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Abstract

Transfer Learning methods are extensively applied with standard CNN architectures for various medical diagnoses. However, these architectures are computationally expensive, tend to be over parameterized, and requires a relatively large labeled datasets which are often not available in the medical image domain. Accordingly, this paper proposes a Multi-Stage Transfer Learning System using lightweight architectures to address problems with limited data and to improve training time. Preliminary results suggest that our model performed well on CT Head images over traditional single-stage transfer learning.

Keywords

Convolution neural networks, transfer learning, lightweight architectures, multi-stage transfer learning.

Introduction

In the current data-driven world, many activities in everyday life are automated because of data science and artificial intelligence. Video streaming suggestions, Internet ads and numerous Deep Learning (DL) based digital assistants are available in the market to make everyday tasks simpler. Similarly, using DL methods to assist clinicians to improve their performance can prove valuable given the rapid increase in health care cost and the risks associated with medical errors. Various benefits of using DL include providing a second opinion, allowing medical support to reach geographic areas where specialized medical expertise is sparse, building cost-effective devices, reducing the labor efforts, and decreasing the incidences of medical errors.

In medical image classification (MIC), Convolution Neural Networks (CNN) represent the current state of the art architectures implementing transfer learning (TL) methods to achieve success (Altaf et al. 2019; Gao et al. 2019). However, classic architectures have limitations such as over parameterization and are computationally expensive to train. In Computer-Aided Diagnosis (CAD), the limitation of large annotated medical image datasets is forcing the researchers to explore TL. Further, while TL is currently successful in MIC tasks, the problem of lacking properly annotated data is impeding TL potential (Altaf et al. 2019). Accordingly, in this study, we propose a Multi-Stage Transfer Learning system using Light-weight architectures (LWA) to tackle the problem of insufficient labeled data and expensive computations in MIC. TL uses pre-trained CNN's in two ways: feature extraction and fine-tuning. The latter has demonstrated success in dealing with relatively small datasets (Dawud et al. 2019).

Background and Related Work

CNN and LWA

CNN are a type of deep neural network architectures usually built with three different kinds of layers (a) Convolutional layers, (b) Pooling layers and (c) Fully connected layers (Yamashita et al. 2018). Convolution layers are the core of the architecture consisting of moving filters, a convolution operation includes the filters sliding (stride) across the width and height of the input image area (receptive field) to multiply the elements of corresponding receptive field and filters. LWA are efficient neural networks trying to mimic the accuracies of traditional deep CNN's with lesser parameters. Training these architectures requires less time and performs efficiently on training cases distributed across multiple servers (Iandola, Ashraf, et al. 2016). SqueezeNets (Iandola, Han, et al. 2016) and MobileNets (Howard et al. 2017) are two of the earliest examples of extreme Light-weight architectures that resulted in a significant reduction in the size of CNN architectures. Following these two successful Light-weight architectures, numerous architectures have been proposed to further improve efficiency. For example, PlexusNet (Eminaga et al. 2019) is a CNN, designed for histologic image analysis that is nine times smaller than MobileNets. NasNets (Zoph et al. 2018) and MobileNetsV2 (Sandler et al. 2019) are some of the other architectures that are improving the efficiency of various image classification tasks. These architectures are widely being tested for TL in MIC. In a recent study (R. Roslidar et al. 2019) compared four CNN models Resnet (He et al. 2016), Densenet(Huang et al. 2017), MobilenetV2 and ShuffleNetV2(Ma et al. 2018) for breast cancer classification task. ShuffleNetsV2 were trained quicker compared to other models. However, they failed to achieve competitive performance with Resnet and Densenet. On the other hand, MobilenetV2 was quicker than standard CNN's and exhibited comparable performance to Resnet. Overall, Densenet performed best with 100 percent accuracy on the test dataset(R. Roslidar et al. 2019), but when a tradeoff for training time is considered, MobilenetV2's performance cannot be ignored as it is a much simpler architecture.

Transfer Learning

Transfer Learning (TL) refers to a scenario where the features learned in one task are leveraged to improve the generalization in another task. This is possible because in many visual recognition tasks, there exists a notion of shared low-level features such as edges, curves, lighting, color etc. (Goodfellow et al. 2016). To exploit these benefits of TL, many researchers use CNN's pre-trained on ImageNet (Deng et al. 2009) (natural images) dataset for various image recognition tasks, especially in MIC (Gao et al. 2019; Yamashita et al. 2018). TL uses pre-trained CNN's in two ways: feature extraction and fine-tuning. In feature extraction, the base layers of a CNN are completely frozen and the problem-specific classifier (MIC in this case) replaces the fully connected layer. Whereas, in fine-tuning, the bottom layers of the architecture are frozen and the top-most layers along with classifier are retrained to learn more abstract features. The current trend is to improvise by applying TL more than once. The main intuition behind using multi-stage transfer learning is to learn representations from the same domain database (medical) and to achieve better results on the target database due to feature similarities (Kim et al. 2017; Samala et al. 2019). One of the first studies to implement two-stage TL in MIC is (Kim et al. 2017), Another study, (Ausawalaithong et al. 2018) used chest X-Ray14 (Wang et al. 2017) dataset in the first stage TL of Densenet architecture to learn the lung nodules information from the images, then retraining the architecture to actually classify lung cancer images.

