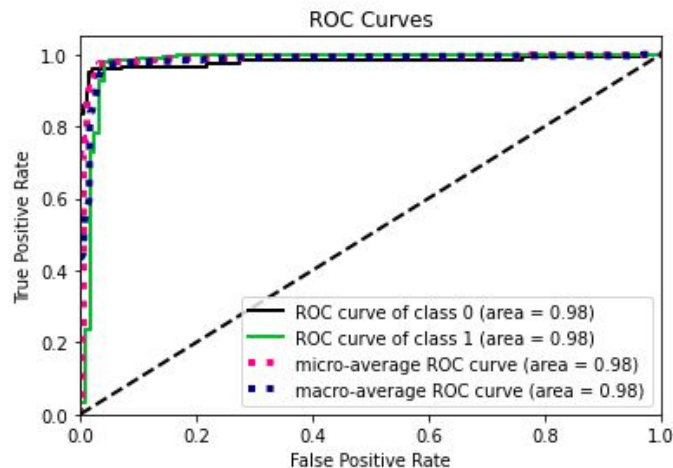
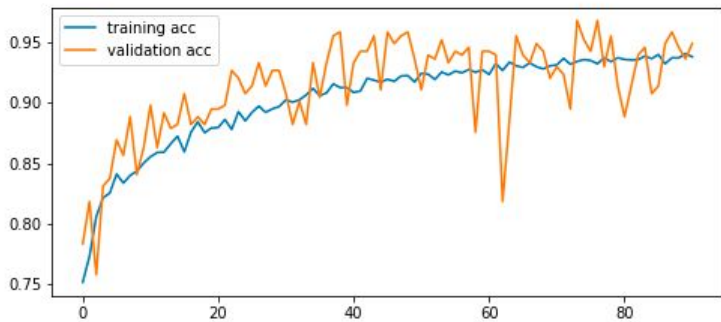
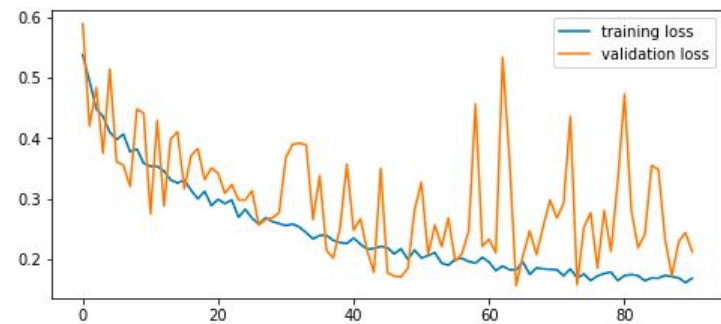
Model	Val Acc	Val AUROC	Val F1	Comments
ResNet152	0.962	0.956	0.969	178 epochs, 24+ hours. too long!
DenseNet161	0.965	0.957	0.972	198 epochs, 24+ hours. too long!
GoogLeNet	0.968	0.965	0.974	74 epochs, less time-consuming

Performance and Time Efficiency: GoogLeNet.

ResNet and DenseNet each has more than 400 parameters, where GoogleNet has less than 200.

Best model: GoogLeNet, Task: Normal/Pneu.

Results and Discussion



Task: Normal/Virus/Bacteria

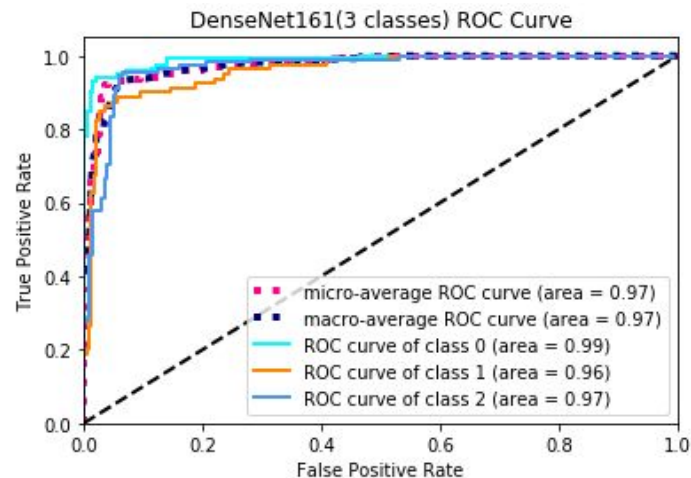
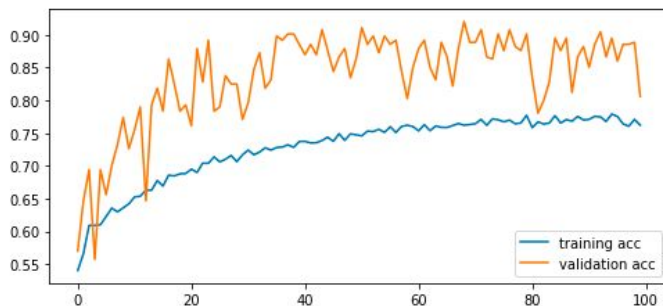
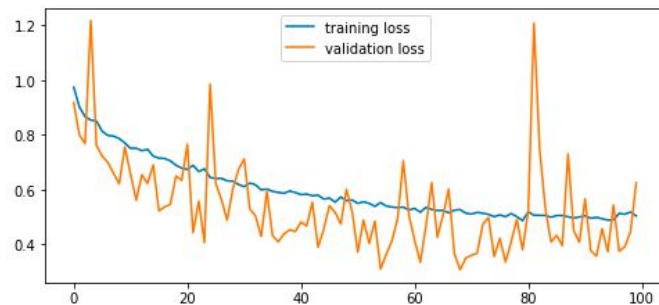
Results and Discussion

