Modelling And Evaluation Of Stylegan For Generation Of Unique African Ankara Design Patterns

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Abstract— **In this paper modelling and evaluation of Style Generative Adversarial Network (StyleGAN) for generation of unique African Ankara design patterns is presented. The StyleGAN is an extensive modified version of the conventional GAN architecture which instead of being able to just generate new images from sample input dataset, the StyleGAN provides the ability to control the new styles or new design patterns that are generated. The key steps followed in conducting the study included data collection, data pre-processing, model development, model training, and model deployment and evaluation. The input image dataset consist of about 3000 different African Ankara clothes with prints or design patterns which were collected from different markets in various locations across Akwa Ibom State Nigeria. The Google Collaboratory was used to execute the model development, training and evaluation with a RAM size of 12.69GB and disk space of 107.72 GB. The results showed that the Frechet Inception Distance (FID) metric scores for the StyleGAN model for all the epochs are acceptable , as they are below the threshold value of 100 and the FID metric score is also increasing steadily (decreasing) with increase in the epoch. Also,the recall, precision and F-measure metrics scores for the StyleGAN model are have acceptable scores (which are above 50 %). The result that the StyleGAN model performed well in all the performance metrics used. Also, when compared with some published research results, the StyleGAN presented in this paper performed better than those other models examined.**

Keywords— Style Generative Adversarial Network (StyleGAN), Google Collaboratory , Frechet Inception Distance (FID), Tensorflow, Keras, Matplotlib, OpenCV_Python

1. Introduction

Africans are traditionally identified by their Ankara and other native print attires which endear them to the rest of the western world [1,2,3,4,5]. These Ankara materials are mostly use as uniforms for marriages, child naming ceremonies, coronations, festivals, burials, church services, decoration at different occasions and events and so on. It has in fact become an object of national pride in which patriotic leaders of Africa wear as a mark of national identification at international events. As a result of the numerous uses and adoption of Ankara, the demand for it is very high and the traditional or manual mode of designing the material is battling to meet up the high demand. This has resulted in scarcity of unique Ankara patterns. This problem has left many with no option than adopting more uniforms at a particular occasion and sometimes subjects themselves to travelling long distances in search of unique Ankara patterns laced with their desired colours suitable for the intended occasion.

However, there has been series of innovations in the printing and designing of these wears which unfortunately requires much of intellectual stress and time from the conceptualization process to the actual designing and printing [6,7,8,9,10]. Most printed Ankara comes with repetition of same design patterns because of the manual mode of production with series of production lines which add up to increasing the cost of the printed Ankara material. Importantly, several researchers have sort out ways of solving the problem of the clothing industries through the adoption of the ease of achieving tedious tasks introduced by the field of Artificial Intelligence (AI) [11,12,13,14,15,16,17]. Using AI models, intensive analysis was done on whether consumers would be willing to buy fabric prints generated by Generative Adversarial Model (GAN). The result of the survey analysis came out very impressively successful. Out of the total number of consumers contacted, 90% of the consumers were willing to purchase AI generated designs [18,19].

Furthermore, many researchers have successfully deployed Artificial Intelligence (AI) technology in the textile and fashion industry to foster the growth of the sector by ensuring customer acceptability of Artificial Intelligence (AI) generated textile products. Style matching

[20], trend forecasting [21], interactive search [22] style recommendation [23] virtually trying clothes on [24], and clothing type and style classification [25] are major already researched areas on generative AI deployment in the textile and fashion industries. Many scholars have equally adopted the flexibility introduced by deep learning aspect of Generative Adversarial Network (GAN) to develop many models like ClothGAN for designing fashionable Dunhuang clothes [26], Colouring Methods for Ethnic Costumes using GAN [27] and so on. Artificial Intelligence and deep learning research in the fashion industry is believed to have strong impact on customers' buying decision, the procedure of textile designs and as such helps the industry to deliver outputs which are user centred. With all the successes of previous researchers, none had digitalized the printing of African fabrics called Ankara. They had minor shortcomings which included over dependency on professional experience, content search, interpretation, application of low technical approach and the digitalization of a model for African traditional attires which promote the heritage of Africans.

