Machine Learning for Exam Triage*

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Abstract

In this project we extend the state-of-the-art CheXNet (Rajpurkar et al. [2017]) by making use of the additional non-image features in the dataset. Our model† produced better AUROC scores than the original CheXNet.

1 Introduction

According to the CDC (CDC [2017]), there are more than 50,000 US deaths annually due to pneumonia. However, the best way currently to diagnose a patient with pneumonia early is with chest X-rays, which require an expert radiologist's eye to analyze. This results in a fairly long turn around that many hospitals would like to reduce. CheXNet (Rajpurkar et al. [2017]), a machine learning algorithm that can analyze chest X-rays in bulk, was built to help solve this problem. In this paper, we improved slightly upon CheXNet, by allowing the network to take in additional information about the patient outside of the X-Ray.

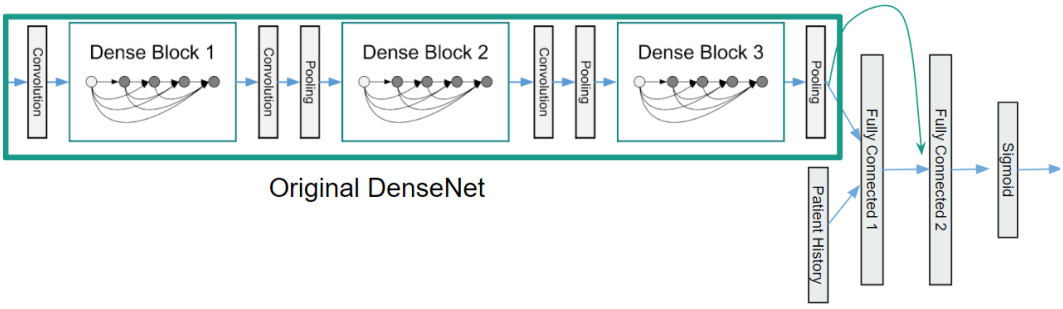
The paper is structured as follows. In Section 2, we give some background on CheXNet Rajpurkar et al. [2017]. Section 3 explains our neural network architecture. Section 4 focuses on the experimental results and Section 5 offers a brief discussion.

2 Background

The previous state of the art on this data set is CheXNet, which is a 121-layer Densely Connected Convolutional Neural Network (DenseNet) that classified X-Ray images at the accuracy of radiologists. The previous state of the art only outputted a binary classification of whether pneumonia was present. CheXNet improved on that by replacing the last fully connected layer to recognize 14 classes - Atelectasis,Cardiomegaly, Consolidation, Edema, Effusion, Emphysema, Fibrosis, Hernia, Infiltration, Mass, Nodule, Pleural Thickening, Pneumonia, and Pneumothorax. Some limitations of ChexNet were the lack of use of patient history and of lateral images.

*This paper is a written presentation of a project in HackAuton 2018
†Code available at https://github.com/Holmeswww/CheXNetPP

3 Network Architecture



Our model uses the original DenseNet (Huang et al. [2017]) with two fully connected layers (ReLU activation). The skip connection (He et al. [2016]) from the last pooling layer of the DenseNet to the second fully connected layer encourages gradient flow, and ensures a worst-case identity map so that our model should perform at least as good as CheXNet (Rajpurkar et al. [2017]).

4 Experiments

We trained our model on the full ChestX-ray14 dataset, using exactly the same learning parameters as in (Rajpurkar et al. [2017]). Our model was trained with a batch size of 16, a 20:10:70 test:val:train split for 44 epochs, and did not train to convergence.

Table 1: Performance of our model compared to the reported performance of CheXNet (Rajpurkar et al. [2017]). Values reported are the AUROC scores each model achieved.

Pathology	ChexNet	Our Model
Atelectasis	0.8094	0.8328
Cardiomegaly	0.9248	0.9012
Effusion	0.8638	0.8911
Infiltration	0.7345	0.7205
Mass	0.8676	0.8814
Nodule	0.7802	0.8175
Pneumonia	0.768	0.7665
Pneumothorax	0.8887	0.9145
Consolidation	0.7901	0.8155
Edema	0.8878	0.9138
Emphysema	0.9371	0.9271
Fibrosis	0.8047	0.8221
Pleural Thickening	0.8062	0.8110
Hernia	0.9164	0.9733

5 Discussion

In this project, we demonstrated how additional non-image features may benefit the overall performance of the model. Future research can focus on training with higher resolution, training with different depth, applying model compression, and hyperparameter optimization. Furthermore, as our model did not reach convergence at 44 epochs, we believe it may perform even better when it reaches convergence.

Acknowledgments

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