A Comparative Analysis Of Generative Adversarial Network Models For The Generation Of A Unique African Fabric Pattern

Ubong Cosmas Udoakaebe[1]
Department Of Electrical/Electronic And Computer Engineering,
University of Uyo, Akwa Ibom State Nigeria

Udoiwod, Emmmanuel Nsese[2]
Department Of Electrical/Electronic And Computer Engineering,
University of Uyo, Akwa Ibom State Nigeria
eudoiwod@gmail.com

Eduediuyai Ekerette Dan[3]
Department of Computer Engineering Federal Polytechnic, Ukana
Akwa Ibom State Nigeria
uyaiabasidan@gmail.com

Abstract— **In this paper a comparative analysis of generative adversarial network models for the generation of a unique African fabric pattern is presented. Specifically, this study adopted the intuitiveness of generative Artificial Intelligence (AI) to build two different versions of Generative Adversarial Network (GAN) model and Self-Attention Generative Adversarial Network (SAGAN) model that automatically generate new unique designs and patterns of Ankara using the input generated from the Ankara dataset created for the study. In order to successfully automate the design of Ankara, a total of 3000 images of different patterns of Ankara were snapped at different locations/ markets in Akwa Ibom state to form the research dataset. The raw images were pre-processed into a uniform pixel size of 200 X 200 pixels before feeding them into the Generative Adversarial Network (GAN), and Self-Attention Generative Adversarial Network (SAGAN) models considered in the study. The two models were trained using Tensorflow deep learning framework on Google Collaboratory. Precision, recall and F-measure values were used in evaluating the models' performances. The SAGAN gave better precision, recall, f-measure and Frechet Inception Distance (FID) values in comparison with GAN model. Hence, with respect to this study, the SAGAN model is selected as the best performing model for generating Unique African prints with appealing colours and patterns depicting African culture.**

Keywords— Tensorflow , African fabric, Self-Attention Generative Adversarial Network (SAGAN), Google Collaboratory , Artificial Intelligence (AI), Generative Adversarial Network (GAN)

1. Introduction

Africans locally and internationally have been identified and dignified by their unique dressing styles and fashion [1,2,3,4,5,6,7]. Readily available and highly sought after African print is Ankara. The Ankara uses are so diverse and ranges from the sewing of the Ankara material with different styles at church events, wedding, coronation to using the print as accessories for bags, shoes and jewelleries. However, Ankara is still being printed locally using a wax-resist dyeing technique called batik [8,9,10,11,12,13,14]. This traditional method of design and printing led to poor printing designs since the success of the method is subjected to the designer's ingenuity, creativity and fashion inclination.

Accordingly, this paper adopted generative Artificial Intelligence (AI) in machine learning [15,16,17,18,19,20,21] to develop two African Ankara pattern generating models, namely; Generative Adversarial Network (GAN) [22,23,24,25,26,27,28,29,30] model and Self-Attention Generative Adversarial Network (SAGAN) model [31]which succeeded in generating unique African prints after training and fine-tuning the model parameters. Particularly, dataset consisting of collection of numerous snapshots of locally sourced African Ankara prints are used to train the models and in turn use the models to subsequently generate unique African Ankara design patterns. Comparative analysis is conducted on the performance of the two models using Frechet Inception Distance (FID), precision, recall and f-measure scores. The best model is then recommended for use in generating the African Ankara design patterns.

2. Methodology

In this paper, development, training and evaluation of two competing models for generating new but unique African Ankara design styles are presented. The two models were are the popular GAN and SAGAN. Basically, Generative Adversarial Networks, denoted as GAN is a generative model architecture, an unsupervised learning that is based on deep-learning methods which can be used to generate new patterns or images from set of input patterns or images dataset. On the other hand, Self- Attention Generative Adversarial Networks denoted as SAGAN is a modified version of GAN which includes attention-driven and long-range dependency modelling in the image generation process. The two models are studied and used to generate new Ankara cloth design patterns from set of input design pattern images and their effectiveness is evaluated and compared using some selected performance metrics. The research process work flow used in the study is shown in Figure 1. As outlined in Figure 1, the processes making up the whole research implementation started out with gathering of the study dataset which comprises of images of different African Ankara fabrics design patterns. The next stage in the research process handled the pre-processing of the images gathered in phase 1 to form the study dataset.

This study experiments were carried out on Google co-laboratory. The fully setup GAN and SAGAN models were then subjected to intensive iterative training in mini batches with each training epoch made to go through Freschet Inception Distance (FID), precision, recall and f-measure metric calculations for evaluation. The fully trained models are saved and deployed on google co-laboratory. These models are then used in printing unique Ankara using seed values ranging from zero (0) to infinity (∞) in order to enforce the uniqueness.