This research introduces a novel African fabric (Ankara) printing model using Style Generative Adversarial Network (StyleGAN) model [28,29,30,31]. First, dataset consisting of snapshots of different Ankara fabrics with different patterns and designs were manually collected for the model training. Then the model was used to automatically generate unique and intuitive new Ankara patterns. The result of the model is a more unique, traditionally aesthetic and acceptable Ankara prints. The performance of the model is evaluated using diverse metrics.

2. Methodology

In this paper, Style Generative Adversarial Network (StyleGAN) is used to develop a framework for generating new and unique African Ankara designs from set of existing Ankara designs fed into the model as input dataset. Importantly, the StyleGAN is an extensive modified version of the conventional GAN architecture which instead of being able to just generate new images from sample input dataset, the StyleGAN provides the ability to control the new styles or new design patterns that are generated. As a form of GAN it relies on deep-learning methods that require model development and training. Hence the key steps followed in conducting the study is as shown in Figure 1 includes; data collection, data pre-processing, model development, model training, and model deployment.

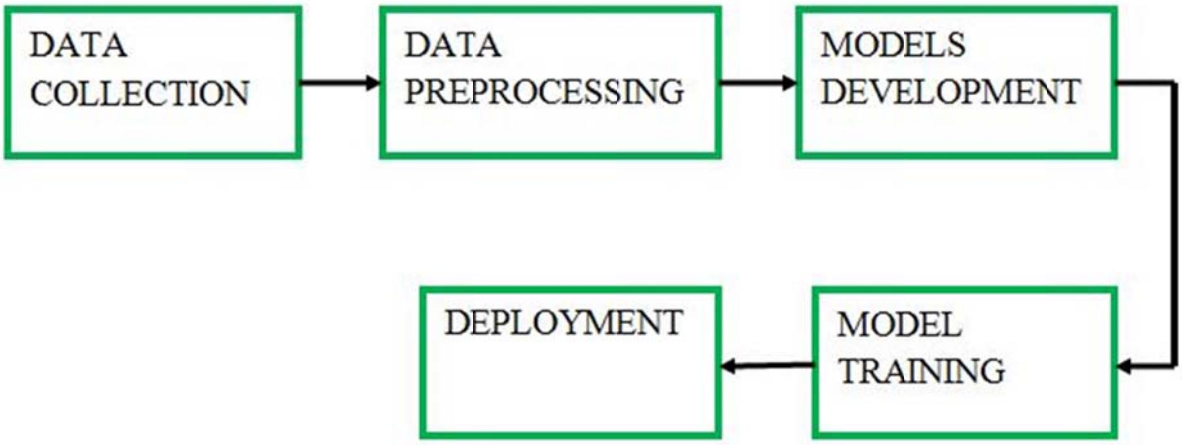

Figure 1 Block diagram showing the key steps followed in conducting the study

2.1 Model input data collection

About 3000 different African Ankara clothes with prints or design patterns were collected from different markets in various locations across Akwa Ibom State Nigeria. The clothes were snapped and their images were compiled for the study. Also some addition Ankara clothes designs images were downloaded from different online websites. The whole images were assembled for the model training and Figure 2 shows snapshot of a part of the dataset of African Ankara clothes design pattern image used in the study.

Figure 2 Snapshot of a part of the dataset of African Ankara clothes design pattern image used in the study

2.2 Feature engineering or data pre-processing

The dataset of Ankara design images were pre-processed using some software libraries and the preprocessing tasks include among other things handling issues of missing data, duplicate data, and inconsistent data in the dataset, performing some forms of encoding and scaling on the data items, and splitting of the dataset. Notably, all the images are scaled to a uniform size of 200 X 200 pixels, as shown in Figure 3.

