Identifying Thoracic Pathologies from Chest X–ray Data

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Background

A frequent and cost–effective medical imaging examination is the chest X–ray. However, a clinical diagnosis can be more challenging than diagnosis via chest CT imaging. In fact, achieving clinically relevant computer-aided detection and diagnosis (CAD) in real world medical sites on all data settings of chest X-rays is still very difficult, if not impossible when only several thousands of images are employed for study.

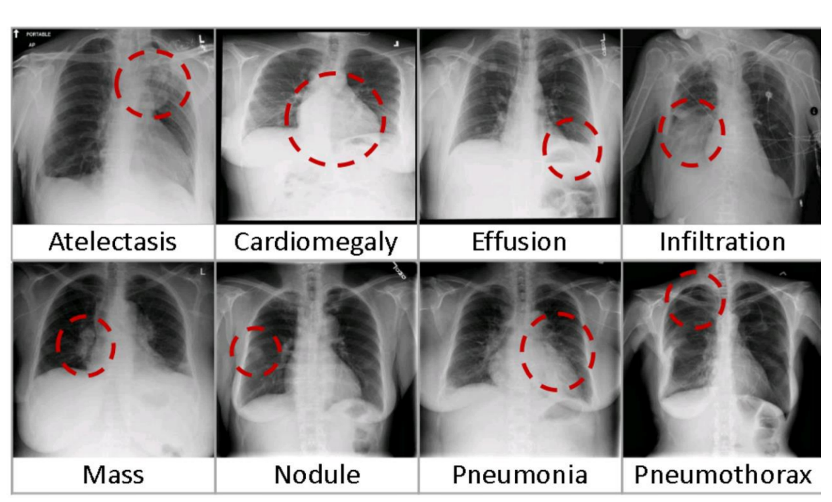
The desire is to teach computers how to detect and diagnose disease. Ultimately, this artificial intelligence mechanism can lead to clinicians making better and quicker diagnostic decisions for patients by using a computer which has been taught to read and process extremely large amounts of scans, to confirm the results radiologists have found and potentially identify other findings that may have been overlooked.

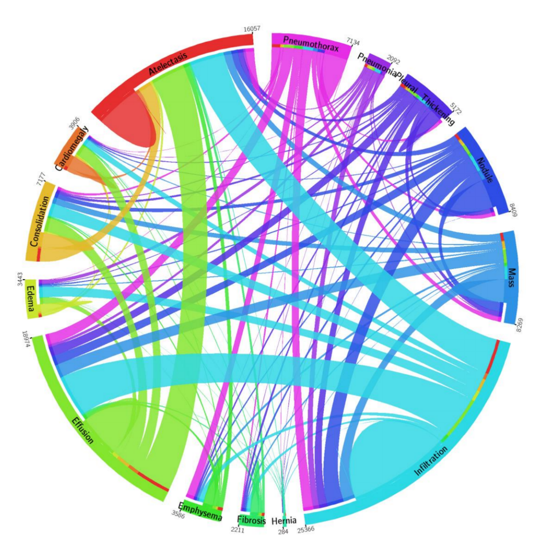
In addition, this may also be able to: (1) help identify slow changes occurring over the course of multiple chest x-rays that might otherwise be overlooked; (2) benefit patients in developing countries that do not have access to radiologists to read their chest x-rays; and (3) create a virtual radiology resident that can later be taught to read more complex images like CT and MRI in the future.

Goal: To train a deep neural network that can reliably classify different thoracic pathologies from human chest X–rays. This will allow for a faster and more accurate diagnoses of several diseases, which will lead to a more efficient care of patients in hospitals around the world.

Data

The NIH Chest X-ray dataset [2] is comprised of 112, 120 X-ray images with resolution 1024×1024 and disease labels from 30, 805 unique patients. The 14 disease image labels (where each image can have multi-labels, see Fig. 1 & 2), were mined from the associated radiological reports using Natural Language Processing (NLP) with accuracy $> 90\%$. Meta data for all images includes: Image Index, Finding Labels, Follow-up , Patient ID, Patient Age, Patient Gender, View Position, Original Image Size and Original Image Pixel Spacing.





Multi–label classification

We used transfer learning and started with pretrained networks such as: ResNet, Xception, Inception, VGG16, etc. On top of each of these pretrained network, a series of fully connected layers were used.