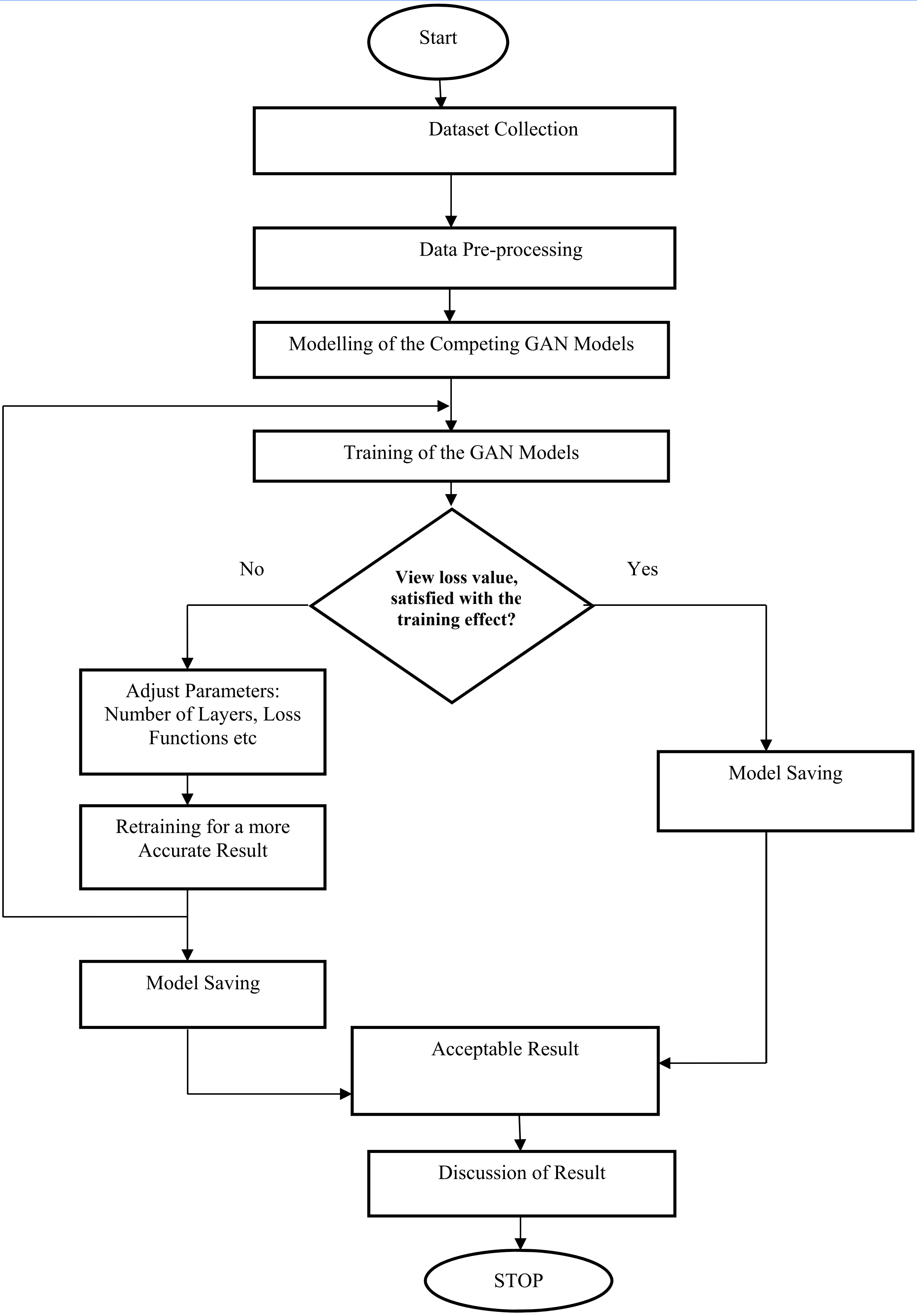

Figure 1: The research process work flow

2.1 Dataset Collection

The first stage of this study was to manually select images of Ankara prints which uniquely depict African heritage in colours, patterns, culture, religion and ancestry. This was achieved by visiting major markets known for selling Ankara dominated with certain designs or patterns. In Akwa Ibom State, Nigeria, Urua Akpan Andem market in Uyo metropolis was the first choice of market for the dataset gathering; there were variety of patterns in this particular market though most designs were conventional patterns. Sellers of these wears were cooperating by revealing designs which are fast selling and many which were not. Gathering of the dataset was done base on these categories of prints. At this location, 1000 images with different patterns of Ankara were snapped.

In order to have a mix of patterns portraying ethnicity and culture, more samples were snapped at a mini market at Hausa residence popularly known as Nasarawa region in Uyo metropolis, where patterns worn mostly by the Hausa-Fulani were obtained to augment the number gathered at Akpan Andem market. Also, 800 images of different Ankara prints were snapped at this location. Another of such locations was the popular Obo Annang Market in Essien Udim town where Ankara patterns worn mostly by people of that area were selected and snapped. A total of 1000 images of different patterns of African fabrics (Ankara prints) were snapped at this location.

In order to meet up with the number of images needed for the dataset, the availability of images of Ankara material on the internet came handy. The internet was explored by scraping with keywords such as 'African Ankara Prints', 'Ankara' and 'aso ebi'. Using this technique, various images of African Prints popularly known as Ankara were downloaded into a folder for further preprocessing on the images before use. Also, to further increase the number of Ankara images, videos with still frames of Ankara wears was captured to form part of our dataset. The last techniques of gathering Ankara images gave a total of 200 images bringing the total number of images for this study dataset to 3000. In any case, there was no laid down criteria for selecting a particular number of Ankara images at any location. The number of the data size at different locations was largely determined by the availability of various design patterns of Ankara at the time of visitation. The size of 3000 dataset size was due to the availability of Ankara patterns at locations visited during study data gathering phase. A snapshot of some of the dataset images gathered for the models development and training are presented in Figure 2.

Figure 2 A snapshot of some of the dataset images gathered for the models development and training

2.2 Pre-processing of the dataset

In this study, the raw Ankara images gathered were subjected to some pre-processing as it helped in improving training efficiency and further boost the system result. The step-by-step approach used for data preprocessing task in this study includes: acquire the dataset; import all the crucial libraries, import the dataset, identify and handle missing data values (*Data Quality Assessment),* encode the categorical data, split the dataset and feature scaling.

