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RESEARCH ARTICLE

Baby Face Generation with Generative Adversarial Neural Networks: A Case Study

Çekişmeli Üretici Sinir Ağları ile Bebek Yüz Üretimi: Bir Vaka Çalışması

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ABSTRACT

Generative Adversarial Networks (GANs) are increasingly applied to train generative models with neural networks, especially in computer vision studies. Since being introduced in 2014, many image generation studies incorporating GANs have demonstrated promising results for producing highly convincing fake images of animals, landscapes, and human faces. We build a GAN structure to generate realistic baby face images from a small data set of 673 color 200×200 pixel images obtained from a Kaggle data set by following previous studies that demonstrated how GANs could be used for image generation from a limited number of training samples. The reason we limit especially as baby faces is that we aim to achieve success with a limited number of training data. For evaluation, experiments and case studies are one of the most considered techniques. The results of this study help identify issues requiring further investigation in comment analysis research. In this context, we presented the loss values of the generator and discriminator during the training process. The discriminator losses are around of 0.7 and the generator is between 0.7 and 0.9. The high quality images are produced about 300th epochs.

Keywords: GANs, Image Generation, Face Generation

ÖZ

Çekişmeli Üretici Sinir Ağları (GAN) son zamanlarda özellikle bilgisayarlı görme çalışmalarında sinir ağlarına sahip üretken modelleri eğitmek için kullanılan popüler bir konudur. GAN'lar 2014 yılında araştırmacılara tanıtıldığından beri, özellikle GAN'larla görüntü oluşturma çalışmaları gittikçe artmaktadır. Bu çalışmalar, hayvanlar, manzaralar, insan yüzleri vb. gibi son derece ikna edici sahte görüntüler üretmek için umut verici sonuçlar elde etmiştir. Bu çalışmada gerçekçi yüz görüntüleri oluşturmak için bir GAN yapısı oluşturulması amaçlanmıştır. Daha az sayıda eğitim verisiyle gerçekçi resimler üretebilmek için veri seti içerisinde sadece bebek yüzleri kullanılmıştır. Çalışma kapsamında bir GAN yapısı inşa edilerek, Kaggle veri tabanından elde edilen 673 adet renkli 200x200 piksel boyutunda bebek yüz görüntüsü veri kümesinden yeni bebek yüzü görüntüleri oluşturulmaktadır. Önceki çalışmalar GAN'ların sınırlı sayıda eğitim örneği içeren veri kümeleri için görüntü oluşturmada kullanılabileceğini göstermektedir. Değerlendirme yöntemleri ile ilgili olarak, deneyler ve vaka çalışmaları en çok dikkate alınan tekniklerden biridir. Bu çalışmanın sonuçları, daha fazla araştırma yapılmasını gerektiren hususların belirlenmesine yardımcı olabilir.

Anahtar kelimeler: Çekişmeli Üretici Ağlar, Resim Sentezleme, Yüz Resmi Sentezleme

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1. INTRODUCTION

Image generation is an important research area in computer vision, and face image synthesis has become important in recent years with a wide range of applications. Despite significant improvements in image generation technologies, face image generation that incorporates image variations while preserving the real image identity is challenging. Face generation is highly dependent on subtle details, which increases the difficulty due to the technical issues in the mapping operation performed from a variation factor to a high dimensional image. On the other hand, effective learning of an original image space is hard because of facial disguises, lighting and identity changes, expressions, and alternate poses.

Generating face images with semantic variations while maintaining the subject's original visual identity is an open research problem (Ye, Zhang, Yang, and Lian, 2019). To address this challenge, face image generation based on GANs has demonstrated success compared with other approaches and operations, such as image generation, image editing, and style translation (Ye et al., 2019). However, the generated images lead to a limited performance for generalization. In this context, GAN-based data augmentation is typically performed in computer vision studies. However, high-quality synthetic data augmentation that improves the training process requires sophisticated types of data (Frid-Adar et al., 2018).