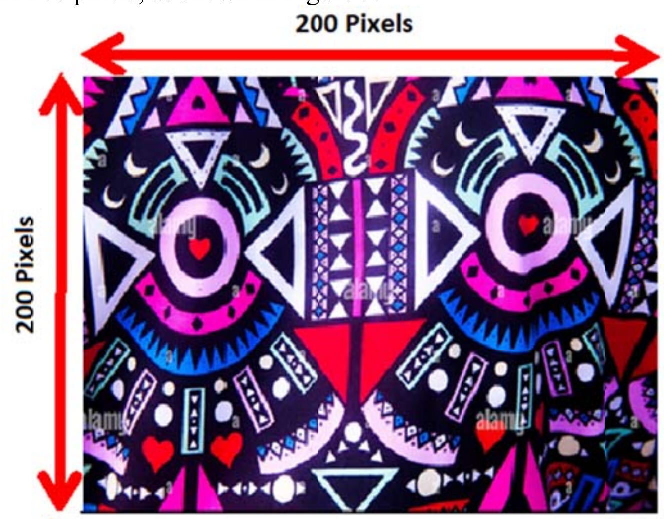

Figure 3 Preprocessed sample image resized to uniform size of 200 X 200 pixels.

2.3 Model development and evaluation

Due to the size, weight of the data and the training speed and type of the data needed for this study and considering the high cost of acquiring a physical desktop or laptop computer with the needed system requirement, Google Collaboratory was used to execute this model development, training and evaluation with a RAM size of 12.69GB and disk space of 107.72 GB.The primary programming language used for this study is python. This was used in collaboration with enabling libraries that includes Tensorflow, Keras, NumPy (that is numerical python), Matplotlib, and OpenCV_Python. Again, the StyleGAN mode was used in this study and it was modelled, trained and evacuated using Google's Tensor flow framework

2.4 StyleGAN model

The StyleGAN enables both increased stability for higher dimensionality problem such as image features extraction as it is applicable to this research experiments and ensuring better feature separation. The StyleGAN generator was not configured to take points from the latent space as input; instead, there were two new sources of randomness used to generate a synthetic image: a standalone mapping network and noise layers. The output from the mapping network is a vector that defines the styles that is integrated at each point in the generator model via a new layer called adaptive instance normalization. The use of this style (patterns) vector gives control over the patterns of the generated image. Stochastic variation is introduced through noise added at each point in the generator model. The noise is added to entire feature maps that allow the model to interpret the patterns in a fine-grained, per-pixel manner. This per-block incorporation of pattern vector and noise allows each block to localize both the interpretation of style and the stochastic variation to a given level of detail.

The model architecture is that of a standard StyleGAN [32] with minor modifications on the progressive module of the training network. Instead of adopting incremental image sampling, a fixed image size of 200 X 200 pixels is sampled at random and maintained throughout the training process. The different segments of the StyleGAN architecture shown in Figure 4 is explained independently starting from the mapping network, the Adaptive Instance Normalization (AdaIN), the stochastic variation (Gaussian noise).

