Deep Transfer Learning For Abnormality Detection

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ABSTRACT

Deep learning has proven to be effective in learning scenarios with massive training data. However, in many real applications (i.e., abonormality detection), there is a lack of sufficient data to a achieve good deep learning model. Considerring the fact that collecting massive labeled training data for a new task is often expensive and time consuming, it is critical to transfer and reuse the knowledge of the labeled related data or simulation data to the new task. To tackle this issue, we propose a deep transfer learning method in this paper. On one hand, we pre-train a basic deep learning model with the related training data. Then, we treat the learning model as a starting point for the current problem to train the new deep learning model. On the other hand, we utilize the Generative Adversarial Nets (GAN) in the learning process to transfer knowledge from simulation data, and further enhances the discriminative power of the model. In addition, we apply the proposed method to abnormality detection problem. Experiments in Bone X-Ray anomaly detection show that the proposed deep transfer model can significantly improve performance compared to the basic deep learning model.

KEYWORDS

Deep learning, Transfer learning, Abnormality detection, Image Processing

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1 INTRODUCTION

The popularity of the newest deep learning methods have been increased in several areas. Although the deep learning network architecture for image processing and speech signal processing is well established, designing a general network architecture for congestion control is still a challenging task. Because there is a need for large amounts of labelled training data [4] to effectively use deep learning for a task. The process to obtain those labelled training data costs large amount of time. Transfer learning [8, 11] is a technique proposed to mitigate this bottleneck. Transfer Learning [10] enables pre-trained models trained for a different task to be used in a new domain. Although transfer learning helps to mitigate the data collection bottleneck, to effectively use it for a task still requires a sizeable amount of labelled data to be collected. In this paper, we will be researching the use of transfer learning [9] in the scenario of a limited amount of data.

Although transfer learning can utilize a small number of tagged samples, the deep learning model trained in the source domain is adapted to the target domain. However, when these tagged samples do not provide sufficient discriminativeness, the deep transfer learning model learned through adaptive methods will not provide good recognition ability. Recently, the Generative Adversarial Network [7] proposed by the researchers consists of a generation network and a discriminative network. GAN learns by letting two neural networks play together. The generated network randomly samples from the potential space as input, and its output needs to mimic the real samples in the training set as much as possible. The input to the discriminant network is the actual sample or the output of the generated network. The purpose is to distinguish the output of the generated network from the real sample as much as possible. The generation of the network is to deceive the network as much as possible. The two networks confront each other and constantly adjust the parameters. The ultimate goal is to make the discriminating network unable to judge whether the output of the generated network is true. In this way, the GAN can use the generated data to enhance the discriminating power of the model. This provides an idea for solving the problem of insufficient discriminative ability of the deep transfer learning model.

The rest of the paper is organized as follows: The second section discusses how to use the knowledge of the relevant domain and a small number of labeled samples to learn the deep tansfer learning model. Then, the third section discusses in detail how to use GAN to enhance the discriminative ability of the deep tansfer learning model. In the fourth section, the feasibility of the proposed algorithm is verified by two experiments. The final section summarizes this article.

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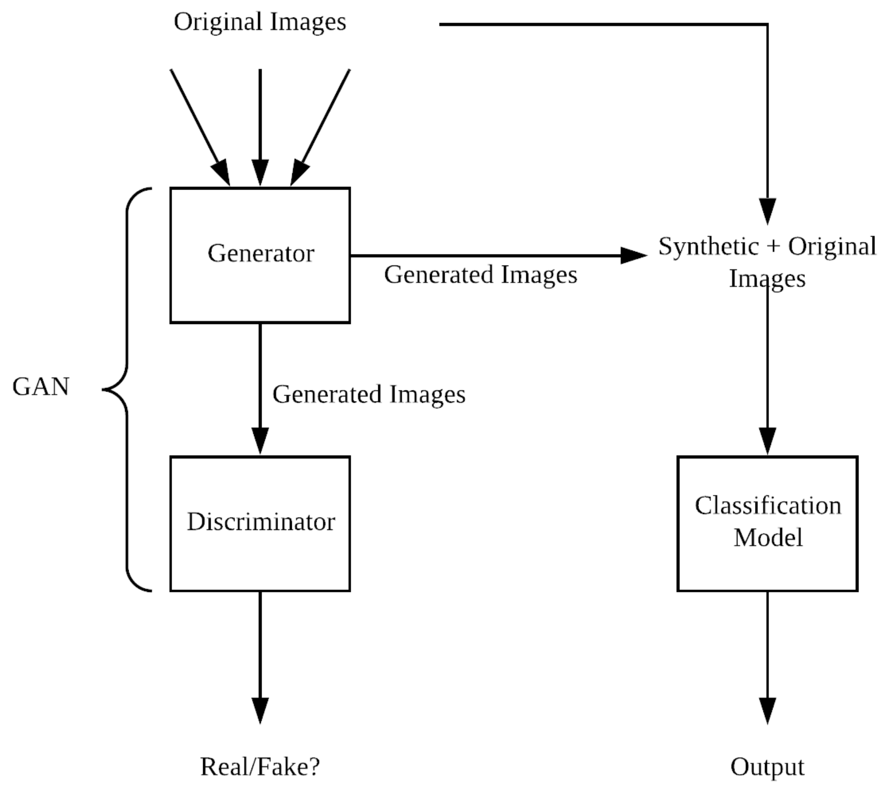

