# Chest X-Ray (CXR) Disease Diagnosis with DenseNet

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### Abstract

*Chest X-ray[1] is a crucial medical imaging technology used by several doctors to diagnose patients. Training a human radiologist is a lengthy and costly process. Deep learning techniques combined with availability of larger data sets increases the feasibility of building automated models with performance close to human radiologists.*

*We present a scalable deep learning model trained on the CheXpert[2] data set of X-ray images to detect and correctly classify 14 different diseases*

### Introduction

A chest radiograph[1], or a chest X-ray (CXR) is one of the oldest and most common forms of medical imaging. A human radiologist requires significant training time and cost to be able to perform a comprehensive chest X-ray analysis with minimal error. Several types of abnormalities can show up in a chest radiograph that can lead to detection and diagnosis of several kinds of diseases but due to the vast number of different abnormalities and the overlapping reasons that might cause them, theres a plenty of room for human error.

The revolution of machine learning and deep learning techniques combined with the availability of larger data sets[2] and big data processing systems[3] makes the analysis of x-ray images increasingly more realistic and the creation of automated models more feasible. The objective of this project is to train an efficient and scalable deep learning model which can learn from a data set of X-ray images to detect and correctly classify 14 different diseases. Automating the X-ray analysis makes the overall diagnosing process faster and less error-prone which significantly improves the patients treatment procedure.

### Approach

1. Data set acquisition
2. Image preprocessing - Apache Spark
3. Training Dense 121 deep learning model - Keras
4. Model validation and fine tuning
5. Model evaluation

### Data acquisition

Dataset was acquired upon registration and acceptance of the Stanford University School of Medicine CheXpert Dataset Research Use Agreement terms and conditions.[2]

### Dataset format

Dataset consists of 224,316 chest radiographs of 65,240 patients. Each imaging study can pertain to one or more images, but most often are associated with two images: a frontal view and a lateral view. Images are provided with 14 labels derived from a natural language processing tool applied to the corresponding free-text radiology reports.

Image files are provided following a specific directory structure :

/[Data set type]/[patient ID]/[Study ID]/[View ID]_[view type].jpg

where data set type can be train (for training set) or valid (for validation set), and view type can be frontal or lateral.

e.g. an input sample of a frontal study for a patient in the training set will be available at :

CheXpert/train/patient00001/study1/view1_frontal.jpg

Each image is stored as a .jpg file with single channel (grey scale) where each pixel is stored as unsigned byte.

A CSV file is provided for each data set type (valid or train). Each image record contains a path, several medical labels for different diseases (such as Cardiomegaly, Edema, Pneumonia, and so on.), along with some demographic information about the patient such as sex and age.

**Dataset Pre-Processing**

CheXpert[2] images are provided in high resolution which is not suitable for use as input to the model. Using a high resolution image significantly increases the number of input feature vectors which would require an increase in the model complexity and training time. Data set images where prepossessed before training using Apache Spark which is a scalable Big data processing technology. Several down-sampling techniques were used to reduce image size.

A neural network (e.g. CNN) is said to have an in-variance property when it is capable to robustly classify objects even if its placed in different orientations.To enrich the input data set and increase the number of available training samples, we performed data augmentation by generating several images with different orientations from a subset of input images.

Each input image is down sampled by resizing to 224*224 pixels. An input image generates one or more augmented versions of itself (e.g. by horizontal flipping). Each output image is assigned an ID of type Long, and inherits all the labels from the original input image.

Preprocessed images are saved to HDFS, which is a highly distributed and scalable Big data storage system. Due to HDFS implementation and API limitations, storing several tiny image files is not an efficient operation. We decided to change the output format of be textual. Each image can be represented with the unsigned values of its byte stream (a vector of length 224*224). Each Spark RDD Partition will save its images as a space separated file with this format: [imageID] [bytes values]

Where Image ID is the newly assigned ID, and the bytes are space separated vector of row based pixel values.

A corresponding CSV file for labels is generated which starts with the Image Id along with all the inherited labels from the original image.

This new output storage format resulted in significant decrease of the preprocessing job run time, and was suitable as a direct input to the model.

**Metrics**

This sentence has one reference citation[1].

This sentence has two reference citations[1,2].

More text of an additional paragraph, with a figure reference (Figure 1) and a figure inside a Word text box below. Figures need to be placed as close to the corresponding text as possible and not extend beyond one page.

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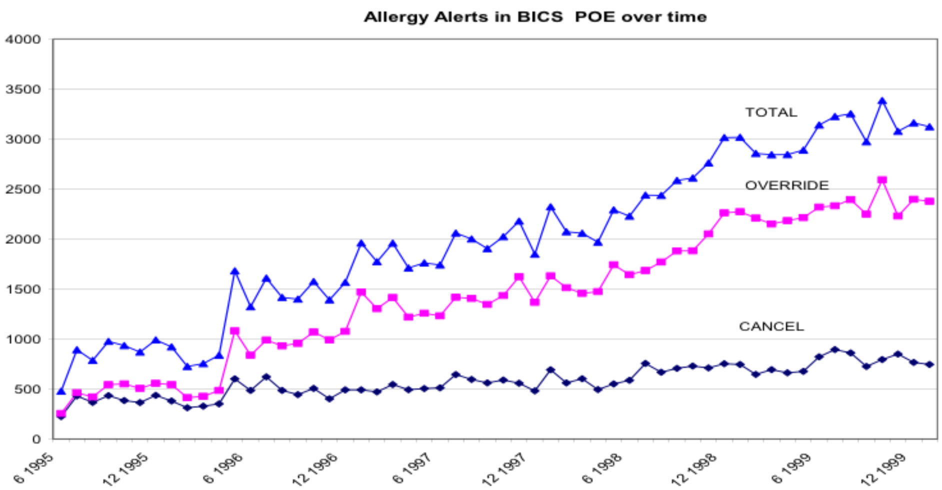


**Figure 1:** Total allergy alerts, overridden alerts, or drug order cancelled.

**Table 1:** Submission type, abstract length, and page length maximum for AMIA submissions.

| **Submission Type** | **Abstract Length** | **Page Length Maximum**** |
|---|---|---|
| Paper | 125-150 words | Ten |
| Student Paper | 125-150 words | Ten |
| Poster | 50-75 words* | One |
| Podium Abstract | 50-75 words* | Two |
| Panel | 150-200 words | Three |
| System Demonstrations | 150-200 words | One |

*: All podium abstract and poster submissions must have a brief (50-75 words) abstract. The abstract does NOT have to be part of the document, but must be entered on the submission website in the Abstract box in Step 2.

**: If your submission is longer than what is specified below, it will be rejected without review.

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### Experimental Results

Experimental results are described here.

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### Discussion

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## Conclusion

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