ISSN: 2586-7652 (Print) Vol. 04, No. 02, September 2021
ISSN: 2635-7607 (Online)
International Journal of Advanced Engineering
Source: http://ictaes.org
Manuscript received: September 5, 2021; Revised: September 15, 2021 ; Accepted: September 24,2021

A system for Design of Handbag Using Generative Adversarial Networks

Tai Lam [1], Tinh Nguyen [2], Nha Tran [3], Hung Nguyen [4]

[1 2 3 4]*University of Education, Ho Chi Minh city, Viet Nam*

4401104188@student.hcmue.edu.vn[1], 4401104196@student.hcmue.edu.vn[2], nhatt@hcmue.edu.vn[3], hungnv@hcmue.edu.vn[4]

Abstract

Nowadays, with the development of the fashion industry in general and the field of designing fashion products in particular, we realize that everybody is paying more and more attention to their appearance. So, the designers have to do many tasks manually. They have to work hard from the most basic step. This process consumes a lot of their time and effort. We want to create something that can help them more convenient in their work and even replace part their job. In this paper, we introduce a system that can create designing of handbag. To build this system, we decided to choose a deep learning model which is very interested by researchers today, Generative Adversarial Networks (GAN).

Keywords: *Generative Adversarial Networks, Convolutional Neural Network, Fashion, Handbag.*

1. Introduction

Generative Adversarial Networks has been known as a framework that create new images from pre-existing data, or designs for handbag in this research. We want to help designers create new designs from which they have created in the past or already on the market. This helps designers avoid doing the same steps over and over again; therefore, it can decrease their boredom and the time to create a new product. They only need to enhance their designs instead of thinking up new ideas, thereby contributing to improving the quality of handbag products.

After having an idea of the system and choosing a suitable model, GAN, we aimed some important goals in this research topic:

- Understanding and applying the deep learning model Generative Adversarial Networks [1] designed by Ian Goodfellow et al in 2014

Corresponding Author : Nha Tran
Author's affiliation : Ho Chi Minh University of Education
Email: nhatt@hcmue.edu.vn
Copyright © ICT-AES

- Build a dataset of popular handbags.
- Build handbag generation system based on GAN model and collected dataset.

Those are the main goals that we set out in this research. Although these goals are not too great, we hope to contribute a little of our ability to help designers in creating and improving the quality of their products.

2. Related work

Generative Adversarial Networks is a wonderful model to perform the task of creating new images, based on previously published works such as: group of authors Singh et al. [2] proposed a system that takes the latest fashion trends and user-purchased outfits as input and generates new outfits, this system helps a person to combine his clothes according to his own opinion and creates a unique style . These new outfits will be based on current fashion trends but at the same time will feature the clothes that the user has purchased previously. Model take images from one domain and generates an image in other domain [3]. In this proposed machine learning based on approach, the clothes generated by the system will personalized for different types of customers. FashionGAN [4] simplified the traditional clothing design process, it directly generated specific sharp images from sketches and fabric samples. The paper proposed an end-to-end virtual garment display method based on Conditional Generative Adversarial Networks [5], this method simply requieds the user to input a desired fashion sketch and a specified fabric image, then the image of the virtual garment has the shape and texture to match the initial fashion sketch, the input fashion sketch and fabric image can be shown out quickly and automatically. FashionGAN also has a reusable feature which means that based on existing designs, designers can be reused to create new clothing images. All the systems mentioned above all very well solve the problem of design in the garment industry.

3. Method

Generative Adversarial Networks is a framework for estimating generative model via an adversarial process, the generative model to try pitted against an adversary in which a discriminative model learns to determine whether a sample is from the model distribution or the data distribution. This architectural diagram is shown in Figure 1.

