Spring 3-27-2019

INCORPORATING SEQUENTIAL FEATURE MAPS FEEDING INTO MULTIPLE PATHS

Rajesh Godasu
Dakota State University

David Zeng
Dakota State University

James Boit
Dakota State University

Seema Bhandari
Dakota State University

INCORPORATING SEQUENTIAL FEATURE MAPS FEEDING INTO MULTIPLE PATHS

Rajesh Godasu, David Zeng, James Boit, Seema Bhandari

DSU GRI Poster

MARCH 27, 2019

Abstract

Convolution Neural Networks (CNN) are current best architectures for Transfer Learning (TL) approaches in providing robust Medical Image Classification (MIC) solutions. In Feedforward CNN's, data inputs are processed in the forward manner without any backward connection between the layers disallowing the iterations. While VGG16, Alexnet are standard feedforward CNN's, Densenets are increasingly becoming popular in TL in MIC studies. In this review, we identified two major Densenet applications. First, a novel sequential Fine-tuning approach is proposed by researchers, the representation maps are considered separately for each layer from all the previous layers to gain complete advantage of all the layers in data scare situations. Second, a sequential framework demonstrates low-mid level features, along with high level representations drawn from fine-tuned Densenet also possess important classification qualities if considered precisely.. While the Sequential feeding of the feature maps is a new approach itself in TL, recent studies have focused on single path feature intake models. We propose a novel research to feed the representation maps drawn from convolutional layers into multiple path feature intake models Inception, allowing the reduction in computations, thereby have larger network depth to improve the performance of the network.

Introduction

Background: Transfer Learning (TL) Techniques combined with Convolutional Neural Network's (CNN) is a growing trend in providing Medical Image Classification (MIC) solutions especially in data scare conditions and assist doctors to perform better . TL uses pre-trained CNN's in two ways:

A) Feature Extraction: The base layers of CNN are completely frozen and (MIC) problem specific classifier replaces the fully connected layer, this operation disallows optimizer to modify the weights of base layer, preventing overfitting of the model while Training.

B) Fine Tuning: Bottom layers of the architecture are frozen and top most layers along with classifier are retrained to learn more abstract features.

Classic architectures including but not limited to Alexnet, Densenet, VGG-16 and Inception have employed TL for various MIC problems.

Techniques: The Techniques identified in this review are Sequential finetuning (SFT) and Sequential Modelling of deep features.

Goal: To propose a novel method of Incorporating sequential feature maps feeding into multiple paths.

Literature Review

Why MIC need new approaches in TL?: Recent study on Tiny imagenet observed that Images with more distinguishing features provide better classification results, TL methods are proved to be successful in cross-platform as models trained on natural images provided great MIC results

Specifically in Medical Images, researchers have expressed concerns with image magnification about different representations being captured at different level of magnifications, a Breast Cancer Histopathology study developed a sequential model to address the above mentioned problem with multilayer deep feature fusion and demonstrated low-mid level layer representation maps are also significant as high level representations if considered precisely. Thyroid nodule classification study incorporating VGG-F network also suggests considering both low-level and high-level features presents better results when compared with traditional single type feature method.

A recent study proposed novel sequential finetuning approach which achieved better TB and Cancer classification results when compared to FT whole network and FT only fully connected, however, there were few misclassified images in both the classes with little reasoning.

From the Literature review, it is clear that the MIC concerns regarding capturing the most discriminate features still requires work and we propose a sequential fine-tuning method with combination of Dense blocks and Inception module expecting the improvement in classification and achieve better classification performance.