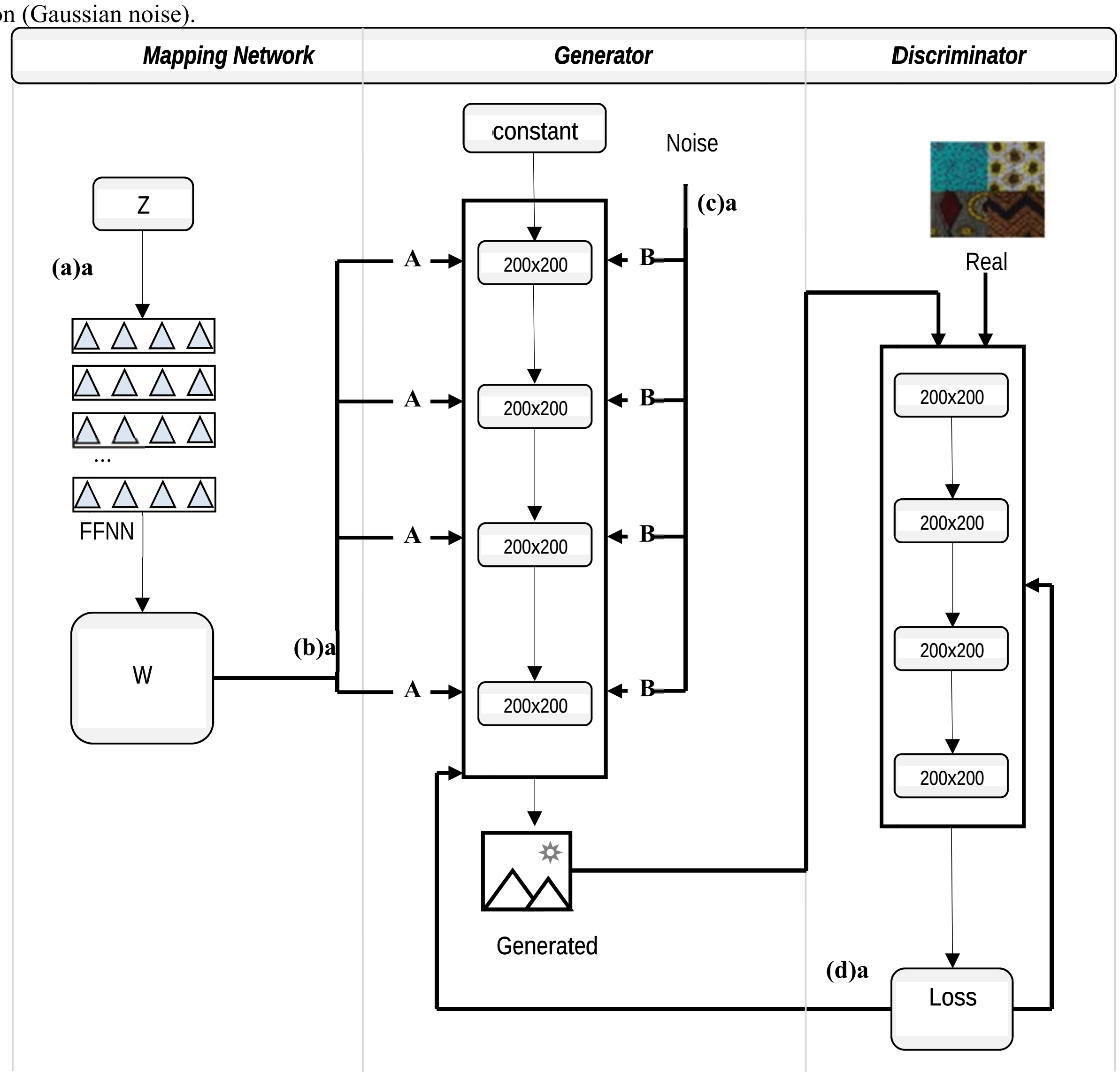

Figure 4 StyleGAN model architecture.

2.5 The mapping networks for the StyleGAN model

In the traditional architecture, the latent code is provided to the generator through an input layer which is the first layer of the feed forward network, but in this experiment, the latent code z in the input layer is projected onto an intermediate latent space ω by being fed through a mapping network and is represented by the relation f: z $\rightarrow \omega$. The mapping of f is then implemented using 8-layer MLP as shown in Figure 5.