This paper generates new, realistic baby face images using a GAN algorithm from a limited number of training samples. A review of the literature concerning face generation is first analyzed that suggests how GANs are useful for generating new images with limited training samples. Next, a GAN architecture is designed to generate high-quality baby face images by optimizing the kernels and activation functions that provide experimental results demonstrating how realistic images can be achieved with less training data.

The remainder of this paper is organized as follows. Section 2 discusses related work on face recognition. Section 3 describes the materials and methods applied in this study, and Section 4 reviews the experimental results. Finally, Section 5 concludes the study and suggests future work.

2. RELATED WORK

When generating diverse types of data, GANs typically incorporate two primary components of a discriminator and generator. With these, the goal of the GAN is to generate data that are close to a real data distribution. It remains an open challenge to produce high-quality images with this process, and many studies consider this in the literature.

In (Li et al., 2019), a histogram-based GAN model was proposed to produce new, highly qualified data. Previous experiments on the MNIST data set generated data similar to the originals, but the generated images remained blurry and indistinct. To overcome this problem, a novel approach was developed that measured the dissimilarity of the generation with the initial data through a histogram along with two objective evaluation strategies of the f-divergence community and Histogram Intersection Kernel. The results demonstrated that the approach was effective at generating high-quality images.

Seeliger et al. (2018) examined the capability of reconstructing natural images using GANs. They trained a GAN approach named the "deep convolutional GAN" (DCGAN) on large data sets to generate arbitrary images from handwritten characters assumed to be natural grayscale images. The results leverage natural image statistics to prevent noisy images and overfitting. As the purpose of the study was to construct a similar image to the input image through the previously trained generator, their results demonstrated that the proposed method could reconstruct a portion of the features from the original image sets.

Mammogram inspection is crucial for radiologists in search of breast tumors and early detection of breast diseases. While systems exist to assist radiologists in these applications, the segmentation of breast tumors and the classification of breast tumor operations remain challenges due to the low signal-to-noise ratio in the images and the variability in tumors. In (Singh et al., 2020), a method was proposed based on breast tumor segmentation and tumor shape classification using a conditional GAN (cGAN) within a Region of Interest in mammogram images. The network recognizes the tumor field and creates a summarizing binary. After training on the Digital Database for Screening (DDSM), this approach outperformed the current state of the art.

Another problem solved with GANs is solar photovoltaic power forecasting used to decrease risks caused by uncertainty photovoltaic power outages in these systems. To increase the success of the forecasting in weather classification, photovoltaic power forecasting modeling is useful to generate new samples with high quality that capture the intrinsic features of the original data. For this modeling, the inadequacy of the training data set is the most difficult challenge, and a GAN combined with a Convolutional Neural Network (CNN) was suggested in (Wang et al., 2019) as a weather classification model. A data-driven model augmented the training data set, and then the CNN-based weather classification model trained the data set. A comparison study was presented between the quality of the GAN-generated data with the CNN classification models and other traditional machine learning classification models.

The study by Zhu et al. (2018) synthesized realistic retinal images from invisible structured notation. This proposed approach was effective at generating various images from identical tubular structured notation and offers many advantages.

Generating feature-based contact images with realistic appearances that enable the detection of people from computer vision applications is challenging for research areas such as image editing and recognition of personal qualities. The generation step is difficult due to variations in the image foreground and background, complex relationships between attributes, and unbalanced and poor quality image data. In (Gunel et al., 2018), the model DCGAN-C was proposed as a derivative of DCGAN to handle these issues by producing synthetic person images with multi-class and multi-label features with less effort compared to graphics-based generation methods. The experimental results suggested that obtaining data sets of a certain quality with specific attributes can be used together with other models during qualification training.

Facial image synthesis, which is the focus of our study, is a crucial research topic today in computer vision and deep learning (Antipov et al., 2017). Some of these studies that utilize GANs are listed in Table 1, which mostly aim to generate high-quality face images while preserving identity.

