A Generative Adversarial Network Approach to Demarcate factual and factitious images in Fashion Design

Dr.M.Swapna[1], C.Sireesha[2],Fatima Mahmood[3]

Associate Professor,Department of Computer Science and Engineering
Stanley College of Engineering and Technology for Women, Abids, Hyderabad-500001,
Assistant Professor, Department of Information Technology,
Vasavi College of Engineering, Hyderabad-500049,
M.Tech-Student, *Department of Computer Science and Engineering*
Stanley College of Engineering and Technology for Women, Abids, Hyderabad-500001.

Abstract: *Styling is one of the essential parts of our day-to-day life. It is a way of expressing oneself and presenting our personality in society. One develops a distinct appearance by combining his or her clothing in accordance with personal preference. Given how rapidly fashion trends change, few of them change drastically and can be less desirable. The collaboration between fashion and computer-based designs has greatly increased as a result of recent developments in the artificial intelligence field, particularly in machine learning. GANs (Artificial Neural Networks that are capable of generating patterns) are among the most intriguing advancements in recent years, with excellent outcomes in a variety of applications, including Fashion Synthesis. Fashion synthesis is a difficult task that entails creating a new style from the existing ones on a source model. In this work, we aim to generate new designs for clothing that is trendy by utilizing Generative Adversarial Networks (GAN). In order to create new clothing, the makers might use these as a blueprint. Such a system will provide the customer with a tailored buying experience.*

Keywords: *fashion, fashion trends, Generative Adversarial Networks (GAN).*

1. INTRODUCTION

Fashion design is the practice of incorporating elements of natural beauty, design, and aesthetics into clothing and its accessories. It has progressed over time and space and is impacted by culture, moral beliefs, and sometimes even by the ruling authorities. A fashion designer's work may include sketch designs for attire, accessories, and footwear. Fashion designers create unique attire, accessories and footwear. With the development of technology, relying solely on fashion designers is no longer justified. With some overhead, emerging technology can be leveraged to replace manual design.

1.1Artificial Neural Networks:

Artificial Intelligence is real, and it helps more than we could have imagined. We make mistakes in our daily lives, especially in the fashion industry causing frustration and disappointment in the manufacturing department. This is where AI comes in. Fashion and artificial intelligence are a new partnership that is sure to succeed for years to come. Although AI applications in the fashion sector are still in their infancy, two of the largest online retailers in the world, Amazon and China's Alibaba, are already utilizing AI technologies, such as GANs.AI technologies are transforming the fashion industry from design to production, shipping, marketing, and sales. There are several methods for generating images. GAN, Variation Autoencoder (VAE), Diffusion models, and many others are among them. GANs have recently been used primarily for such applications due to their increased accuracy.

1. Paper Work

Several works in the fashion industry employ artificial intelligence. [1] To the best of my knowledge, GANs is a new topic that has not been studied in this context. These works are studied in detail in the past research literature and extensive reviews are available [2], [3],[4]. Recently, [1] also summarized the current state of the art.

There are various systems developed using artificial neural networks specifically Generative Adversarial Networks (GANs) which aid in the Fashion industry. Some of them are discussed briefly here:

2.1

[1] Using both GANs and cross-domain relationships, this system generates designs based on existing ones. The system works on colored data and generates new designs based on the dataset. Deep Convolution architecture is extensively used.The new set of clothes will be based on trending fashion but at the same time will have attributes of clothes which were bought by the customers earlier.

2.2

[2]GANs have previously been used (Zhu et al., 2017) to generate new outfits based on the user's descriptions while also allowing the user to see himself wearing those outfits. Here a system that can learn a person's posture is developed. The subject is then dressed in the newly created GAN clothing. This demonstrates that GANs are capable of picking up on intricate garment designs.

