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EFFECTIVENESS OF TRANSFER LEARNING ON MEDICAL IMAGE CLASSIFICATION USING CHEST-XRAY 14 DATASET

James Boit
Dakota State University

David Zeng
Dakota State University

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JAMES BOIT, DOCTORAL STUDENT IN INFORMATION SYSTEMS
FACULTY MENTOR: DR. DAVID ZENG.

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Abstract

Recent advances in machine and deep learning research have made it possible to make significant performance improvement in computer vision problems, such as image classification, localization and objection detection. New hardware such as high-performance graphical processing units (GPUs) provide optimized memory bandwidth that is computationally efficient and best suited for compute-intensive convolutional neural network (CNN or convNets) tasks. We used applied machine learning research methods to deploy a DCNN to classify medical images (for example, the Chest-Xray 14 dataset). We illustrate a technical implementation using transfer learning technique based on the DenseNet-121 architecture pretrained on ImageNet. Preliminary results indicate a 96% accuracy on the binary classification task. Both feature extraction and fine-tuning strategies demonstrate that they are feasible methods for improving performance on medical image classification problems. Therefore, the application of DL models in radiology will gradually improve the role of medical practitioners, improve patient outcomes and especially in parts of the world with limited resources.

Background

- **Background:** Deep learning (DL) is becoming an important tool for diagnosis, and interpretation of medical images by decreasing the time spent in predictions, improving the accuracy in identifying abnormalities and, therefore, enhancing the clinical outcomes of patients.
- **Approach:** Transfer learning (TL) techniques are very effective for specific domains when datasets are small.
- **Strategies:** We used feature extraction and fine-tuning.
- **Architectures:** We identify three major architectures from literature, namely CheXNet, Attention Guided convolutional neural network, and dual-net architecture.
- **Model:** We used the DenseNet-121 architecture pretrained on ImageNet as our baseline model and perform a binary classification on our dataset.

Literature Review

- Researchers have demonstrated that DCNN models can be an effective and efficient mechanism for significantly improving the accuracy of image classification problems of unrelated problems (Krizhevsky et al., 2012; Simonyan et al., 2016; He et al., 2016).
- Performance of different hidden layers of pretrained convNets and optimal-cut off layers and dimensionality reduction methods are key to improving classification performance (Prodanova et al., 2018).
- Wang et al., (2017), demonstrated a multi-label classification task using DCNN architecture to evaluate the performance of their ChestX-ray 14 dataset on four CNN architectures (AlexNet, GoogleNet , VGGNet-16 and ResNet-50) pretrained on ImageNet.
- Baltruschat et al., (2018) used ResNet-50 architecture pretrained on ImageNet to build a model using TL on the ChestX-ray 14 dataset.
- Weakly supervised learning has been used to examine pathology localization through classification of thoracic diseases (Liz et al., 2017;Yao et al., 2018; Zhou et al.,2018; Yan et al.,2018).
- In binary classification tasks, researchers used the ChestX-ray 14 dataset for pneumonia detection using the CheXNet model (Rajpukar et al.,2017;Guan et al.,2018;Xinyu et al.,2018).
- Thus, from literature it is not clear to what extent the findings of TL in medical images are effective towards generalizing the models in the medical domain.