Importing the Dataset : The gathered Ankara dataset was stored in a Google drive mounted on the Google Co-laboratory environment used for the experiments and training of the GAN models. Using the folder path in the file directory, the dataset was read into the model.

Identifying and handling the missing values *(Data Quality Assessment):* The anomaly in Ankara dataset was unavoidably there since as explained, data was gotten from multiple sources where reliability of those sources cannot be ascertained and likely would come in different formats. Such anomalies are due to human error or flaws in the data collection process. In order to facilitate smooth working experience with the dataset, the following tasks were carried out to ensure dataset is of high quality:

Duplicate Values: While pre-processing the images gathered for this study, care was taken to ensure that there were no duplicate values in the Ankara dataset considering that the images making up the datasets came from multiple sources. This was done manually since the size of the dataset was relatively small and the duplication was suspected to be from the images of the dataset that were downloaded from the online source which made solving the problem easier since the problem source was easily identified.

Inconsistent Images: The gathered images were manually inspected to ensure there were no inconsistencies among them. The inconsistency was evaluated in terms of image quality and background colour of the image. Images with overly white background were dropped as well as images with very poor contrast.

Dataset Image Scaling: Images in the gathered Ankara dataset had differing sizes, therefore there was need to resize them to a uniform scale or size before using them as input to the model. Using simple online scaling tool called ResizeImage which offered opportunity for simple usage in choosing the width and height in pixels, allowed room for choosing to either compress the resized image without losing image quality or resize the image in kilobytes or megabytes. This tool was useful in reshaping images collected at the data gathering stage into a uniform pixel size of 200 X 200 pixels (Figure 3) before feeding them into the model for training.

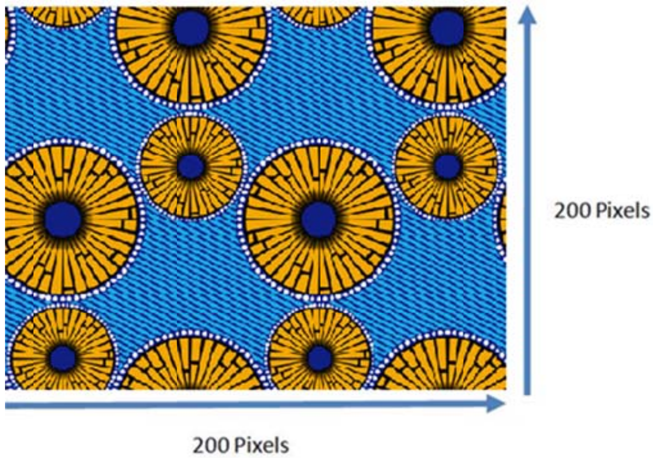

Figure 3 Dataset image scaling size for the Ankara image dataset.

2.3 The network models

This study experiments were carried out on Google co-laboratory. Google's Tensor flow framework was used for the network models development, their raining and testing. In order to efficiently work with images, methods selected for the models in this **study** are that of multi-layer perceptron and deep convolutional neural network while the traditional GAN and SAGAN are the competing models.

2.4 Model I : Generative Adversarial Network (GAN) Model

The GAN model was laced with deep convolutional layers to suit with the image input to the model. At the generator network, the first layer was a fully connected layer which was reshaped into deep and narrow layers. The number of layers was actually set according to experimental needs as they were adjusted or fine-tuned during the training according to the model performances. To the stability of the model, batch normalization was chained to the transpose convolutional layer.

Batch normalization is introduced to mitigate any internal covariate shift problem that may arise during the training. Internal covariate shift occurs due to changes in the distribution of network activations occasioned mostly by changes in network parameters during the training. Batch normalization made the model stable by performing standardization and normalization operations on the input of a layer coming from a previous layer. This was to ensure that sampling of noise inputs at intervals or in mini batches was possible and the training speed of the model was effortlessly augmented. Leaky ReLU (Rectified Linear Unit) activation Function is used at the generator model with exception of the output layer where Tanh activation is used.

At the discriminator model, convolutional classification and down-sampling operations using a simple striding step was done. The activation function of the discriminator was leaky ReLU. This network model handled the task of classifying whether the generated Ankara images are real (from the dataset) or fake (generated by the generator model). The architectural structure of the GAN model is as presented in Figure 4.