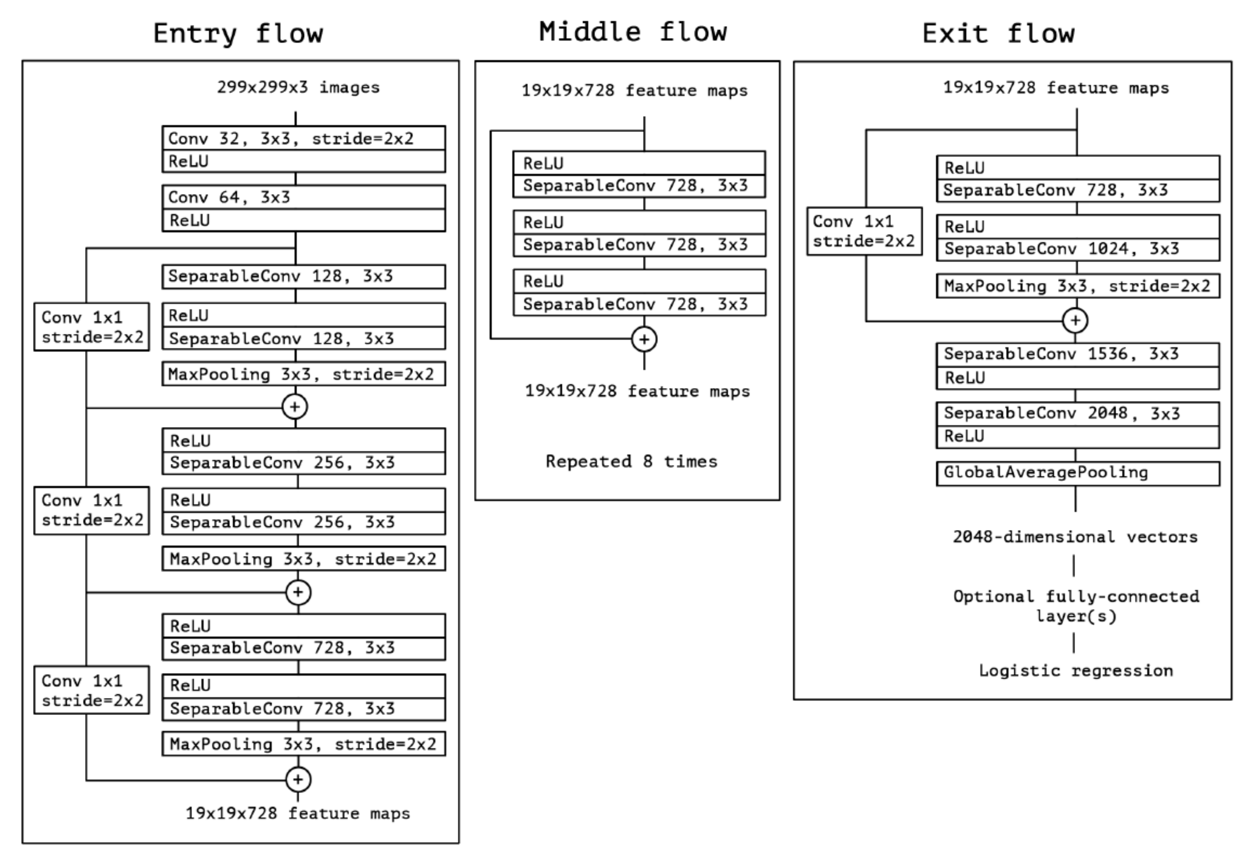
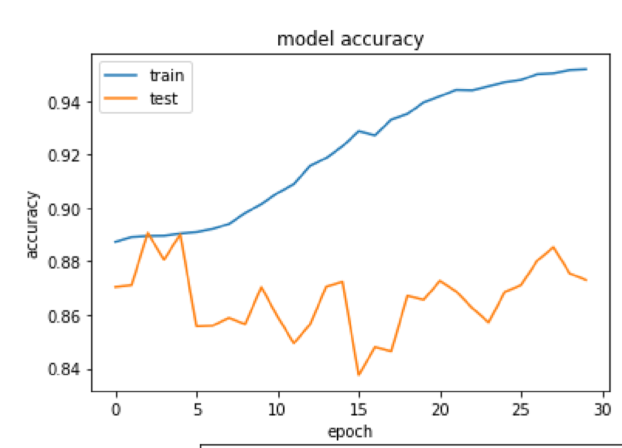
