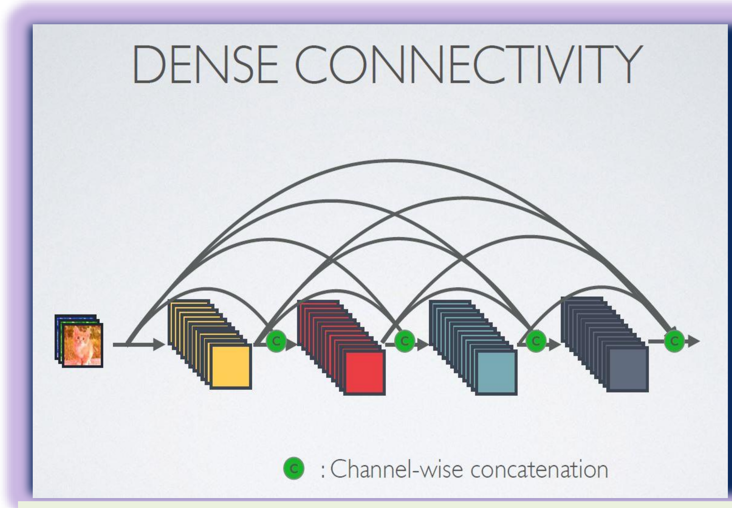

TRANSFER LEARNING IN MEDICAL IMAGES

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Introduction

- **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 which are very effective for specific domains when datasets are small.
- **Techniques:** We identify three major techniques in the literature, namely CheXNet, Attention Guided convolutional neural network, and dual-net architecture.
- **Model:** We use the DenseNet-121 architecture pretrained on ImageNet as our baseline model and perform a binary classification on our dataset.
- **Preliminary results:** Validation accuracy of about 96%.
- **In future:** hyperparameter optimization, adding non-image patient data, finding optimal data augmentation and model architecture, high resolution medical images using GANs.

Literature Review

- **Why DL?** Recent advancements in DL algorithms, specifically DCNN, and accessibility of efficient and powerful graphical processing units (GPUs)
- **T.L solutions:** 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 [2-4].
- In recent studies, Prodanova et al. [5] investigated the performance of different hidden layers of pretrained convNets and found that optimal-cut off layers and dimensionality reduction methods are key to improving classification performance.
- Regarding medical image classification tasks, Wang et al. [6], demonstrated a multi-label classification task using DCNN architecture to evaluate the performance of their ChestX-ray 14 dataset on four CNN architectures (AlexNet [2], GoogleNet [7], VGGNet-16 [3] and ResNet-50 [4]) pretrained on ImageNet.
- Prior studies have focused on the use of pretrained models such as ResNet-50 and DenseNet-121 architectures on medical images. For example, Baltruschat et al. [8], leveraged the 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 [9-14]. In binary classification tasks, researchers used the ChestX-ray 14 dataset for pneumonia detection using the CheXNet model [15-17].
- 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 apply nonlinearity functions and specify or tune model hyperparameters to make predictions of the medical images.
- **Dataset:** publicly available ChestX-ray14 dataset introduced by NIH in [6]. The dataset comprises 112,120 frontal-view chest X-ray images of 30,805 unique patients [6] and summarizes the 14 different thoracic diseases.
- **Baseline Model:** DenseNet-121 architecture pretrained with ImageNet as our base model.
- **Strategy 1:** **Feature extraction**. We remove the last layer (Softmax layer) of the DenseNet pretrained model and then add our dataset for feature extraction and fine-tuning process.
- **Strategy 2:** **Fine-tuning strategy** to unfreeze more layers and train the weights through backpropagation.
- **Training:** Define the dense classifier on top of the base model and train it with the preprocessed medical images and pass it through the **Relu** function and **Sigmoid** activation functions.
- **Data Augmentation:** We use 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.
- **Technical implementation:** Mini-batch stochastic gradient descent, dropout and L2 regularization, batch normalization, optimization of epochs, and data augmentation.
- **Optimization:** We train the model using several Optimizers e.g. Adam, SGD, RMSprop e.t.c with binary cross entropy loss.
- **Framework:** Keras with TensorFlow as backend.
- **Environment:** A GPU environment with a dual TITAN V 12GB memory cards.
- **Evaluation:** Use Validation dataset to fine-tune the higher layers of our model to find the optimal cut-off point producing the best model performance.

Discussion and Results

- **Task:** We empirically illustrate 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.