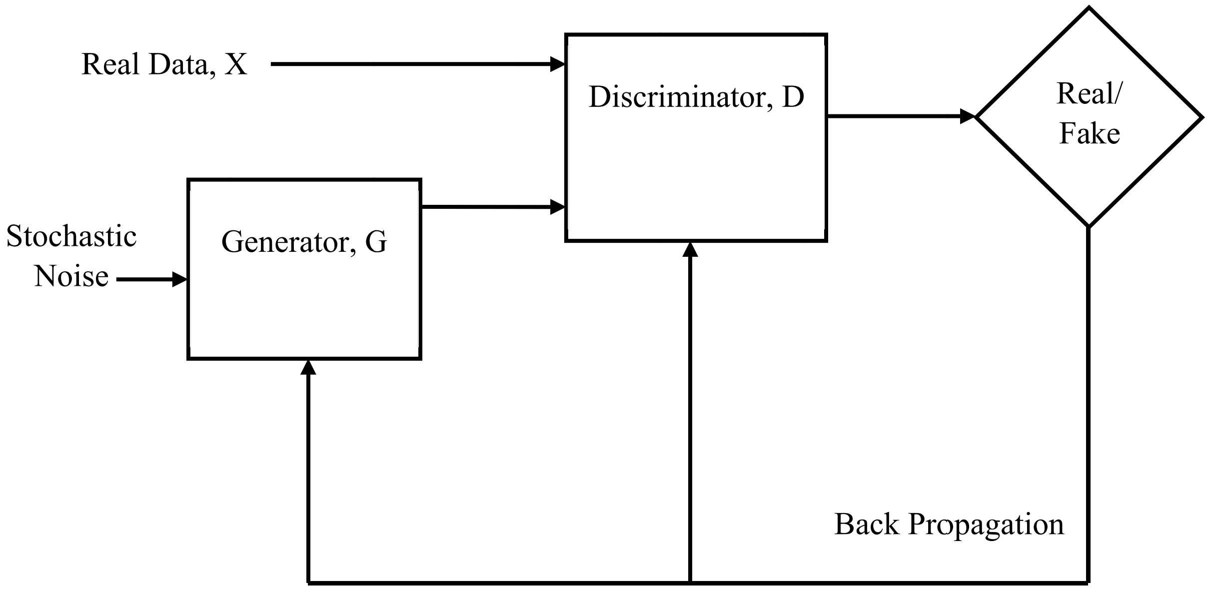

Figure 4 The Generative adversarial network (GAN) model architectural structure
Source: [32]

2.5 Model II : Self- Attention Generative Adversarial Network (SAGAN) model

This experiment adopted the default SAGAN architecture and parameters and was experimented as the competing model for this study. The model was fed with the 200 X 200 pixels' images of the Ankara dataset. Batch normalization was applied at all layers of both the generator and the discriminator networks. Batch normalization (BN) has a way of normalizing input features of a layer to have a zero mean and unit variance. The BN is applied at both the generator and discriminator and this is essential for getting the deeper layers of the models to work without falling into mode collapse. Mode collapse occurs when the generator creates samples with very low diversity. In other words, generator returns the same looking samples for different input signals. The problems of poor parameters' initialization are equally tackled by the introduction of BN. The code for implementation is attached in Appendix III. A default learning rate (lr) of 0.0004 for the discriminator and 0.0001 for the generator was used with $\beta_1 = 0$ and $\beta_2 = 0.9$. The architectural structure of the SAGAN model is as presented in Figure 5.

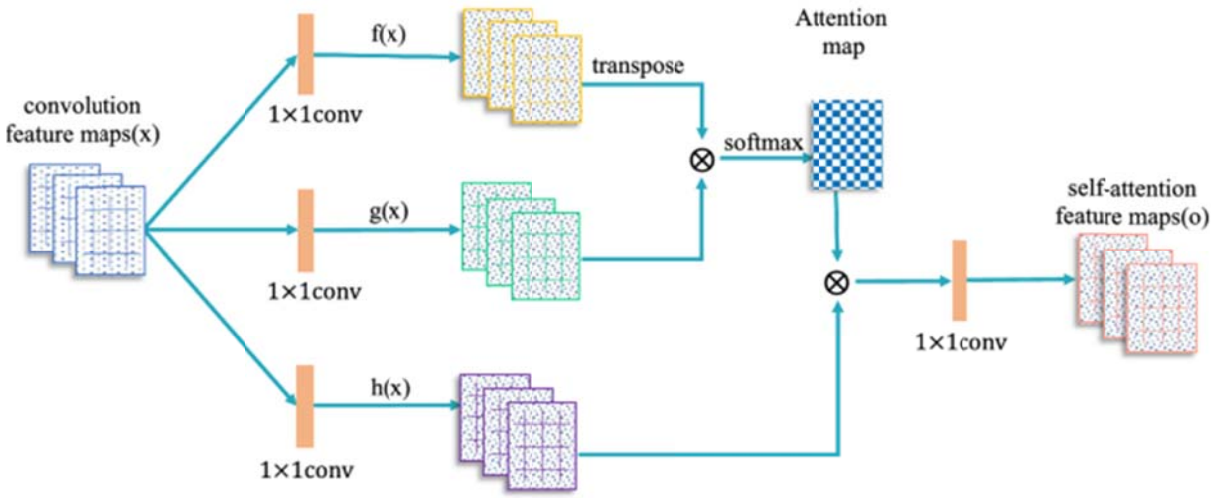

Figure 5 The Self- Attention Generative Adversarial Network (SAGAN) model architectural structure
Source: [33]

2.6 Training and performance evaluation of the models

Tensorflow deep learning framework implemented on Google Collaboratory and running on NVIDIA K80 GPU was used for the training of the two models adopted in this research. Mini batch size of 32 was used in the model training which adopted Adam optimizer with the following settings for the hyperparameters : beta_1, lr = 0.001, learning rate, $\beta 1 = 0.9$, beta_2, $\beta 2 = 0.999$, epsilon, $\ell = 1\ell$ -

07. The models' performance parameters (namely, loss value and accuracy) were monitored at each mini-batch and also at each epoch which was set at a value of 1000.

Binary cross entropy was adopted for the discriminator loss function while Adam optimizer was employed in the discriminator generator networks. Finally, in order to ascertain the workability of the models and at what percentage they are learning or with what rate: Frechet Inception Distances, Precision, Recall and F-Measure otherwise known as F1-score were used in accessing the functionality of the different models trained for the generation of Ankara prints.

3. Results and discussion

After the training of the GAN and SAGAN models was completed, the two models were each used to generate different images of the African Ankara design patterns. Notably, at the end of the first epoch for the GAN model, the resulting output image was noisy as presented in Figure 6, and noisy output image was attributed to the small number of images in the dataset used (about 3000 images) whereas other deep learning networks using large image size of over 3 million give better output images.

