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Multi-path Sequential Fine-tuning of Pre-trained Models for Medical Image Classification Part I

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Multi-path Sequential Fine-tuning of Pre-trained Models for Medical Image Classification Part I

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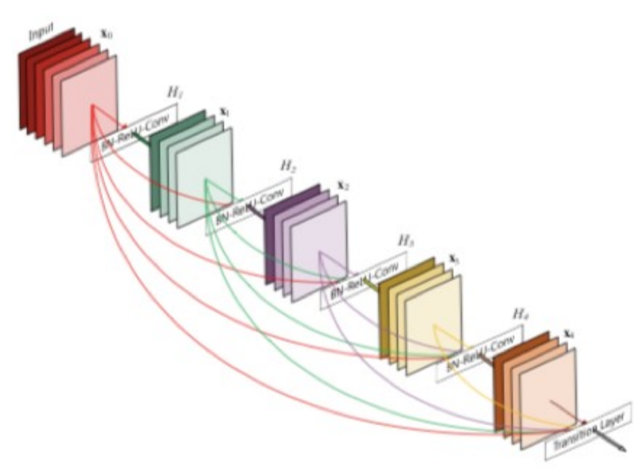
Abstract

While transfer learning techniques such as using a pre-trained model as a feature extractor and fine-tuning a few top layers of convolutional blocks to fit better with the classification tasks of interest have been successfully applied into solving medical image classification problems, less attention has been paid to effective utilizing the feature maps re-learned via fine-tuning at the end of conv layers. We propose a novel technical change in the architecture of deep neural network by sequentially feeding the feature maps via multiple paths of different layers before the transformed feature maps are flatten and feed into the dense layers for final classification. While a modest improvement in performance is achieved, a novel theoretic explanation could significantly contribute to this fast-advancing field.



Background

DenseNets: For each layer, the feature-maps of all preceding layers are used as inputs, and its own feature-maps are used as inputs into all subsequent layers. They **require fewer parameters** than an equivalent traditional CNN, as there is **no need to learn redundant feature maps**. Besides better parameter efficiency, one big advantage of DenseNets is their improved flow of information and gradients throughout the network, which makes them easy to train.

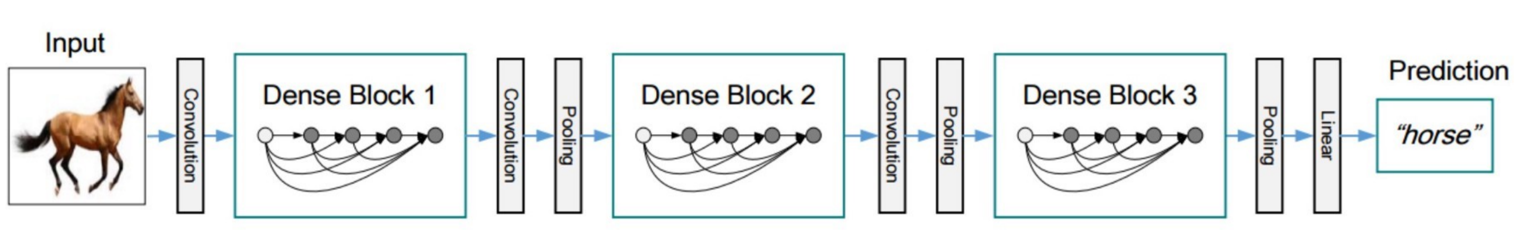
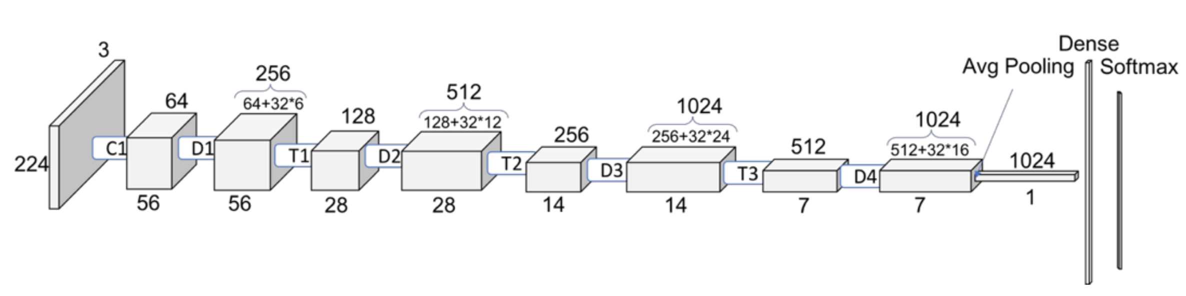