3. MATERIALS AND METHODS

In this section, the GAN is explained along with a presentation of our proposed network.

3.1. Generative Adversarial Networks

GANs have demonstrated promising results in generating original images that resemble real-world images. A typical GAN contains a generative model and a discriminative model. The primary task of the discriminator model is to distinguish training images from the synthesized images produced from the generative model.

The generator maps samples from a low-dimensional latent space, and the discriminator tries to distinguish between the real images and those generated. The training step process occurs for a discriminator *D* and generator *G* simultaneously. The generator *G* takes a latent variable *z* as its input and maps these to space the *G(z,g)* through a differentiable network. At the same time, the discriminator *D* functions as a classifier *D(x,d)* that takes a sample *x* as its input and decides if this image is from the input variables or *G*. This process is expressed using a minimax value function, as in (Mao et al., 2017).

$$\min_{G}\max_{D} V_{GAN}(D,G) = \mathbb{E}_{x\sim p_{data}}(x)[logD(x)] + \mathbb{E}_{z\sim p_z(z)}\left[\log\left(1-D\left(G(z)\right)\right)\right] \quad (1)$$

Table 1
*Publications reporting on the use of GANs for facial image generation**

Study (Ref)	**Purpose**	**Data set**	**Methods**	**Evaluation Metrics**
Antipov et. al., (2017)	identity-preserving face aging	IMDB-Wiki cleaned data set	Age-cGAN	the state-of-the-art age estimation CNN
Bao et al., (2017)	fine-grained category image generation.	FaceScrub, 102 Category Flower, and CUB-200	CVAE-GAN	GoogleNet for discriminability, Inception Score for diversity and realism
Choe et al., (2017)	low-shot learning to train with few images and increase the size of training set with GAN	MS-Celeb-1M Challenge-2: Low-shot learning, CelebA	VAE/GAN, BEGAN, ResNet, Data augmentation	accuracy, coverage
Lu et al., (2018)	attribute-guided and identity-guided face image generation	MNIST and CelebA	Conditional Cycle-GAN	SSIM
Shen et al., (2018)	generating images that preserves identity information and have high diversity and quality	CASIA-WebFace, LFW, IJB-A, CelebA, MS-Celeb-1M	FaceFeat-GAN	four energy functions
Tian et al., (2018)	investigate learning “complete representations” of GAN models	Multi-PIE, CelebA	CR-GAN	L2 distance
Wan et al., (2018)	generating fine-grained face image under specific multiply attributes, such as 30-year-old white man	MORPH Album II	FM-GAN, cGAN	MAE, loss curve
Chen et al. (2018)	proposing a method to synthetize a frontal face recognition in video surveillance scene	real-world scenes	cGAN	KNN, SVM
Lu et al., (2018)	investigating image generation guided by hand sketch.	CelebA, Caltech-UCSD Birds-200-2011, Stanford’s Cars	contextual GAN	SSIM and Verification Accuracy
Liu et al., (2018)	presenting a deep neural architecture for synthesizing the frontal and neutral facial expression image	VGG-Face	NFGAN	Symmetry Loss, Adversarial, Identity-Preserving Loss, Pixel-wise Loss
Bazrafkan & Corcoran, (2018)	replacing the classifier with a regression network	CelebA	Versatile Auxiliary Regressor + GAN, BiGAN	Regression
Zhang et al., (2019)	high-quality face image generation	LFW, CelebA	modified original GAN	accuracy
Peng et al., (2019)	restoring the accomplice’s facial image	a face morphing data base	FD-GAN	IAPMR, accuracy
Chen & Lu, (2019)	providing a general framework based on autoencoders for the task of conditional image generation	CelebA, Cat, LHT-Animal-Face	GANs	KL-divergence (mean±variance),MS-SSIM, average
Duarte et al., (2019)	generating face images of a speaker by conditioning a GAN with raw speech input	videos uploaded to YouTube	GANs	accuracy
(Song et al., (2018)	proposing a novel conditional recurrent GAN that incorporates both image and audio features in the recurrent unit for temporal dependency	TCD-TIMIT, LRW, VoxCeleb	Conditional Recurrent Adversarial Network	PSNR,SSIM