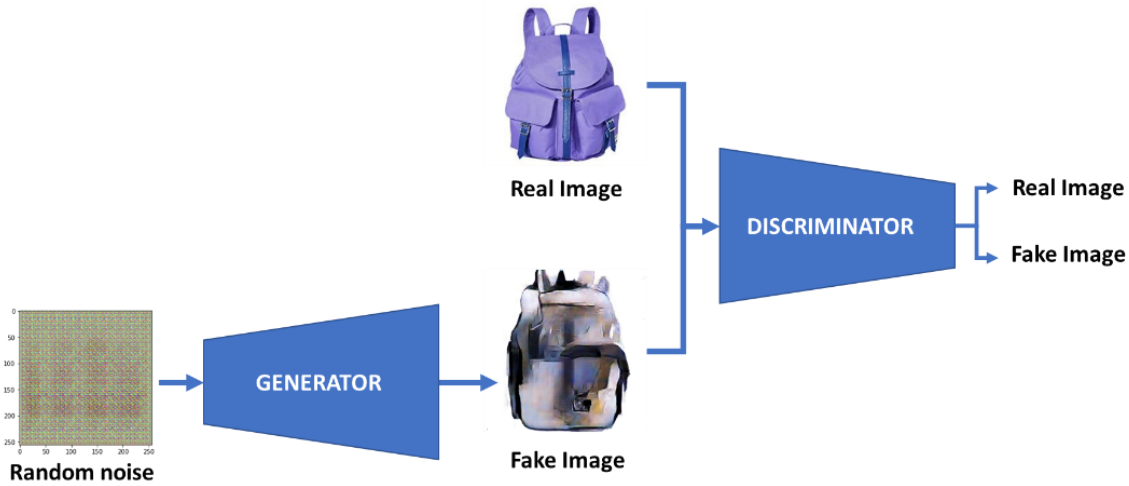


Figure 1. Architectural diagram of Generative Adversarial Networks.

Generative Adversarial Networks consists of two adversarial models. The role of generative model *G* is capturing the data distribution and role of discriminator model *D* is estimates the probability a sample came from the training data rather than *G*. The purpose is generator model learns to generate fake data to fool the discriminator

model. To be able to do this we need to learn a generator's distribution p_g over data $\boldsymbol{x}$. First, the generator builds a mapping function from a prior noise distribution $p_z(z)$ to data space as $G(z; \theta g)$, where G is a differentiable function represented by a multilayer perceptron with parameters θg. And second multilayer perceptron $D(\boldsymbol{x}; \theta_d)$ outputs a single scalar. $D(\boldsymbol{x})$ represents the probability that $\boldsymbol{x}$ comes from training data rather than p_g. Here, G and D are both trained simultaneously, the training D to maximize $logD(X)$ the probability of assigning the correct label to both training examples and samples from G and the training G to minimize $log(1 - D(G(z)))$. If G and D have enough capacity, they will reach a point at which both cannot improve because $p_g = p_{data}$.

Generator takes noise vector z as input, this noise vetor z is randomly generated from a normal distribution, where z has dimension is 128x1, then input feed into the neural networks include fully connected layer via convolution, the number of nodes in the hidden layer is 1024, 512, 256, 128, 64, 32 with activation function is ReLU [Figure 2]. Output layer has the same dimension as the image in the training data with activation function is Tanh.

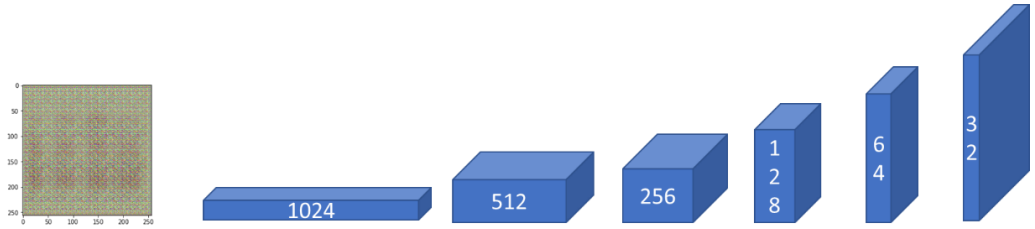


Figure 2. The architecture of generator.

In Figure 3, discriminator takes as input an image with dimension 256x256, then neural networks model is applied with number of nodes in the hidden layer being 32, 64, 128, 256, 512, 1024, the model is symmetric with the generator. Output layer is a node representing the probability that the input image is a real image, the Sigmoid activation function is used.

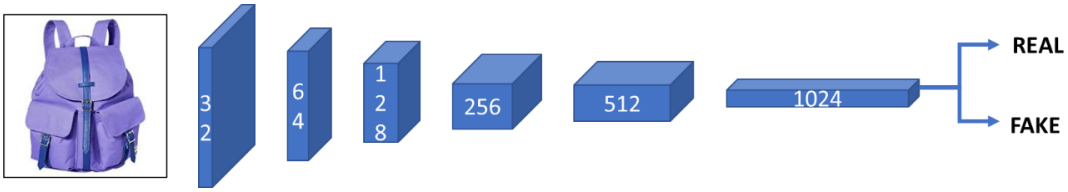


Figure 3. The architecture of discriminator.