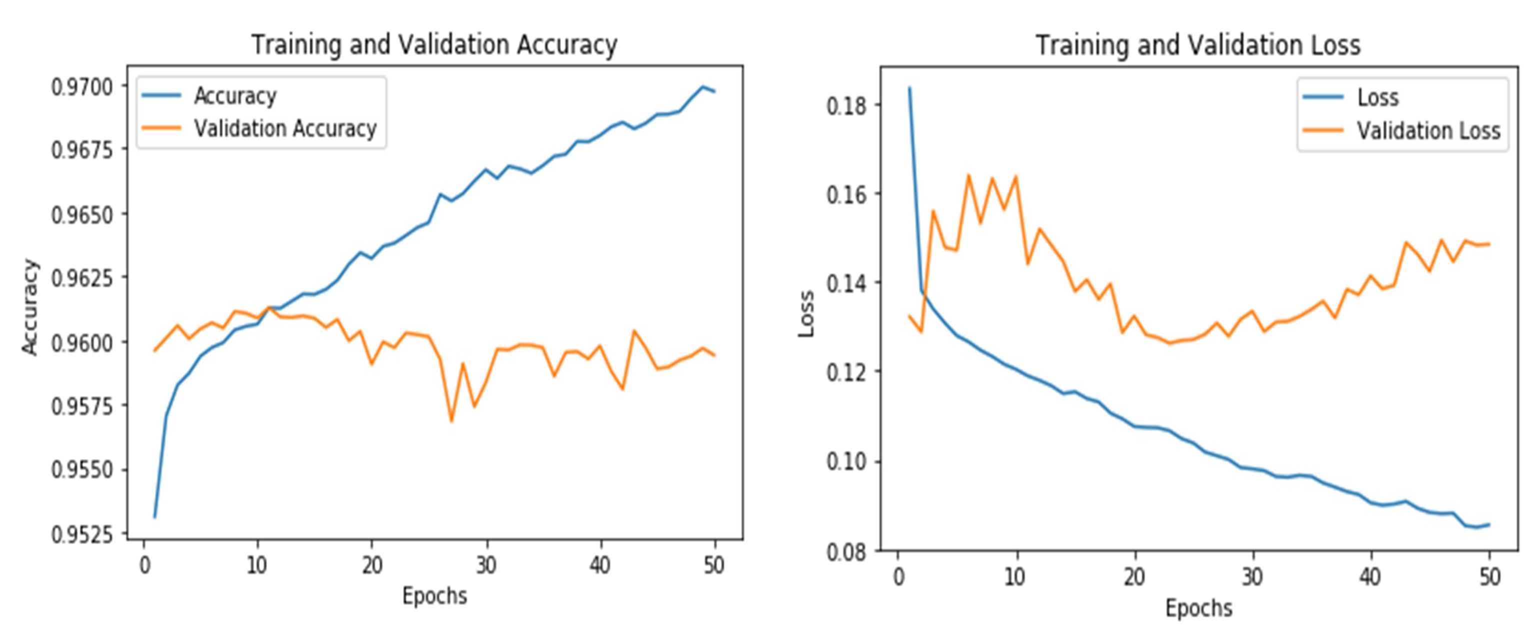
Methodology

- **Function:** We applied nonlinearity functions and specify or tune model hyperparameters to make predictions of the medical images.
- **Dataset:** Publicly available ChestX-ray14 dataset introduced by NIH. The dataset comprises 112,120 frontal-view chest X-ray images of 30,805 unique patients and summarizes 14 different thoracic diseases.
- **Baseline Model:** DenseNet-121 architecture pretrained with ImageNet as our base model.
- **Strategy 1:** **Feature extraction.** We removed the last layer (Softmax layer) of the DenseNet pretrained model and then added our dataset for feature extraction and fine-tuning process.
- **Strategy 2:** **Fine-tuning strategy** to unfreeze more layers and train the weights through backpropagation.
- **Framework:** Keras with TensorFlow as backend.
- **Training:** Defined the dense classifier on top of the base model and trained it with the preprocessed medical images and passed it through the **Relu** function and **Sigmoid** activation functions.
- **Data Augmentation:** We used the Keras ImageDataGenerator method to apply real-time data augmentation to help the DCNN architecture train on more realistic data and obtain a more robust model.
- **Optimization:** We trained the model using several Optimizers e.g. Adam, SGD, RMSprop e.t.c with binary cross entropy loss.
- **Environment:** GPU environment with a dual TITAN V 12GB memory.
- **Evaluation:** Validation dataset to fine-tune the higher layers of our model to find the optimal cut-off point producing the best model performance.