Figure 2. A deep DenseNet with three dense blocks. The layers between two adjacent blocks are referred to as transition layers and change feature map sizes via convolution and pooling.

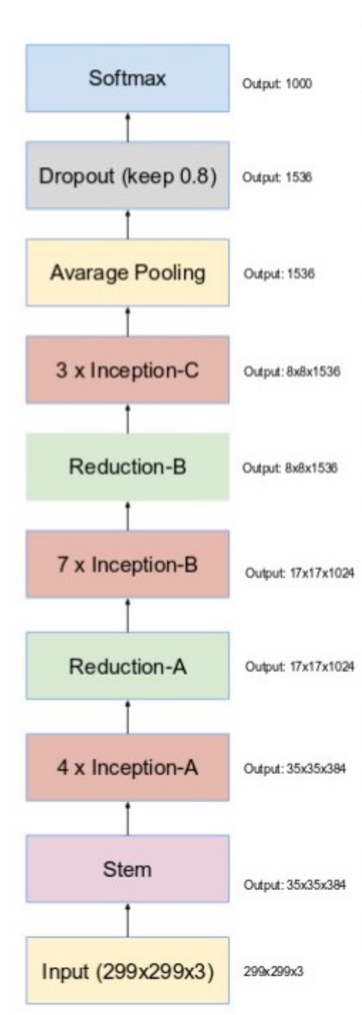
Dense-121. Dx: Dense Block x. Tx: Transition Block x.

Inception: It is heavily engineered and used a lot of tricks to push performance.



Salient parts in the image can have extremely **large variation** in size. Because of this huge variation in the location of the information, choosing the **right kernel size** for the convolution operation becomes tough. A **larger kernel** is preferred for information that is distributed more **globally**, and a **smaller kernel** is preferred for information that is distributed more **locally. The solution:** Having filters with **multiple sizes** operate on the **same level**. The network essentially would get a bit "**wider**" rather than "deeper". **Very deep networks** are prone to **overfitting**. It also hard to pass gradient updates through the entire network.

Auxiliary Classifiers: To prevent the **middle part** of the network from **dying out**. They essentially applied softmax to the outputs of two of the inception modules, and computed an **auxiliary loss** over the same labels.