In this paper, we propose a system that can generate new handbag designs. Our GAN model takes as input is collected handbag images in which generator tries to generate new handbag designs by extracting features and to learn data distribution of training data. The discriminator learns to distinguish between the fake handbags generated from generator and the real data. Initially, the generator will generate handbag designs that are very different from the real handbag images, so the discriminator is easy to distinguish. Through the training process, the generated images will gradually become more realistic so the discriminator must also improve its distinguish ability. The training process will repeat over and over until the discriminator cannot correctly classify whether the images are generated or come from the training data. In fact, the handbag images are labeled is real if the discriminator input is taken from the training data and fake if the input is taken from the generator model's output. Hence, this is a binary classification problem. The loss function of the Generative Adversarial Networks model combines the discriminator target and the generator target simultaneously which is given by equation (1).

$$\min_G \max_D V(D,G) = E_{x\sim p_{data}(x)}[\log D(x)] + E_{z\sim p_z(z)}[\log(1-D(G(z)))] \ldots\ldots..(1)$$

4. Result

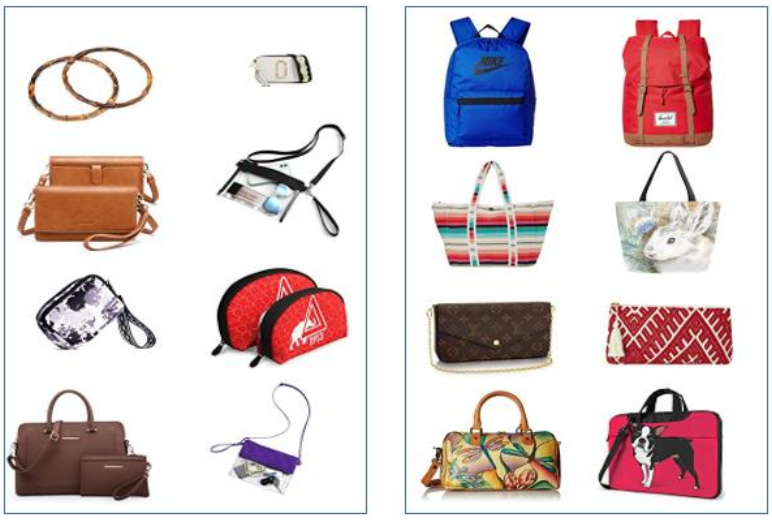
4.1. Dataset Collection

Data is an extremely important factor in applying a machine learning model, and with Generative Adversarial Networks it is no exception. The GAN model in our research uses images of handbags as input. Therefore, we decided to choose types which are popular in the market to facilitate data collection and also to keep up with current fashion trends. After a period of research on many sales websites, we decided to choose typical handbags to apply for the model. The types of handbags that our group choose are shown in Figure 4.



Figure 4. Types of handbag included in our dataset

The goal of the project is to create new handbag images based on trained images, so we only select images containing only handbags so as not to affect the quality of the output images (that is, images which contain only one handbag and background must be white) as shown in Figure 5 (b). To be able to collect a large number of images on the Internet, the manual method will consume a lot of time. Therefore, we adopt several methods to make data collection faster. But the original dataset still has a lot of noise that is not suitable to start training (image is not a bag, mixed with other objects, has a different background which is shown in Figure 5 (a)). To solve this problem the group have only possible to re-filter the images manually. Although this takes a long time, it ensures the quality of the dataset while performing the analysis.



(a) Set of noise images (b) Set of standard images

Figure 5. Problem of original images in datasets.

In this system, the input dataset will be images and the output is also image, so the resolution has an important role in the quality of the generated image. To find out a suitable solution for our model, we started training with different resolutions such as: 64x64, 128x128, 256x256. In the end, we decided to use the input image with a resolution of 256x256, because the image generated at this resolution is of better quality than the others and this size is suitable for our training system [Figure 6].



Figure 6. The process of padding and resize images into 256x256 resolution.

As mentioned in the data limitation section, our group decided to train the above model only with four types of handbags. After having data preprocessing, the number of images in each class is shown in Table 1 below. We will make our dataset public and anybody can use it if they need.

Table 1. Amount of each class

Category	Amount
Backpack	10084
Tote	10625
Clutch	4134
Satchel	4827

4.2. Experimental results

After training the GAN model on the dataset collected, we have achieved a result that satisfies the initial goal [Figure 7]. In general, the image generated from the model has the feature and shape for each type of handbag as shown in Figure 8.

With a quite satisfactory result, we proceed to build a website to help users easily perform design creation operations. Our website is based on Django framework, Python 3.6. It has the advantage of being simple to operate, to generate new handbag images, users only need to select the avatar for the type of handbag they want to design. Once selected, the system will generate a new set of images and display in the center of the screen one by one [Figure 9]. Designers can observe and choose the design that they feel suitable.

We hope that our result will be a premise for us to develop further and the products will be created with better and better quality.