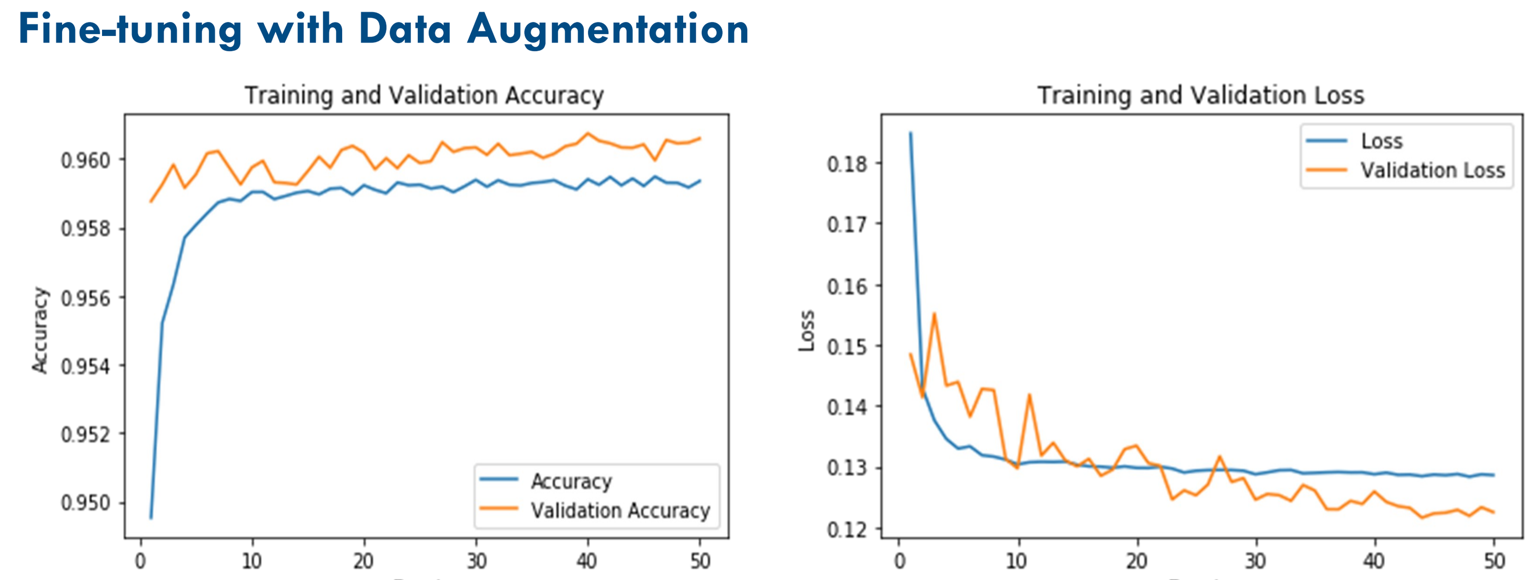
Results

During training and modeling process, we used **feature extraction** and **fine-tuning** methods, and produced the following results below:

Feature extraction without Data Augmentation



Fine-tuning with Data Augmentation



Discussion

- **Task:** We empirically illustrated the application of DenseNet-121 model using **feature extraction** and **fine-tuning strategies** to investigate the effectiveness of TL on medical images.
- **Feature extraction:** We used the *convNets* of the base model as a fixed **feature extractor**, removed the fully-connected layer (SoftMax) and trained a new classifier with our new dataset.
- **Fine-tuning strategy:** We unfroze a specific convNet layer at **'conv5_block16_2_conv'** for fine-tuning and use the rest of the base model convNets fixed/frozen.
- **Preliminary results:** About 96% accuracy on binary classification task.
- **Highlight:** Given the use of both **feature extraction** and **fine-tuning methods**, we show that much more improvements on classification performance is feasible.

Conclusions

- We used **DenseNet-121 architecture** to have a larger playground to investigate more accurately:**1**. the central objective of the effectiveness of T.L on medical image classification, **2**. find the *optimal cut-off point* of different hidden layers, and **3**. determine the generalizability of the model to other *unrelated* medical images.
- We want to shed more light on the **effectiveness** of TL leveraging optimal cut-off layers and thus capturing an accurate estimation of the effectiveness of TL performance on medical image classification.
- **Limitations:** GPU computing environment, and, time-consuming hyperparameter search.
- **In future:** We plan to develop an OCL dictionary as an index of feature representations learned by the ConvNets and identify a benchmark of models with robust performance for specific medical images such as CT scans.