Figure 1: Schema of Conditional DCGAN

2 DEEP TRANSFER FROM RELATED DOMAIN

The expense of data acquisition and costly annotation of dataset limits the development of a deep learning model and it is a critical bottleneck to overcome in order to construct an effective model for a task. A technique that has been proposed to overcome that issue is transfer learning [6]. Transfer learning relaxes the hypothesis that the training data must be independent and identically distributed with the test data, which motivates us to use transfer learning to solve the problem of insufficient training data [6]. Transfer learning works by using weights from a pre-trained model as a starting point for a new model to train on a new task. The pre-trained models are usually highly optimized and tuned as they had been trained for a much longer time on a huge dataset such as ImageNet. This enables a lesser amount of data needed to train a new model, therefore making it computationally cheaper and more efficient. However even with transfer learning, the performance of the model is dependent on the size of the data. As the amount of data a deep learning model is being trained on increases, the performance of the model increases [5]. The results of using transfer learning to train on a subset of the MNIST data compared to the full MNIST data is shown in Table 1.

The results of using ResNet50 for transfer learning to train on the full Stanford MURA dataset with 40 epochs each, is shown in Table 2. From the table we can see that even though we use the migration learning strategy on the pre-trained deep learning model, the model is not ideal in the seven anomaly detection tasks. The main reason for this phenomenon is that there are too few labeled samples for knowledge transfer, which is not enough to provide sufficient discriminating power. Therefore, in order to build an effective deep learning model for a new task, a sizeable amount of data is needed for the model to train on, and acquiring the required amount of labelled data can be costly and inefficient.

3 DEEP TRANSFER WITH GENERATED DATA

Acquiring more labelled data is essential to build an effective deep learning model. However, the process to obtain them through conventional means such as first collecting data then manually labelling them causes deep learning projects to be inefficient and extremely costly. Are there any other ways that we can obtain more data? To acquire more data, we try to generate synthetic data. In the case of our dataset which consist of images, a right technique for data generation has to be chosen carefully. A method that has been proposed by Ruffini et al. [1] is through the use of Generative Adversarial Networks (GANs). GANs is a new framework proposed by Goodfellow et al. [7] in 2014, which works by simultaneously training two models: a generative model G

Table 1: Transfer Learning with Varying Amount of Data

Epochs	Transfer Learning Model	Amount of Data	Accuracy
10	MobileNet	320 (32 of each class)	80.94%
10	MobileNet	41,680	95.63%

Table 2: Transfer Learning on Stanford MURA Dataset

Category	Elbow	Finger	Forearm	Hand	Humerus	Shoulder	Wrist
Accuracy	49.20%	43.60%	48.50%	57.00%	51.40%	43.30%	48.40%

that captures the data distribution, and a discriminative model D that estimates the probability that a sample came from the training data rather than G. This framework corresponds to a minimax two-player game, where the training procedure for G is to maximize the probability of D making a mistake. Over the years, there has been much improvement in GANs as highlighted by [3], novel GANs architectures has been introduced and new applications for GANs have been discovered. As GANs are able to generate realistic images, it makes GANs a perfect choice for my research, to generate synthetic images. The synthetic images can then be used to assist with transfer learning, to train a more effective deep learning model for a new task.

To produce an effective GAN to generate realistic synthetic images for training via transfer learning, research has to be done in building the GAN. Various architectures of GANs have been explained in detail by [3], and the Conditional GAN enables the model to capture additional information regarding the representations for multi-modal data generation [2]. Deep Convolutional Generative Adversarial Networks (DCGAN) excels in image task and therefore, the final GAN architecture that we chose to incorporate into my research is a Conditional DCGAN.

4 EXPERIMENTAL

4.1 Dataset

The dataset used in this paper for my research will be the Stanford Musculoskeletal Radiographs (MURA) Dataset and the Modified National Institute of Standards and Technology (MNIST) dataset (as a toy example). The Stanford MURA dataset consist of bone X-Ray Images of 7 different category: elbow; finger; forearm; hand; humerus; shoulder; wrist, each with labels of them being normal or abnormal. The images are of dimensions of hundreds by hundreds. Whereas for the MNIST dataset, it consist of handwritten digits images with their respective labels from 0 to 9. The images in the MNIST dataset is of a much smaller dimension. As both dataset are images, a Convolutional Neural Network (CNN) will be used to classify those data.