Preliminary Results

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

Feature Extraction process

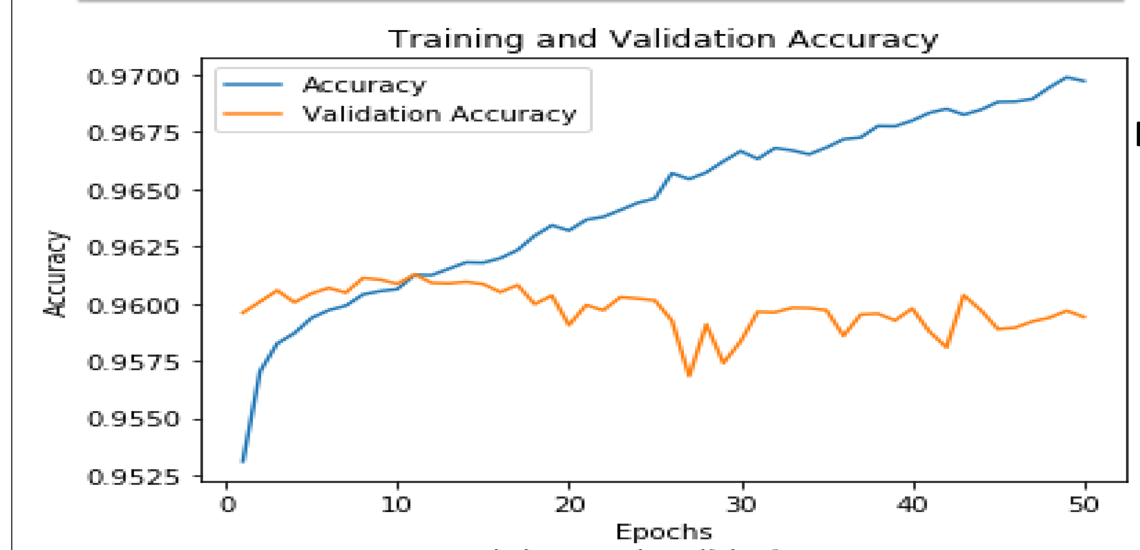

Figure 1

Figure 2

Fine-Tuning with Data Augmentation

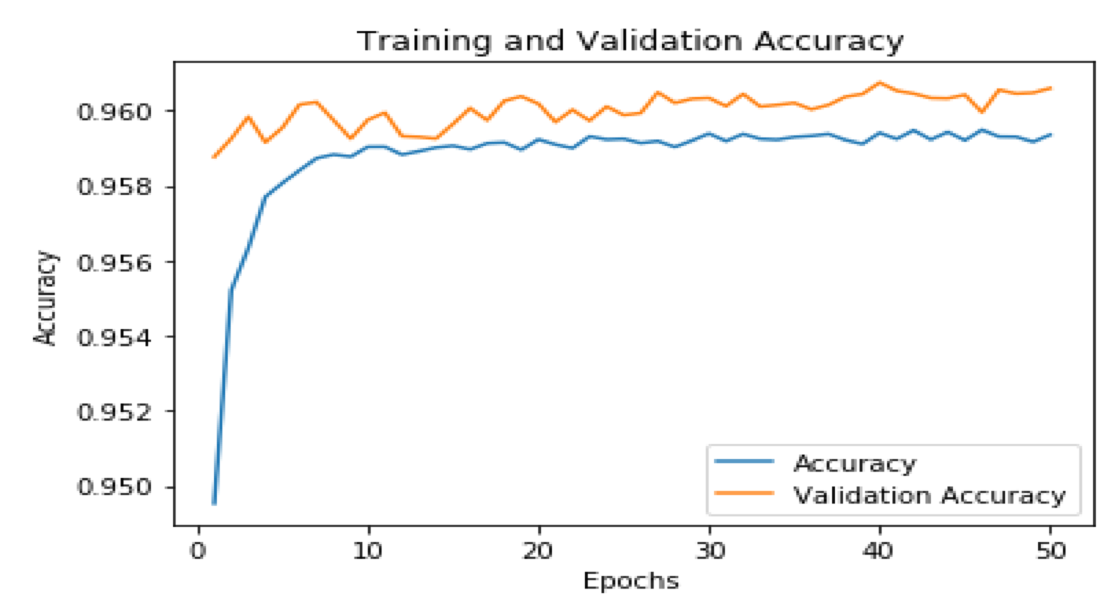

Figure 3

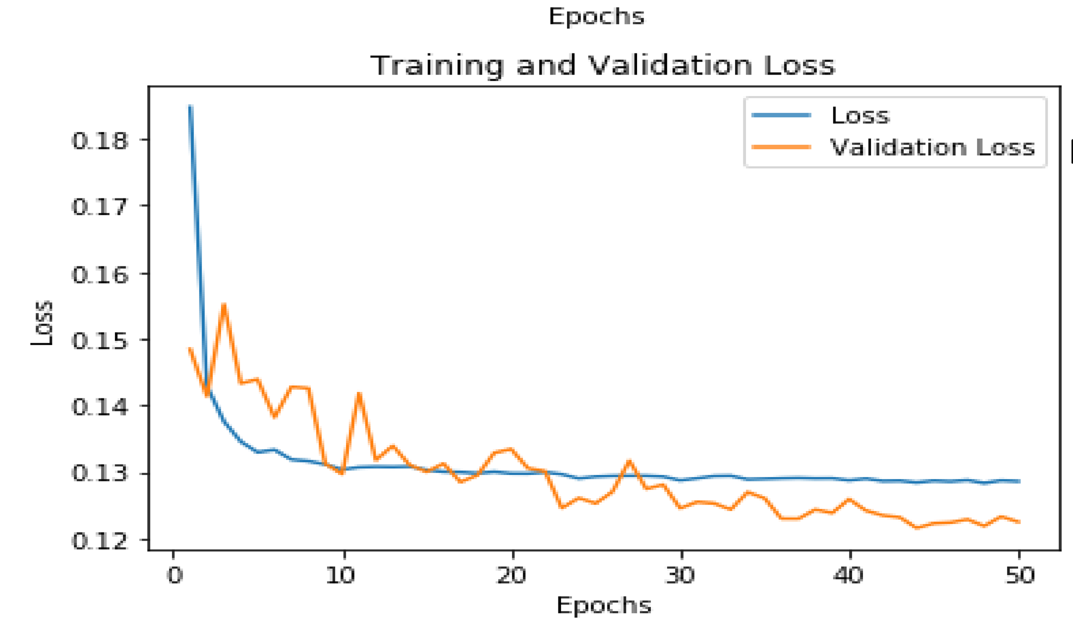

Figure 4

Conclusions

- We use the **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.
- **Feature extraction** and **fine-tuning** strategies will aid in determining the most effective features and model performance on the medical images.

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