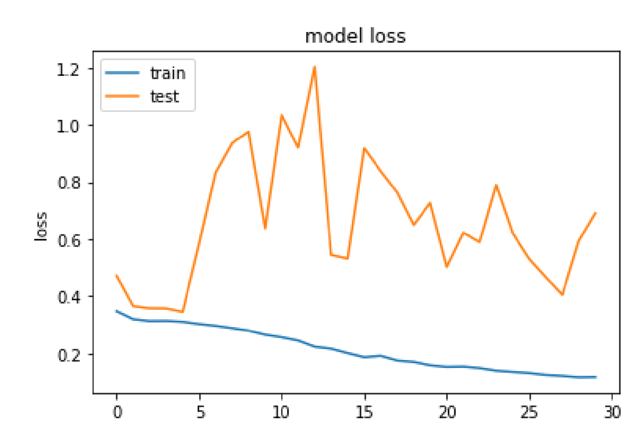
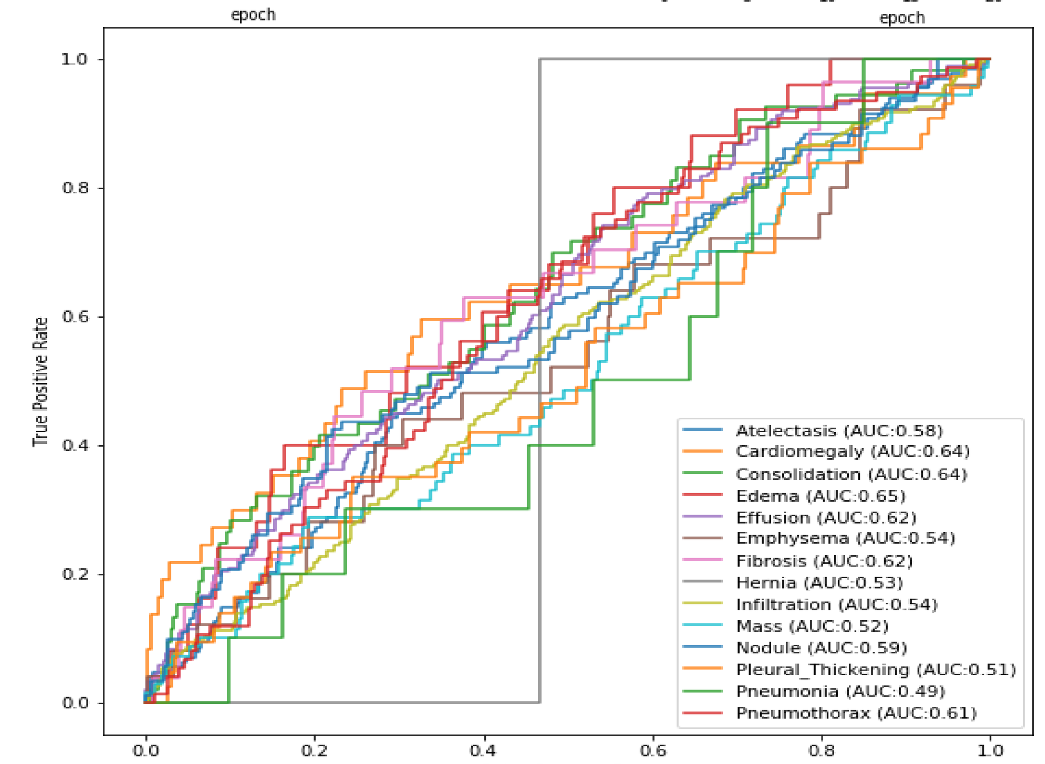