Model	Val Acc	Val Macro AUROC	Macro F1	Comments
ResNet152	0.892	0.965	0.883	96 epochs
DenseNet161	0.920	0.973	0.918	70 epochs
GoogLeNet	0.911	0.958	0.904	47 epochs, less time-consuming

Performance and Time Efficiency: GoogLeNet

Best model: DenseNet, Task: Normal/Virus/Bacteria

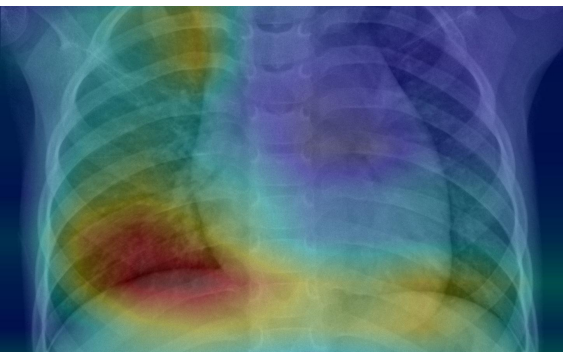
Results & Discussions



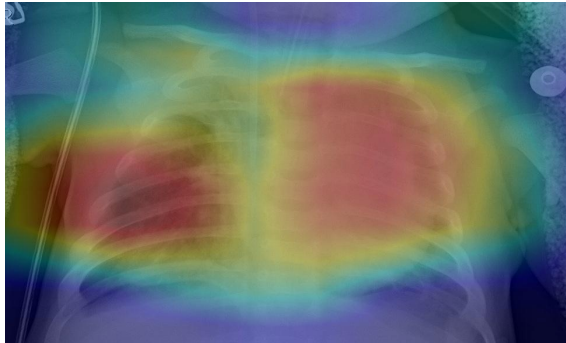
Best model: GoogleNet, Task: Normal/Pneu.

Final Results on Test Set

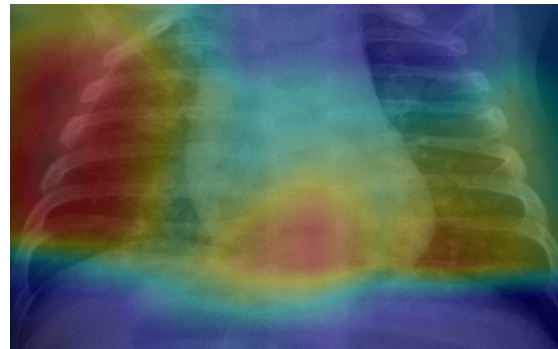
Macro Auc: 0.98 Acc: 0.932



Normal



Pneumonia (Bacteria)



Pneumonia (Virus)

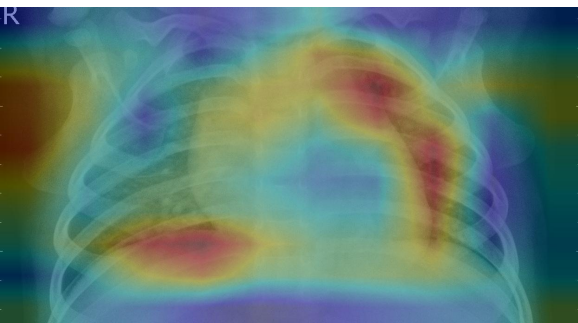
Discussion: slightly different from how doctor recognizes these pictures

Chest X-ray is not the only standard of pneumonia diagnosis. Physical exam and sputum culture should also be considered.

