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An examination of synthetic images produced with DCGAN according to the size of data and epoch

DCGAN ile üretilen sentetik görüntülerin veri boyutuna ve epoch sayısına göre incelenmesi

Canan KOÇ[1*], Fatih ÖZYURT[2]

[1,2] Department of Software Engineering, Faculty of Engineering, Firat University, Elazig, Turkey.
[1]canan.koc@firat.edu.tr, [2]fatihozyurt@firat.edu.tr

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Abstract

In recent years, the popular network of adversarial networks has increased in studies for computer vision. The lack of data used in the studies and the lack of good training for the resulting model draw attention to techniques such as data enhancement and synthetic data generation. In this article, synthetic data was produced using Generative Adversarial Networks (GANs). The data in the dataset used consists of 10000 faces from the CelebA dataset available online. The impact of the increase in the number of data on fake images created by DCGAN, one of the GANs, is the main topic of the article. In the study, the data is divided into two parts. In the first study, fake data were generated from 5000 data, and in the next study, fake data images were forged using all of the data meaning 10000 data. The result was found that the number of data and the increase in epoch were accurately proportional to the success of the fraudulent images created.

Keywords: Generative adversarial networks, Synthetic data, Generative model

Özet

Son yıllarda Bilgisayarla Görü için yapılan çalışmalarda Çekişmeli Ağlar'ın popülerliği artmıştır. Yapılan çalışmalarda kullanılan verilerin yetersiz oluşu ve bunun sonucunda oluşturulan modelin iyi eğitilememesi veri arttırma ve sentetik veri üretme gibi tekniklere dikkat çekmektedir. Bu makalede yapılan çalışmada Çekişmeli Üretici Ağlar (GANs) kullanılarak sentetik veri üretimi yapılmıştır. Kullanılan veri setindeki veriler çevrimiçi olarak bulunan CelebA veri setinden alınan 10000 yüz görüntüsünden oluşmaktadır. Veri sayısındaki artışın GANs çeşitlerinden biri olan DCGAN tarafından oluşturulan sahte görüntüler üzerindeki etkisi makalenin ana konusudur. Yapılan çalışmada veriler ikiye ayrılarak kullanılmıştır. İlk yapılan çalışmada 5000 veri, sonraki çalışmada ise 10000 verinin tamamı kullanılarak sahte yüz görüntüleri oluşmuştur. Alınan sonuçta ise veri sayısının ve epoch sayısının artışının oluşturulan sahte görüntülerin başarısıyla doğru orantılı olduğu görülmüştür.

Anahtar kelimeler: Çekişmeli üretici ağlar, Sentetik veri, Üretici model

1. Introduction

Machine learning has been one of the key areas that we have recently faced in solving problems. Most of the work done in this field requires a large data size and with a large number of data, it is accurate to learn the model created in machine learning. However, there has also been an increase in the direction of this area, especially due to the lack of data sets and the difficulties in obtaining ethical board permits for the data used in the field of health. Researchers have started to look for a variety of solutions. Offering multiple solutions to these issues. Data Augmentation, GAN, and similar algorithms are examples of what can be given to these methods.

Generative Adversarial Networks, GANs, are one of the best and most useful topics in the production of fake data, first proposed by Ian Goodfellow in recent years [1-2]. Although there are many computer programs used to generate data, GANs stand out from the rest with their results and versatility. The GANs are used in many different areas, with

[1]Corresponding author

many different types. StackGANs [3], CycleGANs [4], Age-cGANs [5], DCGANs [6], InfoGAN [7], Laplacian GAN [8] is just a few of them. To increase the number of data, as well as increase the resolution of the low-resolution image, Ledig and his friends recommended the SR-GANs model [9]. In addition, Xiaodong and his friends recommended the DualG-GAN model in 2022 for synthesizing from text to image [10].

In this article, DCGANs were used to produce successful face images. This DCGAN model used is the most common type of GANs model. This type of GAN is to look at the effect of the data increase on the quality of images produced by GAN.

2. Materials and Methods

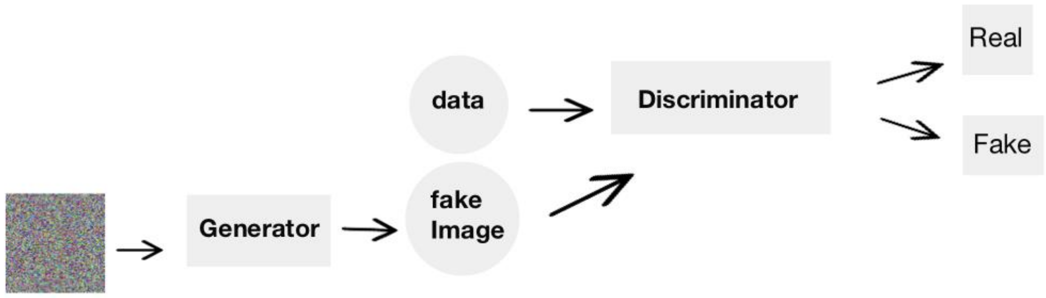
2.1. Dataset

The dataset used in the study consists of 10,000 faces acquired from the dataset, CelebA, shared online [11]. Facial images are mixed as men and women in the dataset. Examples of facial images with glasses, hats, curls, straight hair, different facial shapes, and facial expressions are shown in figure 1.