where *IMDB is the Internet Movie Database, CelebA is the large-scale CelebFaces Attributes Dataset, LFW is the Labeled Faces in the Wild dataset, LRW is the Oxford-BBC Lip Reading in the Wild dataset, Age-cGAN is the Age Conditional GAN, CVAE-GAN is the Conditional Variational Autoencoder GAN, VAE/GAN is the Variational Autoencoder GAN, BEGAN is the Boundary Equilibrium Generative Adversarial Network, CR-GAN is the Learning Complete Representations for Multi-view Generation, FM-GAN is the Fine-Grained Multi-Attribute GAN, cGAN is the Conditional GAN, NFGAN is the Normalized Face-GAN, FD-GAN is the Face De-morphing Generative Adversarial Network, SSIM is the Structural Similarity, MAE is the Mean Absolute Error, KNN is the k-Nearest Neighbor algorithm, SVM is the Support Vector Machine method, IAPMR is the Impostor Attack Presentation Match Rate, PSNR is the Peak Signal-to-Noise Ratio, ResNet is the Residual Neural Network, and BiGAN is the Bidirectional GAN.

3.2. Dataset and Features

For our training and testing procedures, Python version 3.6.2 was used, the GAN models were programmed in Keras 2.1.6, and a high-level API was written in Python running on the Tensorflow or Theano libraries. The computer environment for performing the experiments included an MSI RADEON™ RX 5700 XT EVOKE OC 8GB GDDR6 256Bit DX12 AMD Radeon graphics processor and AMD Ryzen 7 1700 Socket AM4, 3.0GHz –3.7GHz speed with 20MB 65W processor. A preview of a GAN architecture is illustrated in Fig. 1.

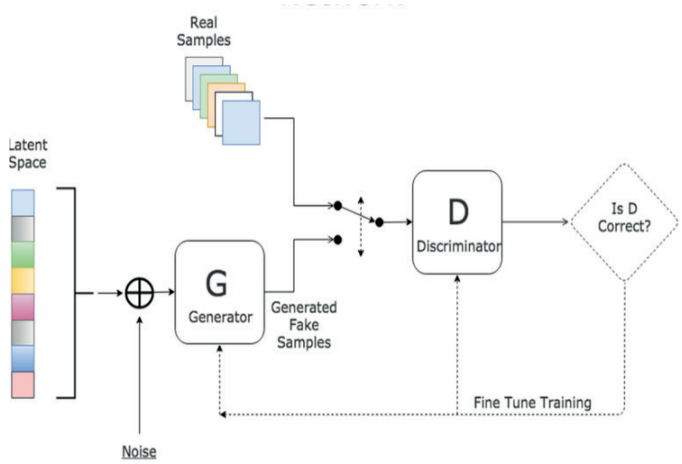

Figure 1. Graphical overview of the GAN architecture (KDnuggets, 2017)

UTKFace is a large-scale dataset of over 20,000 face images with different age, gender, and ethnicity features that spans a broad range of ages from 0 to 116 years. The images cover large variations in pose, facial expressions, occlusion, illumination, and resolution, etc.. Because of hardware limitations, a small subset is used for this study, with 623 images of babies and children. Example images are presented in Fig. 2, where each image is 200×200 pixels in size within the Red-Green-Blue (RGB) color space. We are interested in only the face from each photo, so each image was cropped to 160×160 pixels during preprocessing.