Consequently, the poor output image was remedied by employing some measures which included introduction of Gaussian noise to the generator network at random intervals and application of Adaptive Instance Normalization (AdaIN) at each layer of the convolution for the GAN model (and also in the SAGAN model). After these remedial actions were taken, the quality of the image output from the models improved significantly, as evident in the screenshot of Figure 7, Figure 8 and Figure 9 for the GAN model and the screenshot of Figure 10, Figure 11, Figure 12 and Figure13 for the SAGAN model. Importantly, during the Ankara generation, it was noticed that the image and pattern qualities improved with increase in the number of training epochs. This demonstrated the effectiveness of the models at learning progressively the inert features of the inputted images from the pre-trained dataset.

However, a deeper look at the Ankara prints reveals some white colours as part of the printed Ankara designs repeatedly on the prints of all the three models of this research experiments. This was inherited from the images of the dataset. During dataset gathering, some Ankara designs/prints from the markets were kept on white backgrounds for snapshots, therefore in the cause of training the models; they learn the white backgrounds as part of the Ankara pattern and replicated same in the designs of the generated samples

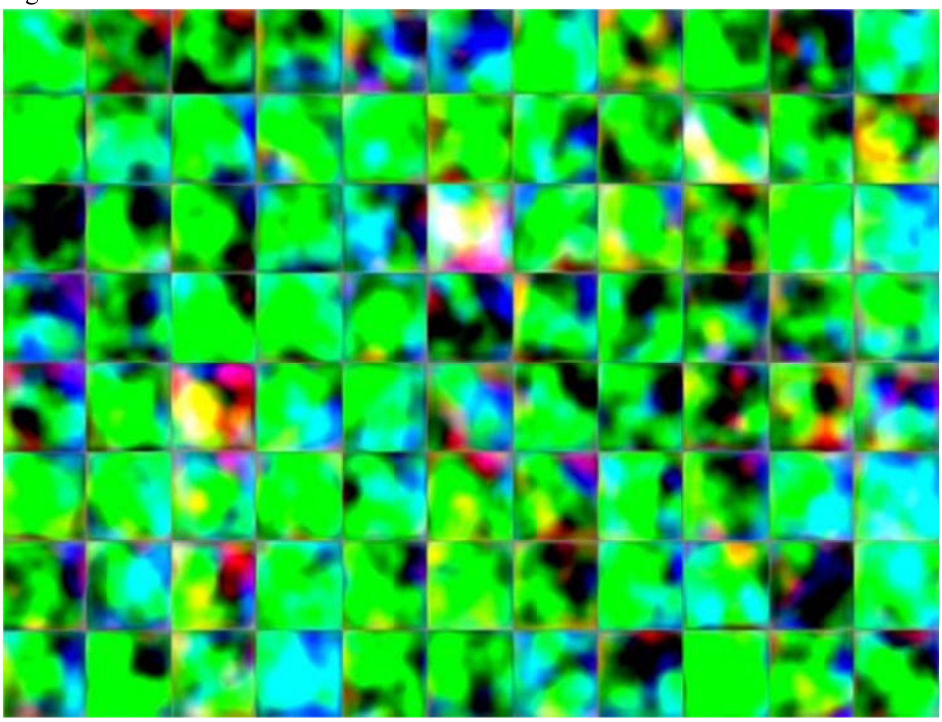

Figure 6: Ankara prints image output from the GAN model at the end of epoch 1 and with FID value of 317.306.

Figure 7 Ankara prints image output from the GAN model at the end of epoch 2 and with FID value of 237.639 .

Figure 8 Ankara prints image output from the GAN model at the end of epoch 3 and with FID value of 161.84

Figure 9 Ankara prints image output from the GAN model at the end of epoch 4 and with FID value of 149.897

Figure 10 Ankara prints image output from the SAGAN model at the end of epoch 1 and with FID value of 72.349

Figure 11 Ankara prints image output from the SAGAN model at the end of epoch 2 and with FID value of 88.345

Figure 12 Ankara prints image output from the SAGAN model at the end of epoch 3 and with FID value of 74.139

Figure 13 Ankara prints image output from the SAGAN model at the end of epoch 4 and with FID value of with 69.795

Considering the multifarious uses of Ankara prints and noting that most customers or Africans are thrilled with unique Ankara designs adorned with special patterns and selected colours mostly to suit the nature of the occasion they want to wear the Ankara designs for, the AI generating models for this research experiments are made with the capability of generating each print with a unique seed that range from zero to infinity. If in the future, the models are adopted for commercial use, the random seeds used in generating Ankara prints would aid in enforcing uniqueness of printed Ankara materials by ensuring that no two customers or users of the model is given the same seed value. The screenshot in Figure 14 demonstrate the application of these random seeds during Ankara generation from the two models.