2.3

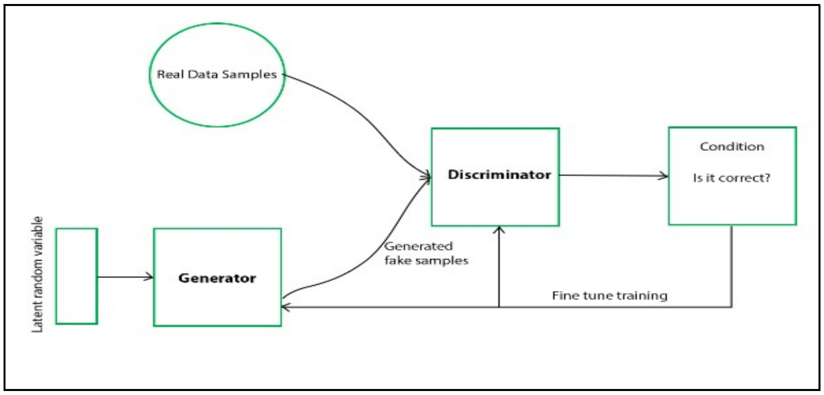
[3] Some of the systems, like Xian et al. (2018), create objects following the texture suggestions by using the textures provided by the user. They can also be used on a range of items, including clothing, footwear, purses, and other items. You can use it to modify the textures' finer details in textured areas. Although this method will allow users to personalize, users will not be able to choose the best design or look for the most fashionable texture patch from the millions of designs available.

2. Objective

We can learn what types of clothing best suit various personalities and attitudes of people by observing how they dress. Typically, assertive personalities tend towards vibrant and dramatic colors. Conversely, timid individuals are more inclined to choose light-shaded colors. Some people have a combination of characteristics, making it difficult to design clothes for them because they are picky about what they wear. Here, we want to provide a method for creating new clothing designs from ones that already exist using generative adversarial networks (GANs).

3. Proposed System

The purpose is to generate a system that produces new designs of clothes based on some existing trends. Several types of research have been conducted in this area which follows different approaches. The production of new trends is done using Keras and TensorFlow. Different modules perform various operations among which generator and discriminator are more significant.The methodology used in developing the system is Generative Adversarial Networks(GAN) and cross-domain relations.



4. Methodology

Our project aims to create a system that generates new clothing designs based on existing fashion. To address the objective in a straightforward manner, we developed the system using Vanilla Generative-Adversarial Network (GAN). Numerous forms of research have been conducted to achieve a similar purpose.

5.Generative Adversarial Networks (GAN):

GANs, or Generative Adversarial Networks, are an approach towards generative modelling that employs deep learning technology including convolutional neural networks. It is an unsupervised machine learning process that entails automatically discovering and studying the regularities or patterns in input data so that the model can be labored to produce or output new examples that resembles the patterns from the original dataset.

GANs are a creative technique of training a generative model by conceiving the issue as a supervised learning task with two distinct models: the generator model, which is responsible for the generation of new instances based on training. and the discriminator model, which attempts to distribute evidence as genuine(From the domain) or fictitious(generated) respectively. The two models are trained in an adversarial zero-sum game until the discriminator model is tricked about half the time, indicating that the generator model is generating realistic examples.