Challenges and Limitations

Generally, CNN models that are built for image classification tasks are overparameterized for MIC to gain performance improvements. Evidently deep models tend to exhibit less change when compared to lightweight models during the training process due to overparameterization (Raghu et al. 2019). Further adding attention modules to gaining discriminative features from the deep layers helps identify features that are not required and improve classification accuracy yet at the expense of increased computational requirements (Wu et al. 2019). Accordingly, an opportunity exists to explore LWA that can be applied in mobile devices for ease of use and efficiency (Khan et al. 2019). TL can further potentially generate more robust solutions with the availability of sufficient labeled data (Altaf et al. 2019). Last but not least, in natural images, the differences in features are significant from one image to another with a broad range of lightning and shape but in medical images, these differences can be minute depending on the problem (Erickson et al. 2018) making it difficult to learn while using traditional TL. An issue that can be mitigated via the use of multi-stage TL.

Multi-Stage Transfer Learning System

Multi-Stage Transfer Learning System

The system proposed in this study contains of two stages of TL, the first stage of fine-tuning allows for the adaptation of medical domain features before it is re-trained on the target dataset. The second stage of fine-tuning supports the classification task. The main intuition is to learn representations from the same domain database (medical) and to achieve better results on the target database due to feature similarities. Before applying the first stage TL, a pre-trained MobileNet model is loaded. The MobileNet is pre-trained on ImageNet that contains key knowledge of general features of natural images and is useful in detecting the general identifiable patterns from medical images. Specifically,

1) **Stage-1:** The ImageNet pre-trained MobileNet is fine-tuned on the Chest-Xray image dataset obtained from Kaggle to adapt the domain of medical images from natural images. The model learns the medical images features during this stage. We used a batch size of 16, Adam optimizer, and 20 epochs in this stage.
2) **Stage-2:** The weights learned in stage-1 are used in stage-2 for the binary classification of Hemorrhage and normal cases on CT Head dataset. We used a batch size of 8, Adam optimizer and 10 epochs in this stage as the dataset is very small.

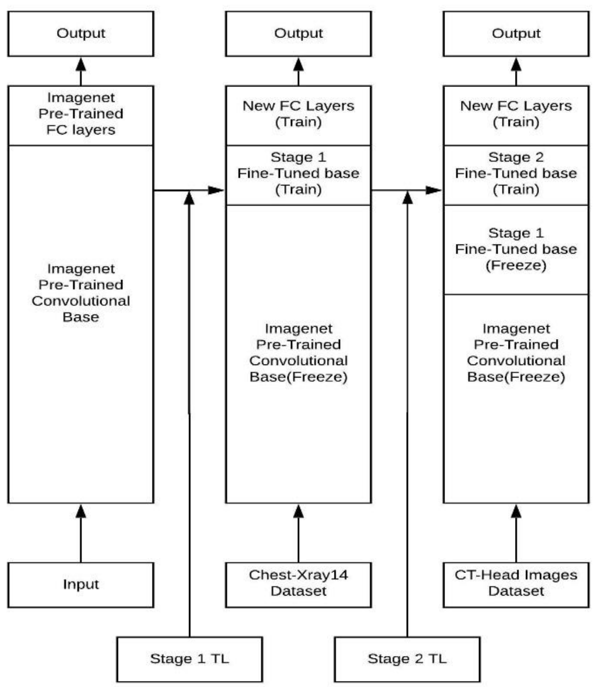

Figure 1. Multi-stage transfer learning system

Datasets

1) **CT-Head:** This public dataset from Kaggle("Head CT - Hemorrhage") has 200 CT images. 100 of them are depicted hemorrhage while the remaining represent normal cases. This dataset is very small and hence it is the right choice as a target dataset for our approach to tackling the limited labeled datasets problem.

2) **Chest X-Ray**: This publicly available dataset("Chest X-Ray Images (Pneumonia)") contains 5,863 images representing the presence or absence of pneumonia and is obtained from Kaggle. This dataset is organized into train, test, and validation folders with two classes pneumonia and normal.

Preliminary Results and Future Work

To evaluate the Multi-stage transfer learning system we used the Chest X-Ray dataset for CT-Head images to classify hemorrhage and normal conditions. Preliminary results show that the combination of Multi-stage TL and lightweight architectures improved classification accuracy from 75 to 87.50 percent when compared to a traditional single-stage TL. Future work will aim to assess the generalization capabilities of the model using different target and bridge datasets. Also, to further improve classification performance we plan to experiment with increasing the number of stages for transfer learning and with using variants of MobileNet. We will also evaluate data enhancement techniques such as GAN models (Goodfellow et al. 2014) which could also result in further improvements in the performance of the model.

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