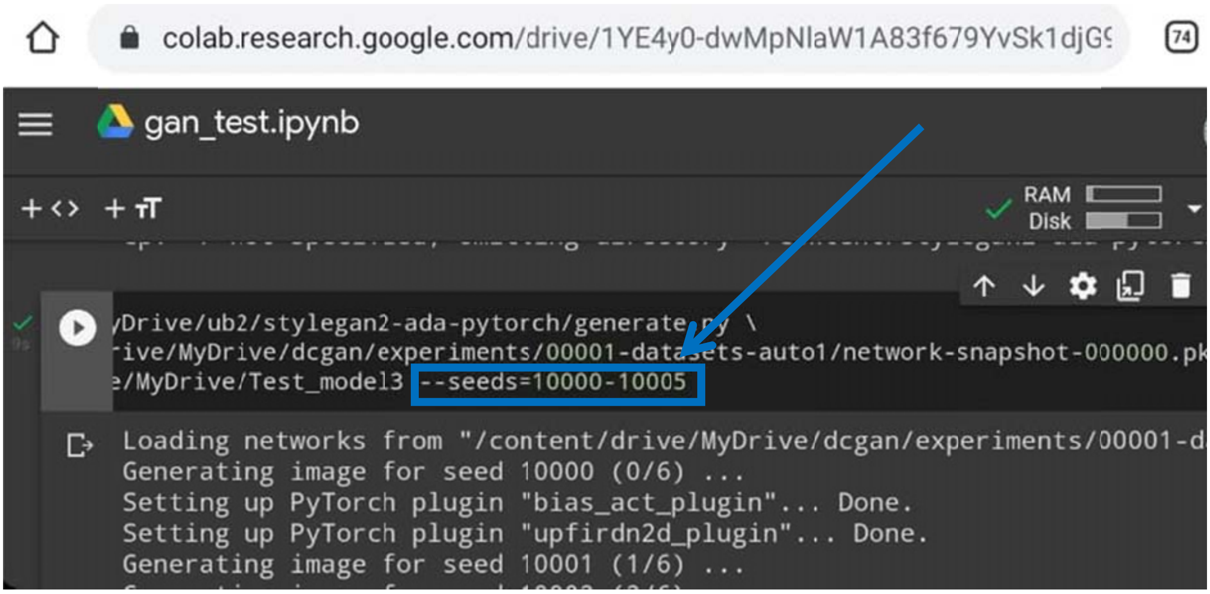

Figure 14 The screenshot showing the application of these random seeds during Ankara generation from the two models.

The results of the FID calculations per epoch on the datasets for the SAGAN model and GAN model are shown in Table 1 and Figure 15. The results showed that the SAGAN model has acceptable **FID metric values** which are all below the threshold set at 100. However, the sudden spike in the FID score of the SAGAN model after the first epoch shows abnormality.

Table 1: SAGAN and GAN FID metric values

Training Epochs	FID Value for SAGAN model	FID Value for GAN model
1	72.349	317.306
2	88.345	237.639
3	74.139	161.824
4	69.795	149.897

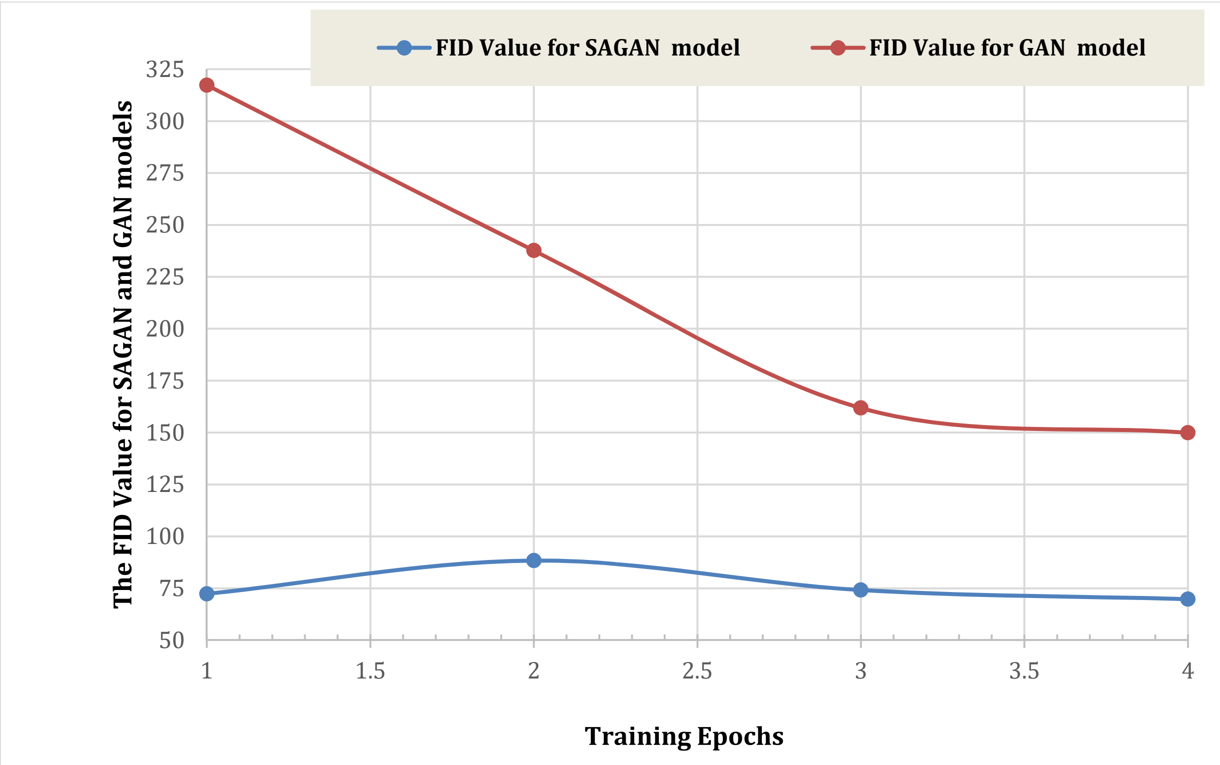

Figure 15 The graph plot of the SAGAN and GAN FID metric values versus training epoch

The results on the Precision, Recall and F- Measure metrics for the SAGAN and GAN model are shown in Table 2 and figure 16. The results in Table 2 and Figure 16 show that the two models scored above 50% in each of the three metrics, namely, the precision, recall and F-measure. However, the SAGAN model with higher performance values in all the three performance parameters, performed better than the GAN model. With the result of the analysis all favouring SAGAN, it was selected as the best performing model. The Ankara prints from this research models reflected that, between the two models studied, the SAGAN generated the most promising samples of unique Ankara. Hence, the SAGAN print gives insight that AI models can generate prints that reflect unique design patterns for African prints.