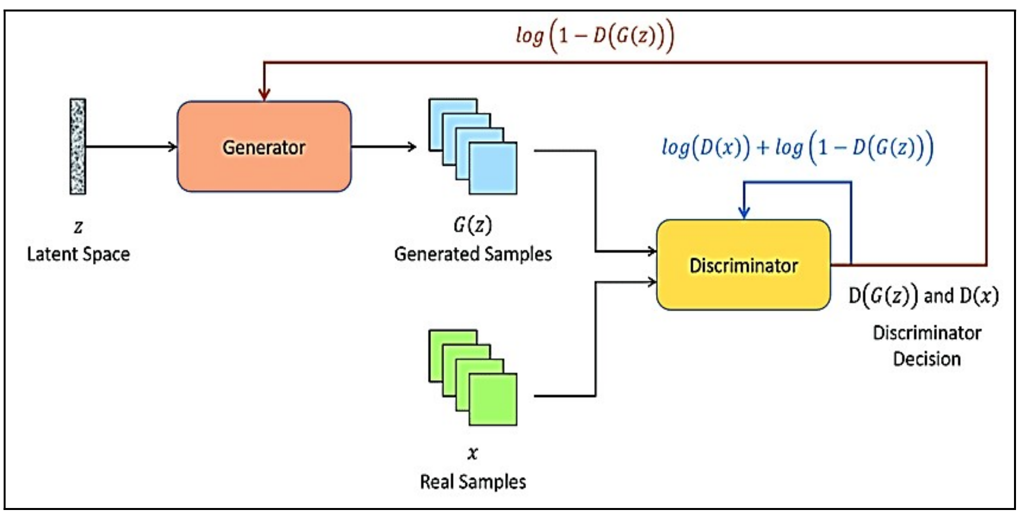


Fig 2.Generative Adversarial Network (GAN) Architecture

5.1.1Generator:

The Generator is fed a random noise(sampled from a latent space), which is responsible for the generation of new instances.. Fake samples are those generated by the Generator. The generator model receives a fixed-length random vector as input and produces a domain sample. The vector is generated at random from a Gaussian distribution and serves to seed the evolution. Observations in this multidimensional vector space will directly correlate to points in the problem domain after training, resulting in a compact representation of the data distribution.

Here first random noise input is given to the generator and it generates random images based on the training. Generator training necessitates a greater level of collaboration between the generator and the discriminator than that of the discriminator.

5.1.2 Discriminator: In a GAN, the discriminator is simply a classifier. It distinguishes between real data and data generated by the generator. It could employ any network architecture suitable for the kind of data being classified. When a fake sample [produced by the Generator] is presented to the Discriminator, it wishes to identify it as such, but the Generator wishes to generate samples in such a way that the Discriminator mistakes it for a real one. In some ways, the Generator is attempting to deceive the Discriminator.

The discriminator model considers a domain example (real or generated) as input and predicts whether it is genuine or fictitious (generated).The actual example is taken from the training dataset. The generator model produces the generated examples.

5.1.3 Training of Generator and Discriminator

The important thing to remember when training a GAN is that the two modules should never be trained simultaneously. Rather, the network is trained in two stages: the first is for training the discriminator and modifying the weights appropriately, and the second is for training the generator although the discriminator training is halted.

Phase 1: As noise, the generator is supplied random data (in the form of a distribution) during phase one of training. The generator generates a set of random images, which are then loaded into the discriminator. The discriminator also uses a dataset of real images as input. The discriminator learns to differentiate between real and fake data by learning or analyzing features from its inputs. The discriminator yields some probability, and the difference between the predicted and actual results is back-propagated through the network, and the discriminator's weights are updated. Remember that back-propagation shuts down at the end of the discriminator during this phase, and the generator is not trained or upgraded.

Phase 2: During this phase, the discriminator is injected a batch of images generated by the generator. The discriminator is not given the real images at this time. By deceiving the discriminator into producing false positives, the generator learns. The discriminator yields probabilities that are compared to the actual results, and the weights of the generator are revised using back-propagation. Remember that during back-propagation, the discriminator weights cannot be modified and should remain unchanged.

5.1.4 Activation And Loss Function:

Let's take a closer look at the objective function or how optimization is performed. It's a min-max optimization concept in which the Generator wants to minimize the objective function while the Discriminator wants to maximize it. There are numerous activation functions available, including sigmoid, Tanh, and ReLu. We used Leaky-ReLu for both the generator and the discriminator in our system. The rationale for recognizing Leaky-ReLu over ReLu is that we cannot have vanishing gradients this way. The only difference between Parametric ReLU and Leaky -ReLU is that the slope of the output for negative inputs is a learnable parameter in the former and a hyperparameter in the latter (parameters with fixed values before starting the model training process).

The Loss function utilized in our system is the Binary cross-entropy. The cost function binary cross-entropy is used in binary classification activities. These are tasks in which there are only two options for answering a question (yes or no, A or B, 0 or 1, left or right).In our case the classes of classification is real or fake.