Figure 1. Examples of actual face images in the dataset

Deep Convolutional Generative Adversarial Networks (DCGANs)

GANs are a machine learning technique consisting of two neural networks that are simultaneously trained [12]. The first of these networks is the Generator network, which produces the fake data, and the other is the Discriminator network, which is used to distinguish the generated fake image from the real image [13]. In general, if you look at words one at a time, the word Generative represents the purpose of the model, to produce new data. The word Adversarial represents a game between two neural networks. When the generator tries to produce the best fake image, the Discriminator tries to distinguish the generated fake image from the actual images. This struggle between the two neural networks is summarized as a game. The word Networks represents two neural networks, called the Generator and Discriminator networks at the base of the model.



Şekil 2. Generative Adversarial Networks (GANs) architecture

The GAN architecture is briefly represented as shown in figure 2. The generator receives the noise vector z first as the network input and tries to produce an image. The generated G(z) dummy image is supplied as an input to the Discriminator network with the X_d actual image. In this section, the role of the Discriminator network is to perform a binary classification to distinguish the actual image (X_d) from the fake image produced by the Generator network (G(z)). The data are given as input, Generator mesh returns a numerical value close to 1 and accepts it as a real image. The generator considers the data from the network as a fake image and returns a numeric value close to 0.

Proposed Method

The DCGAN model used in the article consists of two boundary networks that conflict with each other, as with other GAN models. The generator network uses the Transposed convolution layer when trying to produce the fake image. The Transposed convolution layer mentioned is the exact opposite of the standard convolution process, but the process on the modified input map is the same. In addition, the Batch norm is used in the Generator network. In this process, which is called Batch Normalization, simultaneous learning is done because layers on the network do not have to wait for the previous layer to learn. This allows acceleration in the training. In general, ReLu and Tanh are used as the activation function. ReLu, one of the activation functions used, functions in intermediate layers, while Tanh functions in the last layer.
On the other hand, the second neural network, the Discriminator AG, tries to distinguish between the fake image produced by the Generator network and the actual image. This network has a standard convolution layer, known as the exact opposite of the Generator network. The activation function in the intermediate layer is LeakyReLu, and the function that functions in the last layer is the Sigmoid function. The real image of the fake image produced in the GANs is compared to the Loss function. The Loss function can be defined as what is being tried to optimize or minimize. It is a mathematical function that takes the root of the square of the difference between the actual value of an example and the prediction made and gives the error rate.

$$\text{loss} = \text{maximizelog}\,(D(x)) + \log(1 - D(G(z))) \qquad (1)$$

D(x) = Discriminator output of input
D(G(x)) = Discriminator output of fake image

In the training part of the model, the best result is to create fake images by selecting 30 epochs. To summarize the operations carried out in the study:

$$\text{Min max } V(D, G) = [E_{x \sim pdata(x)}[\log D(x)]] + [E_{x \sim pz(z)}[\log(1 - D(G(z)))]] \qquad (2)$$

Part (1) of the equation tries to maximize output, while part (2) tries to minimize output. x is the actual image sample, and z is the noise given to the generating network to generate the image. The probability of a real picture being real is 1. The probability of a fake picture being real is 0. The values of the discriminant network are at each iteration during the training; It is updated to change the value it gives to the real image to 1 and the value it gives to the fake image to 0. The producer network is trained to ensure that the fake images it produces are close to the truth, that is, it is evaluated as 1. The Generating Network also wants to reduce this error to 0 at each iteration. In this way, as the training process progresses, the discriminating network becomes more successful in distinguishing between real and fake images. The generative network produces more realistic fake images.

3. Experimental Results

Fake face images were created using DCGAN from face images from the CelebA dataset performed in the study. The operation consists of two parts. In the first part, 5000 faces, half of our data set, were used. When the data was trained during operation, work was carried out using different epoch numbers. The increase in Epoch has positively impacted the success of false images (fig. 3, 4, 5, and 6).