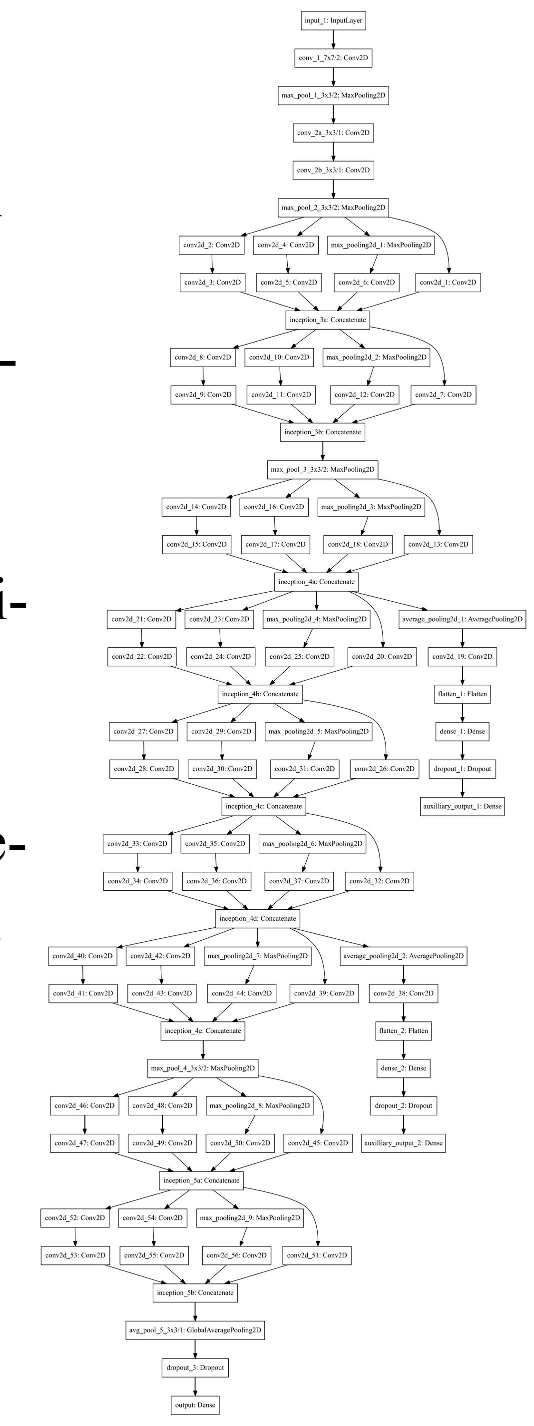


Literature Review

In a recent work on facial recognition, inception modules are integrated into dense blocks and in the transitional layer of DenseNets. And other experiments are done to learn the inter-dependencies of different feature maps, enhancing more useful feature maps while suppressing less important ones to enhance efficiency.

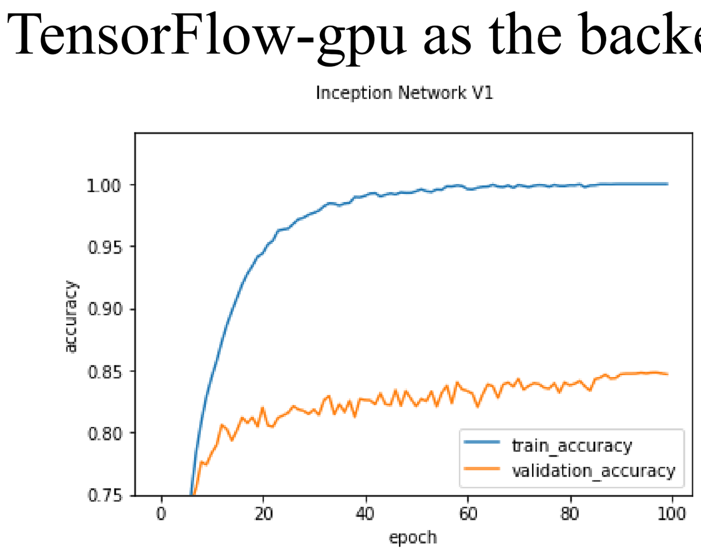
Methodology

A novel architecture is created with Dense Blocks embedded in the inception architecture to effectively learn multi-scale features, characterizing medical images at various levels, to boost features and gradients flow, making deeper networks to characterize complex data distributions, and to learn the inter-dependencies of different feature maps. Three Versions of the DIM1 Network, depending on where the DIM is positioned. Multiple DIMs will be used in DIMx Networks.