The binary cross-entropy can be formulated as:

$$H_p(q)=-\frac{1}{N}\sum_{i=1}^{N} y_i.log\left(p(y_i)\right)+(1-y_i).log(1-p(y_i))$$

5.2 Applications:

GANs now outperform all other generative models. The rationale being , Data labelling is a costly task. As GANs uses unsupervised learning approach , they do not require labelled data to be trained. Currently, GANs produce the sharpest images. Aggressive training enables this. Mean Squared Error-generated blurry images have no chance against a GAN. GAN networks can be trained by only using back-propagation.

GANs are intensively used in image-to-image translations, Text-to-image translations, generating realistic photography, cartoon ification of images,3D-Object generation, photo-blending and numerous other applications.

5.3 Limitations:

One of the major barriers in using GAN is it can be trained only using back-propagation. However, there are serious barriers in training GANs, such as mode collapse, non-convergence, and instability, due to insufficient network architecture design, objective function use, and optimization algorithm selection. Another issue encountered is the diminished-gradient which can be overcome by using the Leaky-ReLu activation function.

6. Results

The data is collected from Fashion-MNIST dataset. The dataset contains total of 60000 data which is split into60000 training data and 10000 test data. Each example is a 28x28 gray-scale image, associated with a label from 10 classes The data is normalized and feature extraction is performed. The model used is simpleGANwhichconsistsof3layers.

The system creates dresses that are both fashionable and have elements of vintage dresses. Two types of data sets are required to build such a system. Fashionable dresses make up the first type of data set, while vintage dresses make up the second. Outputs that are expected. Data sets are being considered. The new design that is generated based on the trained data or existing designs can be shown in the following figures. Initially, the Latent data is represented as noise which is given as input to the system.