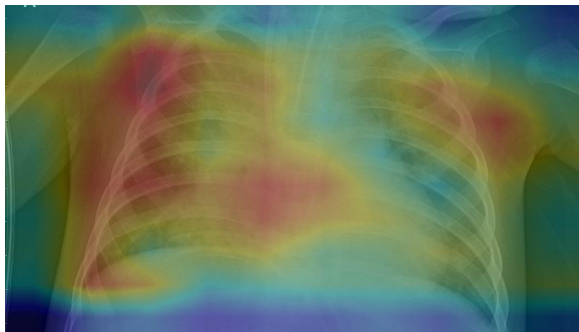
Best model: DenseNet, Task: Normal/Virus/Bacteria

Final Results on Test Set

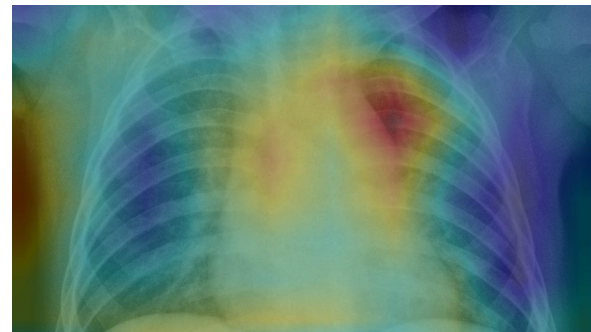
Macro Auc: 0.98 Acc: 0.913



Normal



Bacteria



Virus

Discussion: slightly different from how doctor recognizes these pictures
Chest X-ray is not the only standard of pneumonia diagnosis. Physical exam and sputum culture should also be considered.



Does Transform Learning Help?

Two-class:

Model	Val Acc	Val AUROC	Val F1	Comments
GoogLeNet	0.968	0.965	0.974	74 epochs, 12 hours+
Pre-trained GoogLeNet	0.971	0.969	0.977	73 epochs, < 10 hours

Three-class:

Model	Val Acc	Val Macro AUROC	Macro F1	Comments
GoogLeNet	0.911	0.958	0.904	47 epochs, ~ 12 hours
Pre-trained GoogLeNet	0.898	0.979	0.893	78 epochs, ~ 8 hours

Do we care more about performance or time efficiency?



Future work...

Chest X-ray images of pneumonia caused by fungi, parasites.

Covid-19 CT and chest X-ray images.

Evaluate how severe the disease is.

Combination of chest X-ray, physical exams and sputum culture.



Contributions

Yuyue Zhou: GoogLeNet, Research, split_data.ipynb, Hyperparameter tuning, Evaluate and test models

Isabel Zhou: ResNet152, DenseNet161, dataset.py, main.py, train_valid.py, visulization_results.ipynb, visulization_CAM.ipynb

Thanks to Lu Li: MD & PhD Candidate at Wuhan University, our medical advisor

References

Christian Szegedy, Wei Liu, Yangqing Jia, Pierre Sermanet, Scott Reed, Dragomir Anguelov, Dumitry Erhan, Vincent Vanhoucke, and Andrew Rabinovich. Going Deeper with Convolutions. *2015 IEEE Conference on Computer Vision and Pattern Recognition(CVPR)*. 2015: 1-9.

Daniel S. Kermany, Michael Goldbaum, Wenjia Cai, M. Anthony Lewis, Huimin Xia, and Kang Zhang. Identifying Medical Diagnoses and Treatable Diseases by Image-Based Deep Learning. *Cell*. 2018, 172(5): 1122-1131

Daniel S. Kermany, Kang Zhang, and Michael Goldbaum. Labeled Optical Coherence Tomography(OCT) and Chest X-Ray Images for Classification. *Mendeley Data*, v2, 2018.

Gao Huang, Zhuang Liu, Laurens van der Maaten, and Kilian Q. Weinberger. Densely Connected Convolutional Networks. *2017 IEEE Conference on Computer Vision and Pattern Recognition(CVPR)*. 2017, 243: 2261-2269.

Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep Residual Learning for Image Recognition. *2016 IEEE Conference on Computer Vision and Pattern Recognition(CVPR)*. 2016, 90: 770-778.

Tim Lynch, Liza Bialy, James D. Kellner, Martin H. Osmond, Terry P. Klassen, Tamara Durec, Robin Leicht, and David W. Johnson. A Systematic Review on the Diagnosis of Pediatric Bacterial Pneumonia: When Gold Is Bronze. *PLoS One*. 2010, 5(8): e11989.