4.2 Qualitative Results on MNIST Dataset

The images from MNIST dataset of handwritten digits are of small dimensions 28x28, making them an ideal toy example for quick experimentation and research in implementing the Conditional DCGAN architecture, before applying the similar architecture to the Stanford MURA dataset. For my experiment, we randomly picked 32 images of each category of digit for the Conditional DCGAN to be trained on. The implementation of the Conditional DCGAN can be found in the footnote . The Conditional DCGAN is trained for 3000 epochs. Samples drawn from the Conditional DCGAN is shown in Figure 1.

The results shows that synthesized images from a carefully trained GAN is able to greatly improve the models accuracy, however it does not perform as well as a model that has been trained by lots of real data.

4.3 Qualitative Results on MURA Dataset

The images from Stanford MURA dataset are of a much higher dimensions, in the range of hundreds by hundreds, hence constructing an effective Conditional DCGAN for this dataset is very difficult. Samples drawn from the implemented Conditional DCGAN is shown in Figure 2.

The images generated by the Conditional DCGAN for the Stanford MURA dataset does not look realistic enough to move on to the next stage of the experiment. This is due to the lack of computational resources and time. Even though the images generated are not good enough, it can be observed that the images contains some information regarding the category of the image. A well-trained GAN for this dataset would be even able to synthesize realistic abnormal data, as the Stanford MURA dataset suffer from imbalance dataset.

5 CONCLUSION AND FUTURE WORK

In this paper, we explored the idea of using GAN to assist with transfer learning. Constructing and training an effective GAN to generate realistic synthetic images for transfer learning, is a possible solution to tackle the cost associated with the collection of data. For the MNIST dataset of handwritten digits, the synthesized images actually helps to improve the

Figure 2: Samples from Conditional DCGAN (MNIST). Training a transfer learning model on 32000 synthetic images (3200 images for each category of digit), the results are shown in Table 3.

Table 3: Transfer Learning on Synthetic Data

Epochs	Transfer Learning Model	Data	Accuracy
10	MobileNet	320 (32 of each class)	80.94%
10	MobileNet	32000 (synthesized data)	**91.88%**
10	MobileNet	41680 (full data)	95.63%

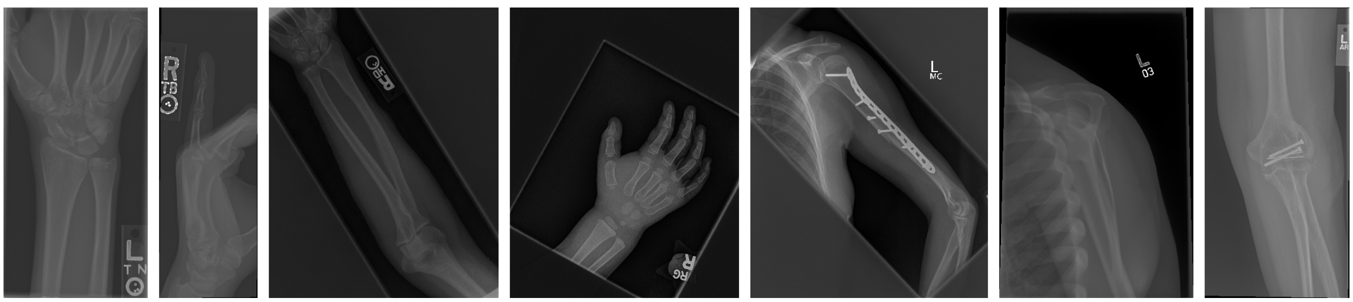

Figure 3: Samples from MURA Dataset

deep learning model, although not as good as using the full data available. However for big dataset like the Stanford MURA dataset, the construction of an effective GAN will be difficult as GAN is a relatively new technology and much research is still ongoing to solve the issue with mode collapse that frequently occurs when training GANs.

A limitation of my research would be that the images picked to be trained by the GAN were randomly picked. Theoretically, if the images were picked with enough variation and samples, the model will be able to learn the distribution of the data better, therefore improving the kind of data generated. If the data acquisition is not an issue, one should always prefer that as it will help to produce the best deep learning model with transfer learning. However, synthesizing realistic data can help to assist in the lack of data as a temporary solution. A carefully and properly trained GAN can even be used to generate instances of rare or anomalous data in an imbalanced classification problem, as the cost to obtain those data are even much more expensive and time consuming due to its rare occurring nature.

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