Fig. 3: Xception network.

Results

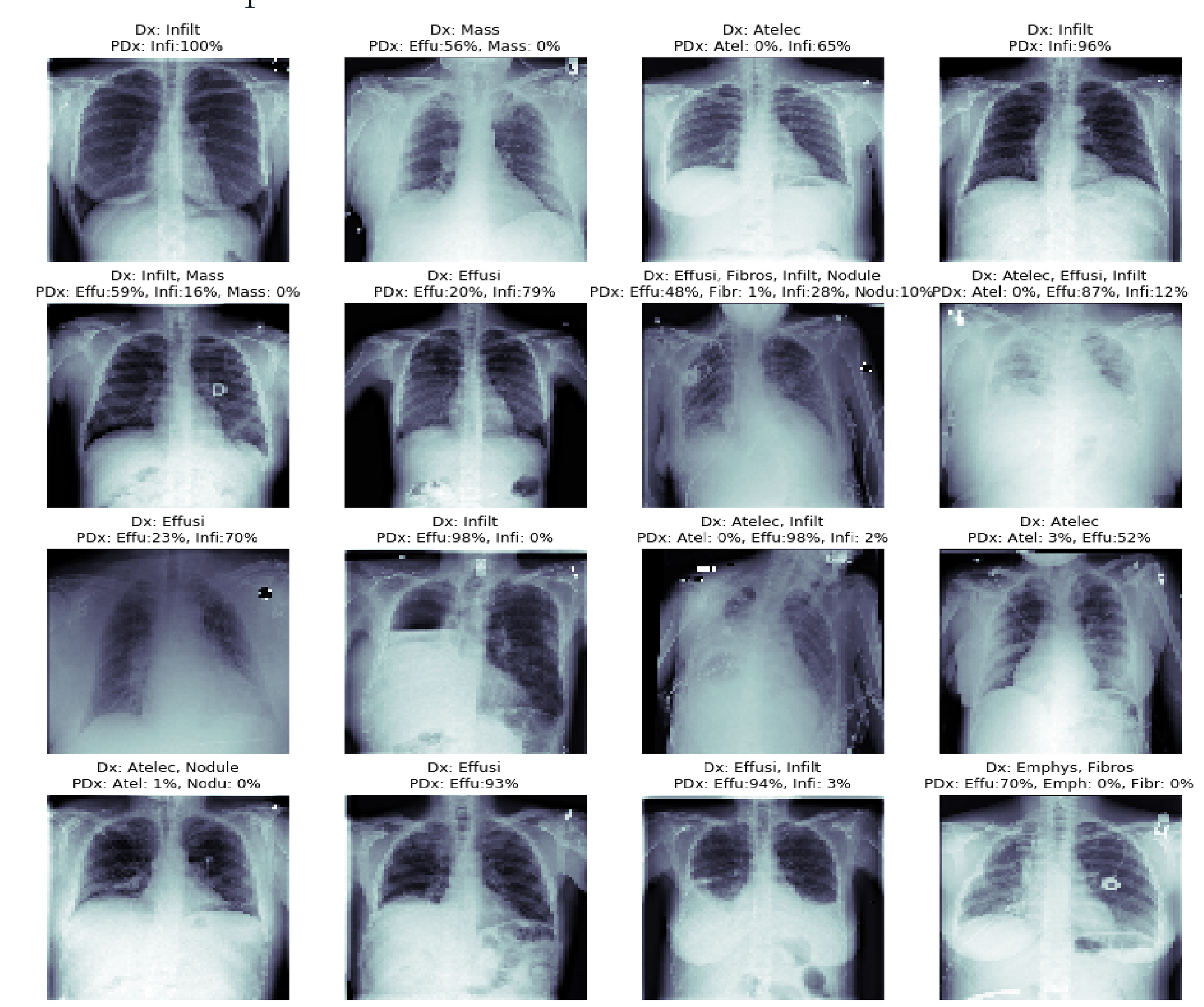






Results

Our network is able to classify each X–ray image into multiple labels if more than one disease is present.



Conclusion

- Introduced a model which is able to predict pathologies from chest X–ray images with high accuracy ($\sim$88% on the test set).
- Our network performs Multi–label classification, which allows one X–ray to be diagnosed to more than one disease.
- Can allow for better care of patients around the world.
- Limitations: did not use GPU's, labels are not always correct, and did not train on the whole dataset.

References

[1] *NIH Chest X-Ray data.* https://nihcc.app.box.com/v/ChestXray-NIHCC/folder/36938765345.

[2] *Random Sample of NIH Chest X-ray Dataset.* https://www.kaggle.com/nih-chest-xrays/sample.

[3] *X-Ray Chest Analisys.* https://www.kaggle.com/rodcardoso92/x-ray-chest-analisys/data.