Table 2 The results on the Precision, Recall and F- Measure metrics for the SAGAN and GAN model

Model	Precision (%)	Recall (%)	F-measure (%)
GAN	62	58.1	56
SAGAN	68.2	67	66.3

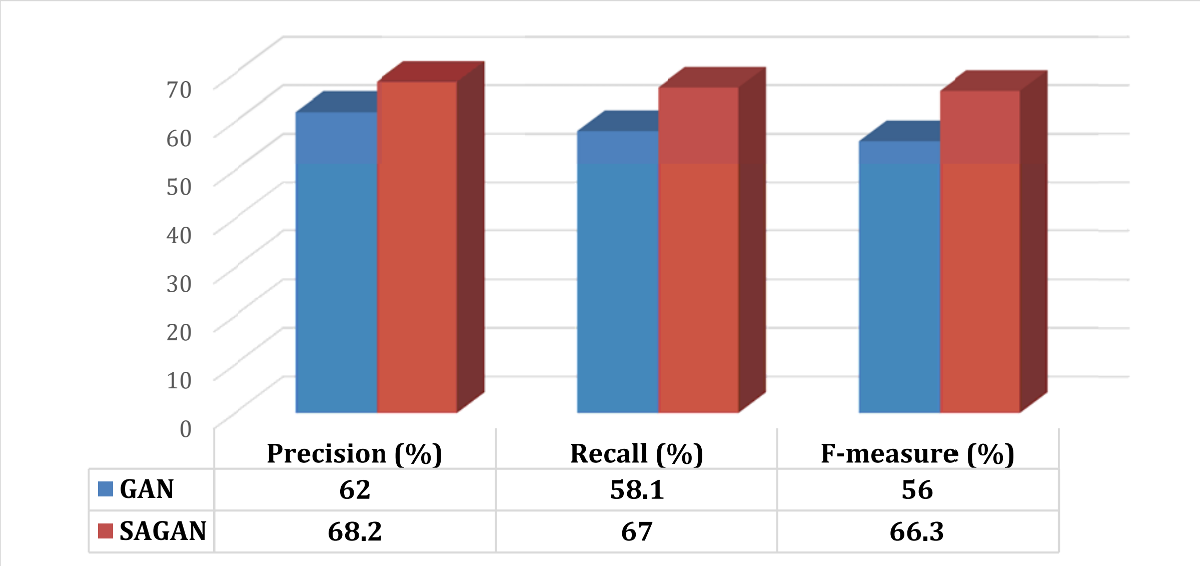

Figure 16 The bar chart of the Precision, Recall and F- Measure metrics for the **SAGAN and GAN model**

It was also observed that while gathering the dataset images from the markets, most of the Ankara materials were kept on white background for snapshot. This equally affected the result of the model since it is obvious that the models had learn the background as part of the dataset and ended up generating prints with brighter contrast. In future research, precaution would be taken while augmenting the Ankara dataset to avoid a repeat of this anomaly.

4. Conclusion

Application of two GAN models for generating unique African fabric pattern is presented. The two GAN models considered in the study are the classical Generative Adversarial Network (GAN) and the Self-Attention Generative Adversarial Network (SAGAN). A locally sourced images of different patterns of Ankara fabric were snapped and compiled as the input dataset for training the two models. The raw images were first pre-processed and then used in training the models using Tensorflow deep learning framework on Google Collaboratory. Precision, recall and F-measure values were used in evaluating the models' performances. In all, the SAGAN gave better precision, recall, f-measure and Frechet Inception Distance (FID) values in comparison with GAN model. Hence, with respect to this study, the SAGAN model is selected as the best performing model for generating Unique African prints with appealing colours and patterns depicting African culture.

Reference

1. Von Schnitzler, A. (2014). Performing dignity: Human rights, citizenship, and the techno-politics of law in South Africa. *American Ethnologist*, *41*(2), 336-350.
2. Sobh, R., Belk, R., & Gressel, J. (2014). Mimicry and modernity in the Middle East: fashion invisibility and young women of the Arab Gulf. *Consumption Markets & Culture*, *17*(4), 392-412.
3. Katende-Magezi, E. (2017). The impact of second hand clothes and shoes in East Africa.
4. Tamale, S. (2014). Exploring the contours of African sexualities: Religion, law and power. *African Human Rights Law Journal*, *14*(1), 150-177.
5. Moran, M. H. (2017). Missing bodies and secret funerals: The production of" safe and dignified burials" in the Liberian Ebola crisis. *Anthropological Quarterly*, 399-421.
6. Pal, R. (2017). Sustainable design and business models in textile and fashion industry. In *Sustainability in the textile industry* (pp. 109-138). Springer, Singapore.
7. Mawere, M. (2014). *Divining the future of Africa: Healing the wounds, restoring dignity and fostering development*. African Books Collective.
8. Gott, S., Loughran, K. S., Quick, B. D., & Rabine, L. W. (2017). African-Print Fashion Now! A Story of Taste, Globalization, and Style. *African Arts*, *50*(1), 42-59.
9. Osayimwese, I. (2019). Invisible Woman: Reclaiming Josephine Ifueko Osayimwese Omigie in the History of the Zaria Art Society and Postcolonial Modernism in Nigeria. *African Arts*, *52*(2), 66-79.