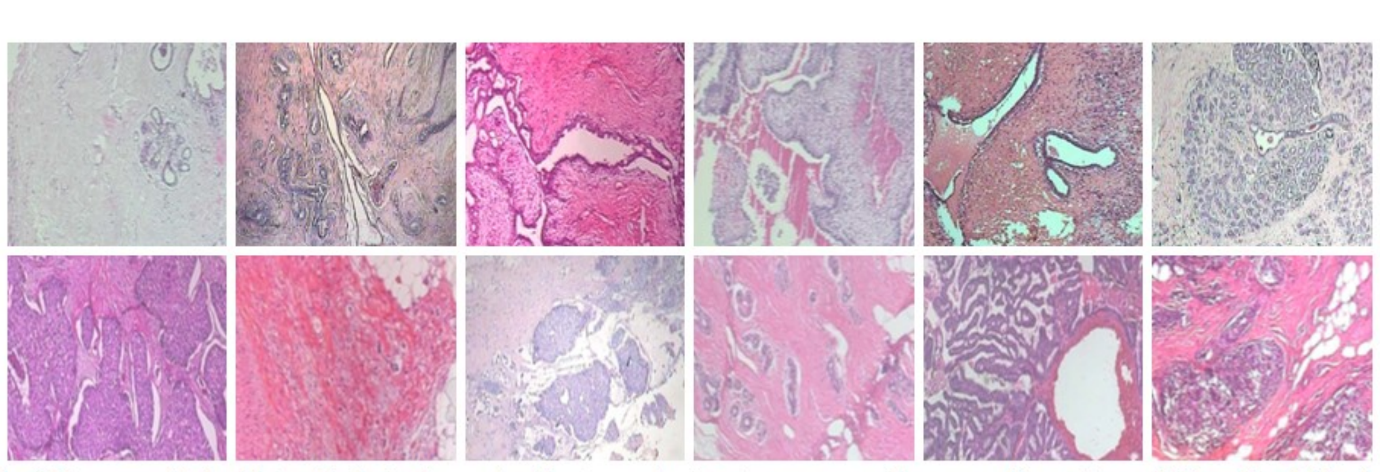
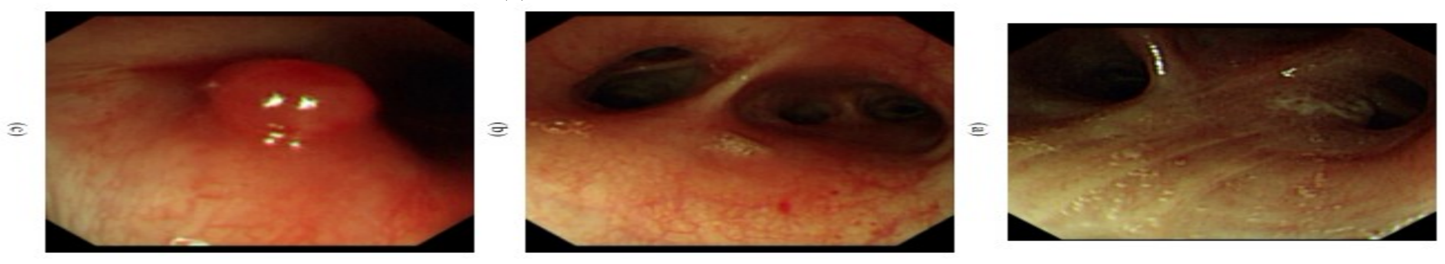


Figure 1. Heterogeneity in histopathological samples(first row: benign tumor, second row: malignant tumor) from BreakHis dataset at magnification factor of 40X.

A cancer case was misclassified as a normal case (a), a normal case was misclassified as a cancer case (b), a TB case was misclassified as a cancer case(c)



Methodology

Research papers on Transfer Learning in Medical Images, Convolutional Neural Networks and their applications in Medical Image classification have been investigated.

"Convolutional Neural Networks", "Transfer Learning" + "Medical Image Classification" and "Sequential Fine Tuning" are the keywords and search queries used in Google Scholar to find the articles.

Proposed Method and Discussion

The proposed network inspired by previous works on Transfer Learning and Combined CNN architectures, has two Dense blocks and an Inception module.

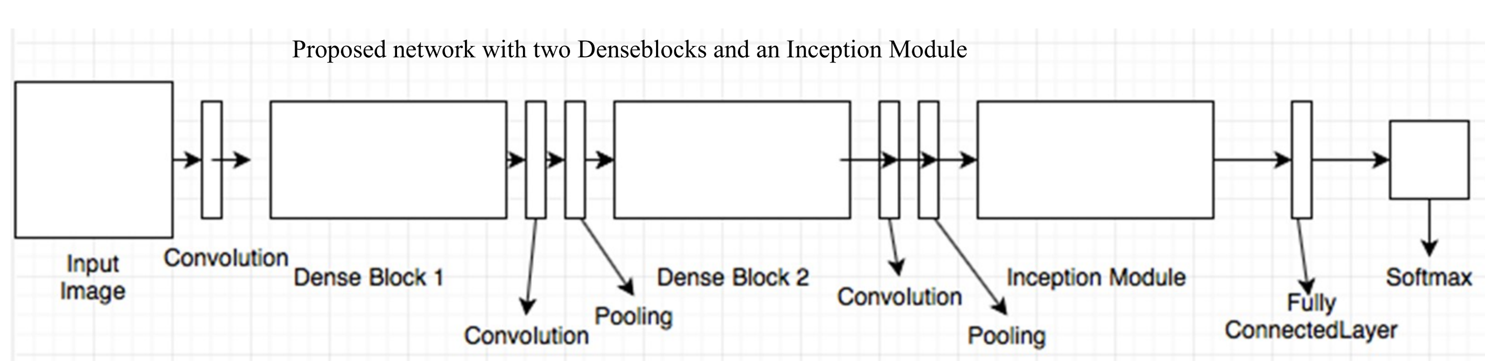
Each Dense block is followed by Transition Layer consisting of convolution layer and pooling layer, Inception module is followed by fully connected layer and SoftMax.