Figure 2. Example images used from the UTKFace dataset

4. MODEL ARCHITECTURE

GANs are developed as a high-level framework that includes components of the generator and discriminator networks, a loss function, and training and optimization algorithms. Each hyperparameter of the model must be selected for creating the most appropriate network structure for the dataset under consideration. The discriminator model processes the 160×160 pixels input RGB images through five convolution layers with 128 neurons and the LeakyReLU activation function, a 2×2 stride for downsampling, and applies the Adam version of stochastic gradient descent with a learning rate of 0.0002 and momentum of 0.5. For the classification, the neurons are flattened, and a sigmoid function makes the prediction to determine if the image is real. A dropout rate of 0.4 is also applied after the flattening process. The generator model in the network takes a point from the latent space and the 160×160 pixels image as input and creates a new image. In the case, the space is a 100-dimensional hypersphere with each variable drawn from a Gaussian distribution with a mean of zero in the latent space and a standard deviation of one. The generator provides different mappings into the latent space for specific output images. This model includes four convolution layers and a four-time up-sampling and uses the LeakyReLU activation function for each up-sampling with a hyperbolic tangent (tanh) as the activation function for the output layer. The details of the discriminator and generator models are listed in Tables 2 and 3.

During the training step, the Adam optimizer (Kingma and Ba, 2014) is configured with a learning rate of 0.00002 and a beta of 0.5. The model is trained with a batch size of 64 over 300 epochs. The latent vector dimension is fixed to be 100 to generate images sufficiently. The Leaky ReLU nonlinearities are used in some of the convolution layers, where $LReLU(x) = max(x,0) + \alpha min(x,0)$ with $\alpha = 0.2$. The intension of this step is to train the weight of the model in the generator by using the output value and error of the discriminator. Cross-entropy (Ghahramani et al., 2014) is used as the loss function, and the discriminator and generator iterate to minimize or maximize the cross-entropy loss with x denoting an input sample. The objective for the GAN training with cross-entropy is expressed as

$$\min_G \max_D V(D,G) = E\left[\log\left(D(x)\right)\right] + E\left[\log\left(1 - D\left(G(z)\right)\right)\right]. (2)$$

Table 2

Details of the discriminator architecture

Layer	Kernel/stride	Neurons	Activation
Conv1	(5x5) / (2,2)	128	LeakyReLU
Conv2	(5x5) / (2,2)	128	LeakyReLU
Conv3	(5x5) / (2,2)	128	LeakyReLU
Conv4	(5x5) / (2,2)	128	LeakyReLU
FC1	-	1	Sigmoid

Table 3

Details of the generator architecture

Layer	Kernel/stride	Neurons	Activation
Conv1	(4x4) / (2,2)	128	LeakyReLU
Conv2	(4x4) / (2,2)	128	LeakyReLU
Conv3	(4x4) / (2,2)	128	LeakyReLU
Conv4	(4x4) / (2,2)	128	LeakyReLU
FC1	(5x5) / (2,2)	3	Tanh

5. EXPERIMENTAL RESULTS

Our GAN model was trained over 300 epochs, each with 100 images. Ten images were generated from the epochs are presented in Fig. 3. As expected, with only a few initializing processes, the generated images have poor quality. The experimental results demonstrate that recognizable baby faces begin to generate around the 210th epoch. The best results are obtained between the 270–290th epochs. However, the baby faces include some failures at the 300th epoch.

The loss values of the discriminator and generator are plotted in Fig. 4. An ideal GAN has a discriminator loss of around 0.5 with a higher generator loss (between 1.0 to 2.0). Three losses appear to be stable from 100 to 300 epochs where the discriminator for real and fake samples has a loss of around 0.7, and the generator is slightly higher between 0.7 and 0.9. The expectation for the model is to generate recognizable images by epoch 300, and as expected, satisfying images are generated here. On the other hand, as Fig. 4 shows the discriminator losses for real images and the generated fake images along with the generator loss for the generated fake images, the results show the discriminator losses decreasing to a small value and the generator loss increasing to higher values. This suggests that the training is about to overfit and cannot be further improved. As seen from the generated images, the final epochs include some failures due to the model beginning to fail.