10. Keogh, M. D. (2017). *Wo Hwe Wo Nua/You See Your Sibling: Locating Batik within Ghana's Textile Practices* (Doctoral dissertation, Indiana University).
11. Warritay, O. T. (2017). *Empire's New Clothes: Undressing Neoliberal Development Through the Lens of African Print Textiles/Dress* (Doctoral dissertation, Cornell University).
12. Gürses, A., Açıkyıldız, M., Güneş, K., & Gürses, M. S. (2016). *Dyes and pigments*. Springer.
13. Oyebode, S. I. (2019). *Yoruba Adire Signs as a Method of Communication in Contemporary Art Practice in Diaspora Africa*. University of Johannesburg (South Africa).
14. Evans, M., Twigger Holroyd, A., Walker, S., Cassidy, T., & Jung, J. (2018). Strategies for revitalization of culturally significant designs, products, and practices. *Teoksessa S. Walker, M. Evans, T. Cassidy, J. Jung & A. Twigger Holroyd (toim.), Design roots: Culturally significant designs, products, and practices*, 341-359.
15. Riedl, M. O. (2019). Human-centered artificial intelligence and machine learning. *Human Behavior and Emerging Technologies*, *1*(1), 33-36.
16. Alimadadi, A., Aryal, S., Manandhar, I., Munroe, P. B., Joe, B., & Cheng, X. (2020). Artificial intelligence and machine learning to fight COVID-19. *Physiological genomics*, *52*(4), 200-202.
17. Stewart, J., Sprivulis, P., & Dwivedi, G. (2018). Artificial intelligence and machine learning in emergency medicine. *Emergency Medicine Australasia*, *30*(6), 870-874.
18. Helm, J. M., Swiergosz, A. M., Haeberle, H. S., Karnuta, J. M., Schaffer, J. L., Krebs, V. E., ... & Ramkumar, P. N. (2020). Machine learning and artificial intelligence: definitions, applications, and future directions. *Current reviews in musculoskeletal medicine*, *13*(1), 69-76.
19. Nuseir, M. T., Al Kurdi, B. H., Alshurideh, M. T., & Alzoubi, H. M. (2021, June). Gender discrimination at workplace: Do Artificial Intelligence (AI) and Machine Learning (ML) have opinions about it. In *The International Conference on Artificial Intelligence and Computer Vision* (pp. 301-316). Springer, Cham.
20. Thrall, J. H., Li, X., Li, Q., Cruz, C., Do, S., Dreyer, K., & Brink, J. (2018). Artificial intelligence and machine learning in radiology: opportunities, challenges, pitfalls, and criteria for success. *Journal of the American College of Radiology*, *15*(3), 504-508.
21. Galbusera, F., Casaroli, G., & Bassani, T. (2019). Artificial intelligence and machine learning in spine research. *JOR spine*, *2*(1), e1044.
22. Aggarwal, A., Mittal, M., & Battineni, G. (2021). Generative adversarial network: An overview of theory and applications. *International Journal of Information Management Data Insights*, *1*(1), 100004.
23. Gonog, L., & Zhou, Y. (2019, June). A review: generative adversarial networks. In *2019 14th IEEE conference on industrial electronics and applications (ICIEA)* (pp. 505-510). IEEE.
24. Jabbar, A., Li, X., & Omar, B. (2021). A survey on generative adversarial networks: Variants, applications, and training. *ACM Computing Surveys (CSUR)*, *54*(8), 1-49.
25. Aggarwal, A., Mittal, M., & Battineni, G. (2021). Generative adversarial network: An overview of theory and applications. *International Journal of Information Management Data Insights*, *1*(1), 100004.
26. Gonog, L., & Zhou, Y. (2019, June). A review: generative adversarial networks. In *2019 14th IEEE conference on industrial electronics and applications (ICIEA)* (pp. 505-510). IEEE.
27. Jabbar, A., Li, X., & Omar, B. (2021). A survey on generative adversarial networks: Variants, applications, and training. *ACM Computing Surveys (CSUR)*, *54*(8), 1-49.
28. Gupta, A., Johnson, J., Fei-Fei, L., Savarese, S., & Alahi, A. (2018). Social gan: Socially acceptable trajectories with generative adversarial networks. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 2255-2264).
29. Karras, T., Aittala, M., Hellsten, J., Laine, S., Lehtinen, J., & Aila, T. (2020). Training generative adversarial networks with limited data. *Advances in Neural Information Processing Systems*, *33*, 12104-12114.
30. Chen, Y., Lai, Y. K., & Liu, Y. J. (2018). Cartoongan: Generative adversarial networks for photo cartoonization. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 9465-9474).
31. Zhang, H., Goodfellow, I., Metaxas, D., & Odena, A. (2019, May). Self-attention generative adversarial networks. In *International conference on machine learning* (pp. 7354-7363). PMLR.
32. Liu, L., Zhang, H., Ji, Y. and Jonathan Wu, Q. M. (2019). Towards AI Fashion Design: An Attribute-GAN Model for Clothing Match. *Neurocomputing*, 4: 15 – 29.
33. Zhang, H., Sun, Y., Liu, L., Wang, X., Li, L. and Liu, W. (2018). ClothingOut: a category-supervised GAN model for clothing segmentation and retrieval. *Neural Computing and Applications,* 32: 1-12.