DATA AUGMENTATION ON SKIN LESION IMAGE DATA USING GAN FOR INCREASED CNN PERFORMANCE

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Abstract - *The skin lesion is abnormal growth or damage of skin cells. There are 7 different types of skin lesions out of which only 4 classes are cancerous. For a better treatment of skin lesions, it is important to detect them in an early stage. For this task, we take the help of automated classification of skin lesions. As of now, Deep learning is providing the best solution possible to the classification of skin lesions.*

But deep learning needs millions and millions of samples to effectively learn the underlying representation of any dataset. In the case of skin lesions, the available data is very low, for example, there are only 10,000 images available in the open-source dataset used for skin lesion classification problems. For overcoming this problem we need augmented data and traditional data augmentation is effective only till a specific stage after that it produces some data samples. So we propose the use of state-of-the-art deep learning architecture Generative Adversarial Network for creating realistic images of skin lesions. This can be used to augment the data set for the classification problem. This will solve bot data insufficiency and data imbalance problem in case of skin lesion.

Key Words: Deep Learning, Generative Adversarial Network, Skin Lesion classification, Data Augmentation.

1.INTRODUCTION

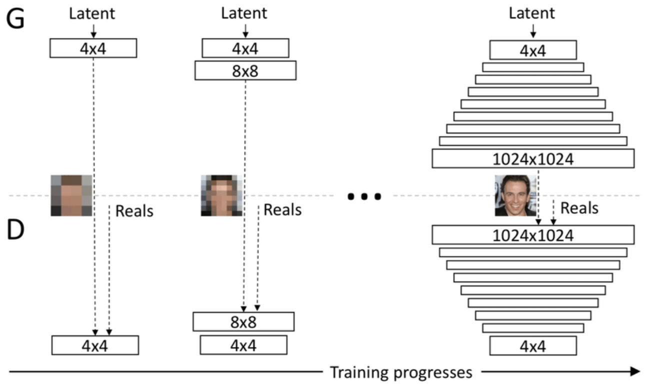
Deep learning has brought a significant change in computer vision problems. The ability of deep learning architectures to learn the underlying representation of a dataset has enabled it to give better results on computer vision tasks. Deep learning algorithm has achieved the human level of excellence in many image classification tasks. To take full advantage of this technology we need to use a dataset having millions of images that are not available in many cases so to solve this problem we use traditional augmentation. But traditional augmentation can generate only a limited number of samples from given samples. To increase the performance of the classification problem we can create an augmented dataset using Generative Adversarial Network. As the name suggests GAN is an adversarial network in which we use two different neural networks and then combine them in one neural network. First, we train the discriminator which is trained with the real data set, and then this discriminator can classify between real and fake images. Then we use this discriminator with another neural network known as a generator we usually pass noise to the generator depending upon the architecture of GAN and the image from this generator is then passed to discriminator that tells us if the image is fake or real, with the help of feedback from the discriminator we train the generator to create a realistic image. There are many types of GAN differing from each other based on their architecture and data feed but all of them work on the same principle.

2. BACKGROUND AND RELATED WORK

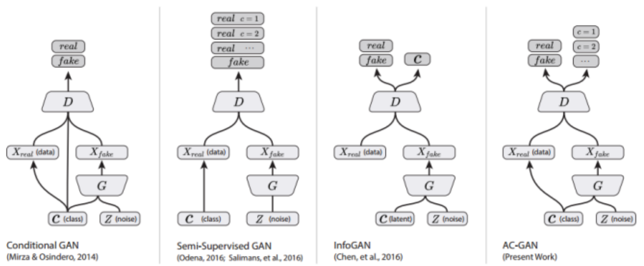
[7] Generative Adversarial Network was first time proposed in this paper. GAN is the framework of the Generative model through an adversarial process, in this process two neural networks are trained together one is the generator and the other is the discriminator. The generator is used to capture the data distribution and the discriminator is used to tell if the data are given to it as input is coming from the original dataset or generator G. The entire framework can be trained using the Back Propagation algorithm.

[8] In this paper author describes how GAN can be useful for problems like liver lesion classification and using DCGAN they generate an artificial dataset for liver lesions and use it to improve the accuracy of Convolutional Neural Network based classifier. The difference between a classifier with traditional augmentation only and a classifier with GAN-based augmentation can be seen in the result. The Paper also describes how DCGAN is more advantageous in classification problems having different classes. In this, we can see how GAN-based augmentation is very beneficial for the problem of insufficient data.

[10] In this paper, the author describes a new training technique for GAN. The technique is known as progressive GAN in progressive GAN we initially take low-resolution pictures and then by adding layers to both discriminator and generator progressively we refine the quality of the photograph and finally we get a photo of 1024X1024p quality. The architectural diagram of PGAN is given below



[11] In this Paper author describes a conditional GAN. We used to give noise as input and using the noise generator generated the data. In conditional GAN we give some auxiliary information to the generator as well as the discriminator. This information can be anything for example we can give class labels as auxiliary information. The architecture diagram of ACGAN is given below



3. ANALYSIS OF RELATED WORK

After reading the related work we have analyzed that in classification problems using CNN one of the major bottlenecks is less availability of data. This is the problem that is common in many medical automatic classification systems and to overcome this problem we can use Generative Adversarial Network for augmenting the data. There are different types of GAN architecture available we can use any one of them after experimenting with them to see which gives the best result for our problem of skin lesion. In the case of liver lesion classification DCGAN has performed far better than ACGAN. The performance of ACGAN is better than classification without augmentation but worse than the DCGAN. ACGAN uses auxiliary information because that it is called conditional GAN. In the case of liver lesion discriminator used in ACGAN was an auxiliary classifier therefore it can be used as a test classifier after training of the network.

