AFRIGAN: African Fashion Style Generator using Generative Adversarial Networks(GANs)

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Abstract

Afrocentric fashion images suitable for machine learning tasks are not well represented in open datasets. In this work we present AFRIGAN, a generative adversarial model for contemporary African fashion images. AFRIGAN can be leveraged as a tool for realistic image data synthesis, design iteration and experimentation for contemporary African fashion styles. This model is openly available here.

1 Background

1.1 Fashion and Machine Learning

Fashion is the most widely used mode of expression. The combination of one's opinion creates an ever-changing style of clothes worn by those with cultural status. A fashion trend occurs when others mimic or emulate this clothing style[1]. Recently, machine learning has been employed in fashion. These applications include but are not limited to visual dress matching, virtual garment display, automatic cloth attribute description, cloth suggestion, generative design and forecasting fashion trends [3, 14, 13, 9, 4, 18]. Generative Adversarial Networks (GANs), a type of machine learning algorithm are particularly useful in fashion for generating fashion styles.

1.2 Generative Adversarial Networks (GANs) and GAN Architectures

Generative Adversarial Nets was proposed in 2014 as a framework for estimating generative models via an adversarial process[8]. Generative Adversarial Networks (GANs) are neural networks that take random noise as input and generate outputs that appear to be a sample from the distribution of the training set. GANs achieve this by training two models simultaneously - a generative model (an artist) that captures the distribution of the training set and a discriminative model (a mentor) that estimates the probability that a sample came from the training data and not the generative model.[2]

There are many types of GAN architecture such as CycleGAN, StyleGAN, pixelRNN, text-2-image, DiscoGAN, IsGAN, ProgressiveGAN for different use cases [6, 10, 5, 16, 15, 11, 17]. This work explores the use of StyleGAN architecture, a state of the art GAN architecture known to reliably produce high resolution images from a variety of datasets.[10]

1.3 AFRIGAN

This work presents AFRIGAN a generative adversarial network model for generating realistic contemporary African Fashion Images. There has been a number of interesting work done with GANs in fashion but they are not Afrocentric. As at the time of this project, the closest related work

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that explores the use of GAN in African art was to generate new African masks[7]. AFRIGAN is designed both as a tool for image synthesis and a domain specific work where others can share the experience of the practical application of Artificial Intelligence in African fashion. Figure 1 shows a simple framework for AFRIGAN. This model was trained on the AFRIFASHION1600 dataset. This dataset has 1600 images and 8 different classes of African fashion images[12] and based on StyleGAN architecture for its state of the art performance in data-driven unconditional generative image modeling.

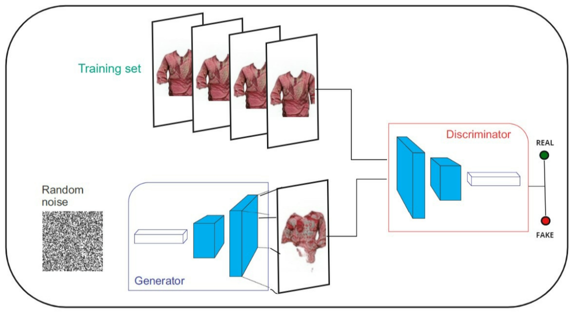

Figure 1: AFRIGAN framework

2 Methodology

Data Preprocessing and Augmentation: All training images from AFRIFASHION1600 dataset were resized to 512 X 512 and formatted as Tensorflow Records. Data augmentation such as mirroring, hue and saturation was included as a preprocessing step.

Model Training: The available dataset is limited in size so transfer learning was leveraged. The model was trained using the Tensorflow Implementation of styleGAN2. Weights from a pretrained styleGAN2 model trained on faces were loaded and fine-tuned using the preprocessed dataset.

Training time and Epochs: A total of 256 epochs were trained using Google Colaboratory notebook and its GPU. Each epoch was trained for an average of 60 minutes and the checkpoints saved.

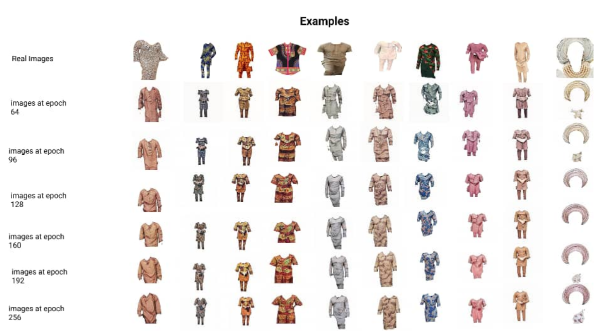

Figure 2: Sample of real images and generated images from AFRIGAN at different epochs

3 Results and Discussion

Figure 2 shows the progression of AFRIGAN at defined epochs on the same image sample. At only 64 epochs the model generated realistic looking images and as expected with further training there was improvement in the image resolution.

4 Conclusion

In this work we presented AFRIGAN, a generative adversarial network model for generating realistic African fashion images. The model, code and how to use, are openly available here.

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