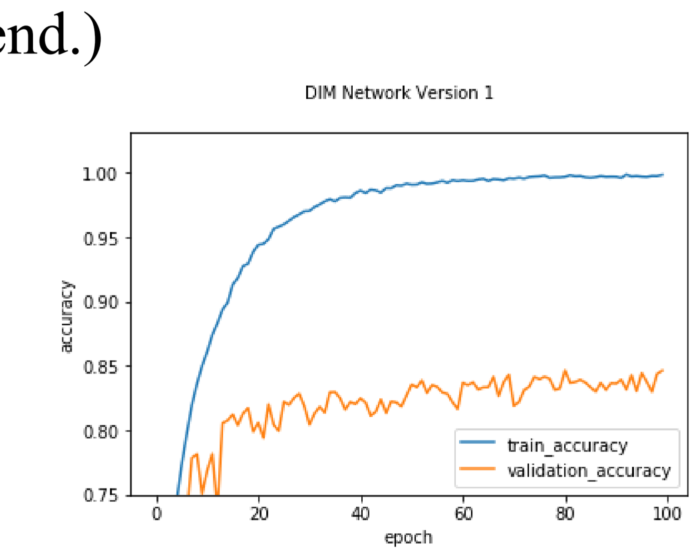


Results

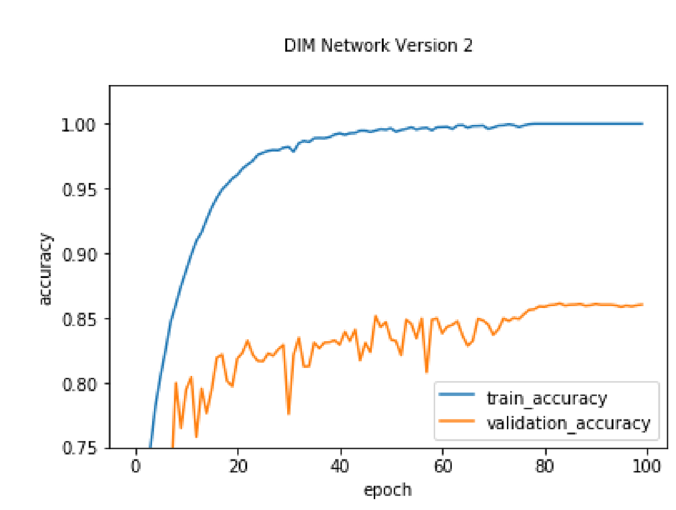
The validation accuracies (100 epochs, mini-batch: 32, sgd with momentum and adaptive learning rate: drop 4% every 8 epochs; model parallelism with 2 TITAN V GPUs, softmax operations are executed by CPU; models are implemented with Keras and TensorFlow-gpu as the backend.)



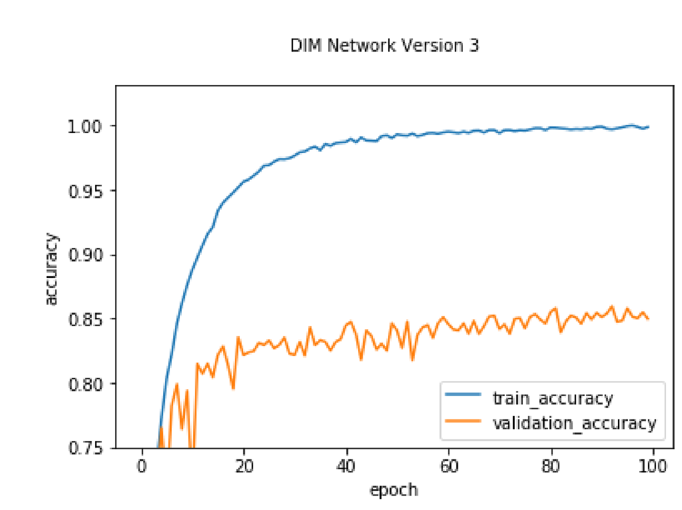
Inception V1 (6.4 m parameters)
Val_acc at Epoch 98: 84.84%



DIM1 Network V1 (5.85 m parameters)
Val_acc at Epoch 81: 84.66%



DIM1 NetworkV2 (6.05m parameters)
Val_acc at Epoch 93: 86.12%



DIM1 Network V3 (6.01 m parameters)
Val_acc at Epoch 93: 85.94%

Conclusions

With DIM replacing auxiliary classifiers, DIM1 Networks appear to achieve higher performance with fewer parameters than the standard Inception Network, indicating higher efficiency than auxiliary classifiers to prevent early/middle layers of the network from dying out.

Future work: strategically position the DIMs and an auxiliary classifier to shed more light on the behavior of the DIMx Networks and identify the optimal one. Theoretical explanations: encouraging interactions among learned feature maps is more efficient than changing loss functions. Then use it as the pre-trained model in medical image classification tasks such as diagnosis with cardiac and chest images.