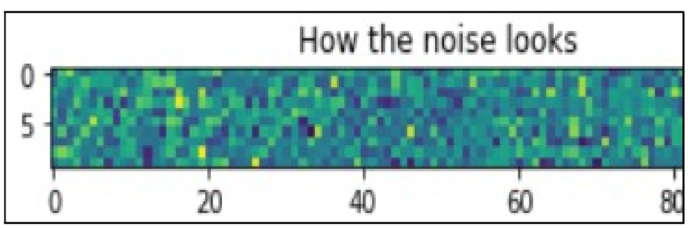


Fig3.Latent Data (Noise) input to Generator

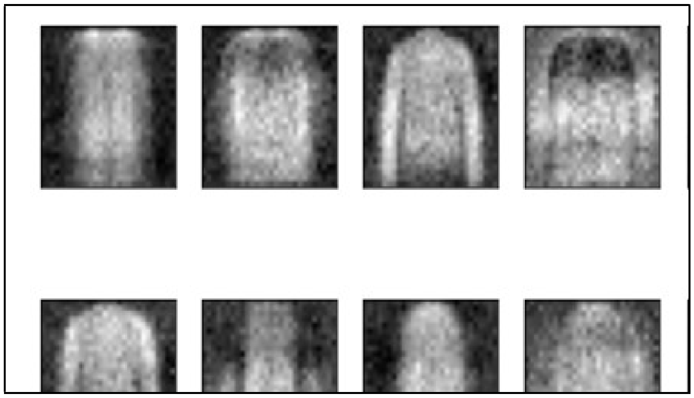


Fig 4.Images Generated while Training

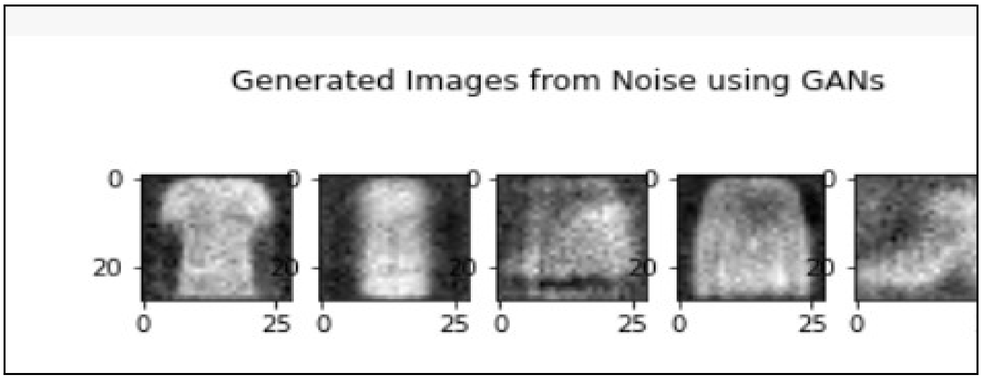


Fig 5.New images generated from Gan

7. Conclusion and Future Scope

Finally, we were able to generate new designs and patterns for virtual clothing using this method. These new designs are prevalent. This system can be programmed to recognize customer preferences and generate customized and personalized designs. However, the system's performance is highly dependent on the size of the data set. The output designs generated cannot be predicted and may not be in accordance with the customer's preferences. No prediction can be computed over the pairing of images from the cross-dimension. This system only generates images in grey scale as the dataset itself is non-RGB Further enhancement can be made where the customizations of the designs can be specified by the user through mobile applications(Howard et al., 2017).

As [1] uses a DC-GAN architecture in developing such a system, hence there accuracy can be significantly high and are faster. Almost similar accuracy can be achieved by using an appropriate loss function but the overhead involved in simple GAN is the training time.As the number of data samples increases, the time taken by the generator and discriminator to get trained increases. There is no control over the domain-domain pair while generating the image. So to conquer this, the entire dataset should contain only a single pattern and upon selecting different data sets one can hover over various styles and designs to be generated.

Further work can be carried out by implementing the system with a more efficient architecture that not only generates but also improves the resolution of the generated image. Additional features like filtering of the designs based on patterns and genders can be induced. One can modify the system by linking the dataset to the customized requirement such that customized designs can be generated. Since the dataset used in this paper contains only grey-scale images, the generator can further be trained to produce more stylish and lively designs.

REFERENCES

[1] Generation of fashionable clothes using generativeadversarial networks-A preliminary feasibility studyMontek Singh, Utkarsh Bajpai and Vijayarajan V.School of Computer Science and Engineering (SCOPE), Vellore Institute of Technology, Vellore, India, andSurya Prasath.

[2] Howard, A.G., Zhu, M., Chen, B., Kalenichenko, D., Wang, W., Weyand, T., Andreetto, M. and Adam, H.(2017) “Mobilenets: efficient convolutional neural networks for mobile vision applications”,

[3] Towards AI Fashion Design: An Attribute-GAN Model for Clothing Match Linlin Liua, Haijun Zhanga,, Yuzhu Jia, Q. M. Jonathan Wub

[4] Generation of fashionable clothes using generative adversarial networks A preliminary feasibility study Montek Singh, Utkarsh Bajpai and Vijayarajan V. School of Computer Science and Engineering (SCOPE), Vellore Institute of Technology, Vellore, India.

[5] He, R., Lin, C. and McAuley, J. (2016),“Fashionista: a fashion-aware graphical system for exploring visuallysimilar items”, Proceedings of the 25th International Conference Companion on World WideWeb,International World Wide Web Conferences Steering Committee.

[6] “Learning to discover cross-domain relations with generative adversarial networks”,Proceedings of the 34th International Conference on Machine Learning-Volume 70, Sydney,NSW-2017.

[7] Najafabadi, M.M., Villanustre, F., Khoshgoftaar, T.M., Seliya, N., Wald, R. and Muharemagic, E. (2015),“Deep learning applications and challenges in big data analytics”.

[8] “Texturegan controlling deep image synthesis with texture patches”(2018),Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition

[9] https://machinelearningmastery.com/ generative-adversarial-networks-gans/

[10] https://realpython.com/generative-adversarial-networks/

[11]https://anderfernandez.com/en/blog/ gan-in-python/