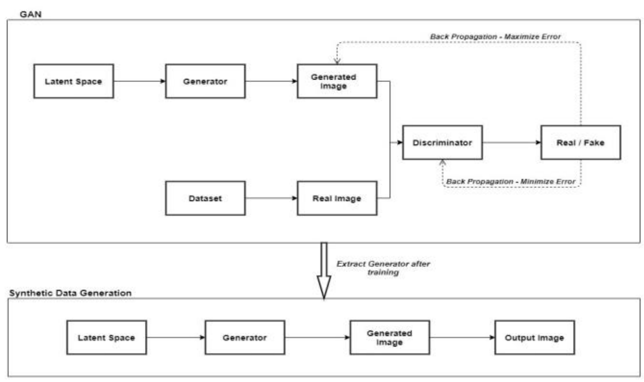
As we have tried to find the data-related skin lesion there are only 2 datasets available in the public domain. One dataset has 10000 data samples divide into 7 classes and the other has only 2000 data samples. Simple most Convolutional Neural Network has 1000 parameters and with such a small dataset there is a very high possibility of overfitting which will cause the model to learn unwanted information about training data and will fail to generalize when we present a data sample out of the training set. Due to which the classifier won't be able to solve our problem of classifying skin lesions.

To solve the problem of overfitting we need more amount of data. Traditional augmentation can give us data up to a limited amount. So, we propose to use the method of data augmentation for skin lesions using a Generative adversarial Network. We can use this data augmented with help of GAN with our real data and traditionally augmented data which will increase the amount of data available for training classification neural networks. Significantly and using this data we can surely reduce the chances of overfitting.

4. ARCHITECTURE

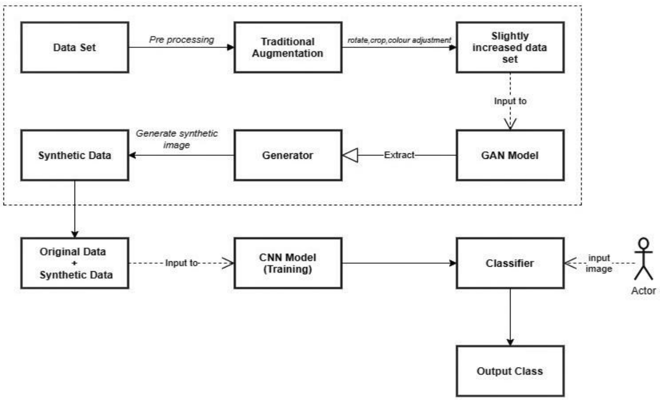
We will be using three neural networks in our architecture one for classifier and two for building the GAN. In GAN one neural network will be doing the work of the Generator and another neural network will be doing the work of the Discriminator. The discriminator will be trained using real samples and it will work like a binary classifier it will be made up of a convolutional neural network. The Generator is used for generating images from noise.

The generator will pass images produced to the discriminator and it will classify images as real or fake. Using the feedback from the discriminator generator can improve the quality of generated images. Discriminator and generator are connected using the Backpropagation algorithm. We will train our model and once training is completed, we can extract the generator model and produce images using the generator.



5. WORK FLOW

As shown in the diagram we will first do pre-processing on data. In which we will clean the data and perform some traditional augmentation on it and after performing traditional augmentation. We will convert the image data into a tensor so that we can pass it to our neural networks. Once data is converted into tensor it is passed to the GAN model and after completion of training, we extract the generator. Use the generator to generate a synthetic image and using this synthetic image we will build our synthetic image dataset. After merging it with the original dataset we will pass it to our CNN model used for classification purposes. After training, we will extract the classifier model and perform testing on the classifier to check the results.



6. PROPOSED METHODOLOGY

We propose to use GAN for synthetic data augmentation for a skin lesion. Synthetic data augmentation can solve both our problems class imbalance problem and data insufficiency problem. It will help us in reducing the chances of overfitting of classification model and give us the better result on newly tested data.

7. ADVANTAGES

- Increased Dataset
- Reduced chances of overfitting
- Reduction of class imbalance
- Increased performance of the classifier

8. DRAWBACKS

- The amount of time for training is increased
- More Resource is required
- Training GAN is dynamic due to which we have to supervise it closely

9. CONCLUSION

There are two major problems with skin lesion classification using CNN. One is insufficient data and the other is class imbalance and to address both of the problems we need more data. Traditional augmentation can help us up to a certain extent after that we have to search for novel methods. After observing progress made by GAN in medical image augmentation, we conclude that GAN is one of the ways sung which we can surely increase the quality and quantity of dataset. This will help us to increase the performance of the classification of skin lesions.

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