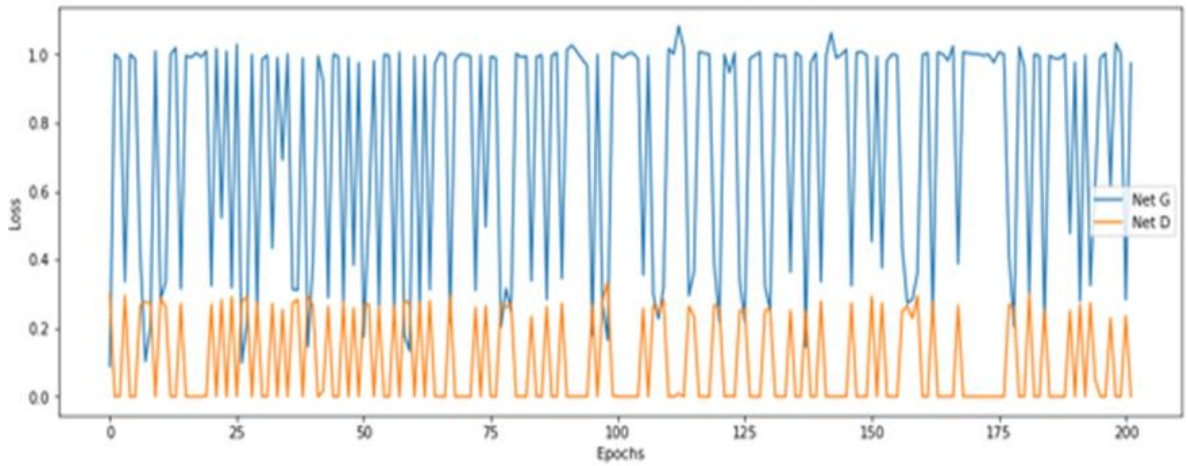


Figure 4. Generator and Discriminator Loss during training.



Figure 8. Some output images.

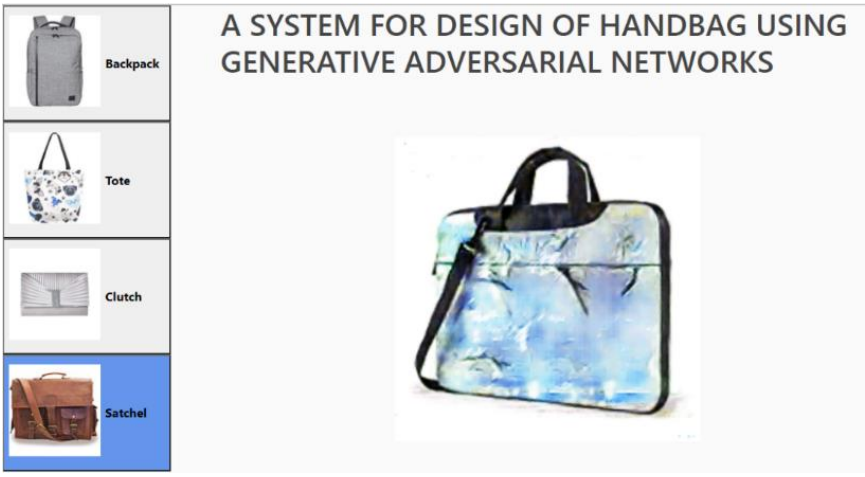


Figure 5. The website interface of our system

5. Conclusion

In general, the "A system for Design of handbag using Generative Adversarial Networks" is able to create the appearance of new handbags. Each type of handbag was generated with its own characteristics so that we can easily distinguish, which is a pretty good result for our research group. Thereby, we found that the model worked well according to the theory that was originally proposed to create a system that could generate "raw" designs, then the designers would "make up" added to these.

Although the project has satisfied the set goals, the system still needs to be further developed to be able to meet the actual needs. So, we have a few development directions for the system as follows:

- About style: Increase the number of classes in the dataset. Because each type of handbag has its own characteristics, the aim to be able to "mix" the designs of many different types of bags together to create new types of bags.
- About the method: The GAN model has many variations. Each type has certain advantages and disadvantages. With the goal of creating images with new features with good resolution, we recommend using StyleGan to be able to meet the increasing demand in accordance with reality.

References

[1] Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., Courville, A.C., & Bengio, Y. (2014). Generative Adversarial Networks. ArXiv, abs/1406.2661.

[2] Singh, Montek & Bajpai, Utkarsh & V., Vijayarajan & Prasath, Surya. (2020). Generation of fashionable clothes using generative adversarial networks: A preliminary feasibility study. International Journal of Clothing Science and Technology. 32. 177-187.

[3] Zhu, J., Park, T., Isola, P., & Efros, A.A. (2017). Unpaired Image-to-Image Translation Using Cycle-Consistent Adversarial Networks. 2017 IEEE International Conference on Computer Vision (ICCV), 2242-2251.

[4] Yirui, Cui & Liu, Q. & Gao, C. & Su, Zhuo. (2018). FashionGAN: Display your fashion design using Conditional Generative Adversarial Nets. Computer Graphics Forum. 37. 109-119.

[5] Mirza, M., & Osindero, S. (2014). Conditional Generative Adversarial Nets. ArXiv, abs/1411.1784.