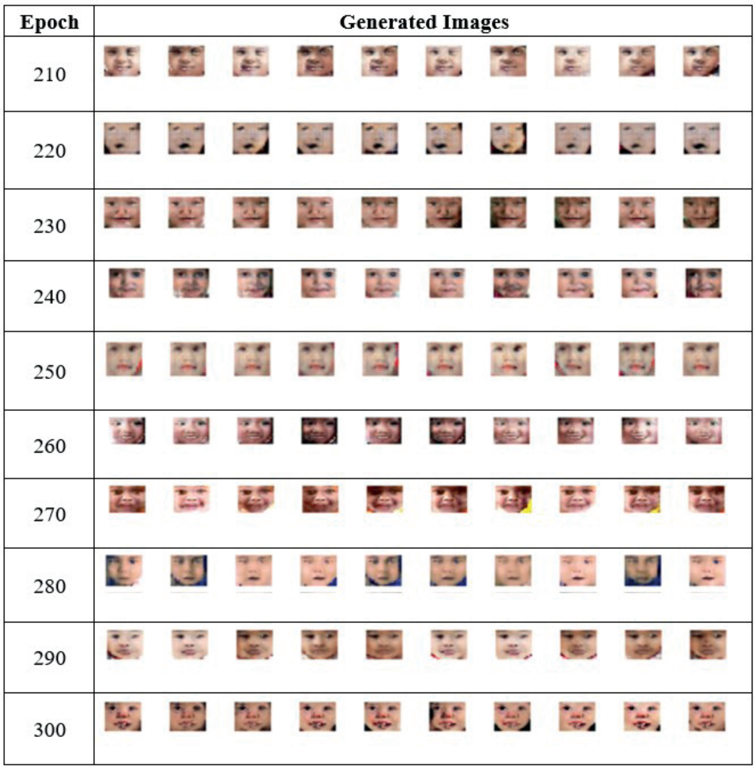

Figure 3. Examples of the generated images over the epochs

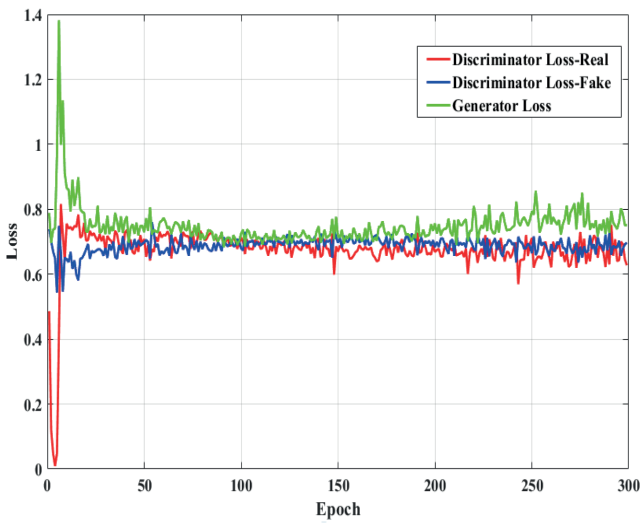

Figure 4. The loss values of the generator and discriminator during the training process

6. CONCLUSION

Image generation techniques are important for various computer vision applications because of the collection of labeled data is costly. Face generation is a complex task that requires a model to learn from a general data distribution. In 2014, research began on GAN models to generate different patterns, such as animals, faces, and objects. In this study, a collection of input baby faces are used to create original, recognizable baby faces.

With this approach, we designed a model to generate realistic face images using a GAN architecture with a latent space representation. The goal was for the model to produce recognizable images of baby faces with a small number of training data that included variations in color, orientation, and posture. With this adaptive model approach, realistic images were generated with limited training data. For future work, we plan to extend this study by improving the quality of image generation and investigate more powerful generative models.

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