Figure 3. Fake face images produced with 5,000 data (10epoch)

Figure 4. Fake face images produced with 5,000 data *(20epoch)*

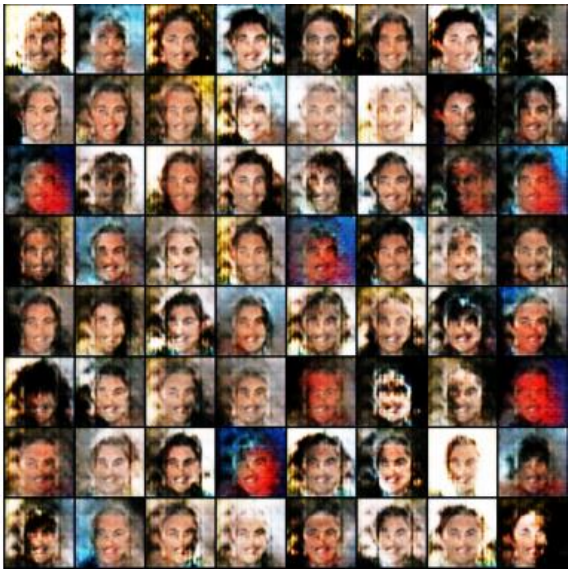


Figure 5. Fake face images produced with 5,000 data (30epoch)

Figure 6. Fake face images produced with 5,000 data (40epoch)

In the second part of the study, all the data contained in the dataset, all 10000 data, are included in the study. Fake images produced have become clearer with an increase in the number of data. This section has also tried different epoch numbers, and the best result is when 40 epoch is selected (fig. 7, 8, 9, and 10).

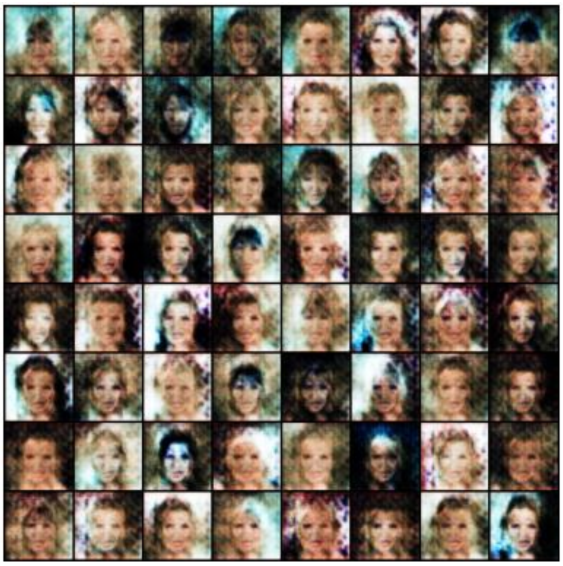


Figure 7. Fake face images produced with 10000 data (10epoch)

Figure 8. Fake face images produced with 10000 data (20epoch)

Figure 9. Fake face images produced with 10000 data (30epoch)

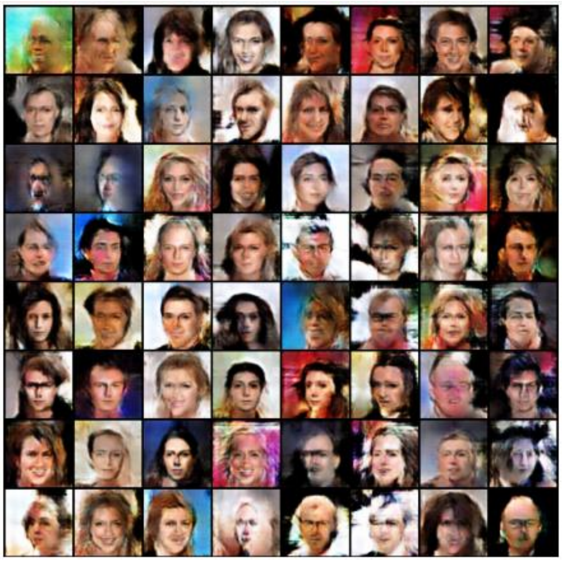


Figure 10. Fake face images produced with 10000 data (40epoch)

4. Conclusion

As a result of the study, it was seen that the amount of increase in the number of data caused a significant change in the clarity of the fake images. Likewise, the effect of the increase in the number of epochs on the result of the study is noticeable. In future studies, significant changes can be made in the clarity of the fake images to be produced with GAN, with a higher number of data and the addition of changes in the number of epochs. This study can be the basis of many studies.

5. Author Contribution Statement

In this study, Author 1 contributed to making the design, and literature review, contributed to forming the idea, and the analysis of results; Author 2 contributed to checking the spelling and checking in terms of content.

6. Ethics Committee Approval and Conflict of Interest

There is no need for an ethics committee approval in the prepared article. There is no conflict of interest with any person/institution in the prepared article.

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