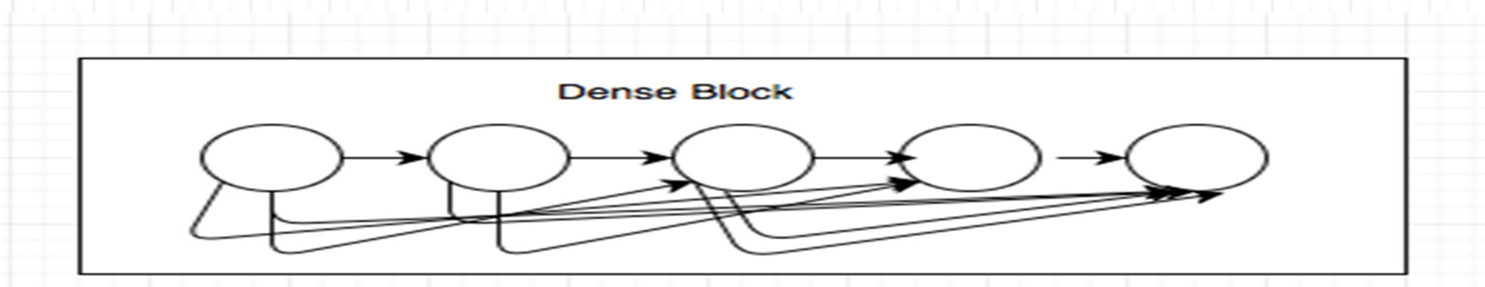
Dense blocks allow the connection of any layer to all the further layers, this connectivity helps in the feature reuse by a layer from all the prior layers.

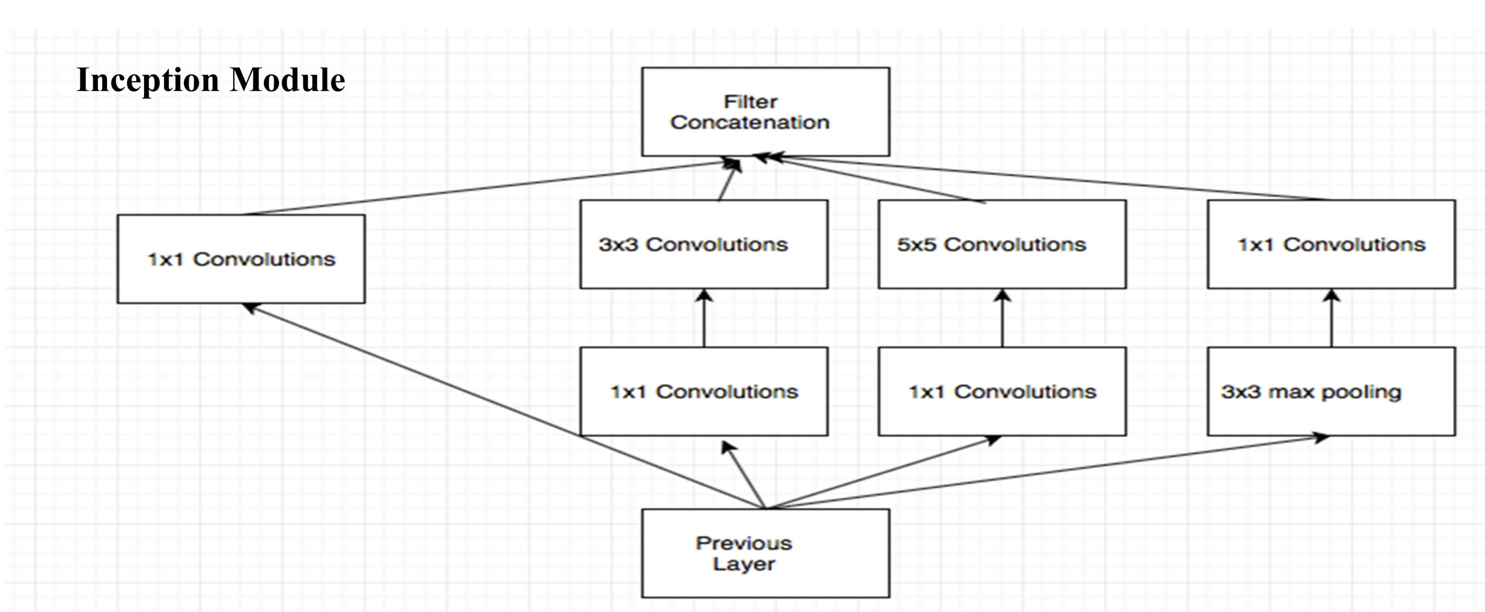
In Sequential fine-tuning, the feature maps are considered separately and fed to the next layer as inputs.

The Difference between traditional sequential fine-tuning proposed by and this model is the use of inception module to sequentially feed the feature maps into multiple paths allowing to increase the width of network and help capture representations of multiple sizes.

Inception module uses 1X1 convolution filters prior to 3X3 and 5X5 helping to reduce number of convolution operations.







Conclusions

Incorporating Sequential Finetuning into multiple paths brings in the multiple benefits from both Densenet blocks and inception modules, we expect to observe the improvement in performance with this method compared to traditional single pass feed forward networks.

In Future works, experiments to test the performance can be done by using publicly available datasets. Variations in the network can be applied by using multiple inception modules and by using the inception modules in between the Denseblocks.