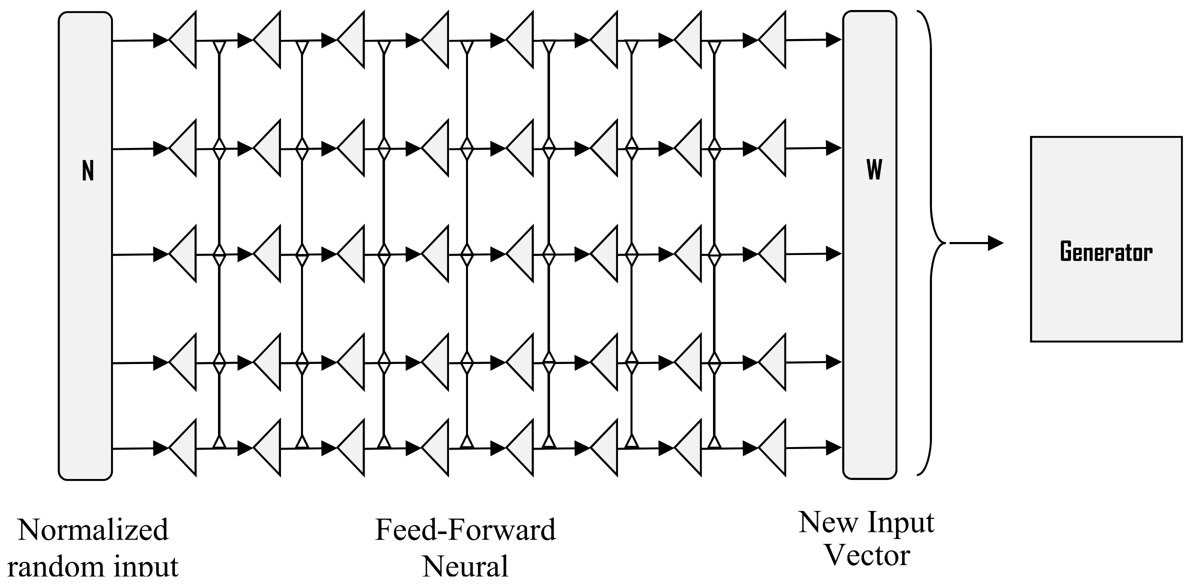

Figure 5 The mapping network of StyleGAN

2.6 The Adaptive Instance Normalization (AdaIN)

The Adaptive Instance Normalization (AdaIN) is a normalization method which aligns the mean and variance of the content features with those of the style (pattern) features. The instance normalization is in charge of normalizing the input to a single style specified by the affine parameters, as shown in Figure 6. Learned affine transformations specialize ω to style y which controls AdaIN operations after each convolution layer of the synthesis network. Thus, through ADaIN, the feature map is translated into a visual representation.

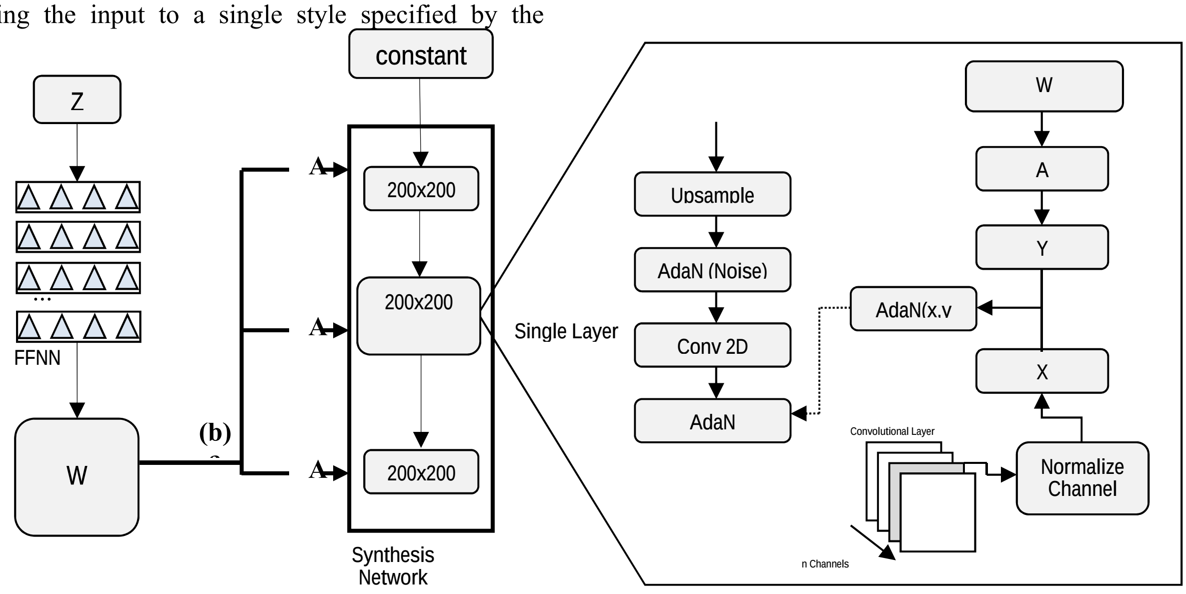

Figure 6 Adaptive instance operations of a StyleGAN

2.7 Stochastic Variation

The noise inputs into the model which were applied in addition to image samples from the gathered Ankara dataset took the form of two-dimensional matrices sampled from a Gaussian distribution. The Gaussian distribution were scaled by up-sampling to match the dimensions within the layer which were kept at 200 X 200 pixels and applied to each channel which help introduce variation within the feature space.

The Gaussian noise is a statistical noise having a probability density function equal to normal distribution also known as Gaussian Distribution. Random Gaussian function is added to image function to generate this noise. Training a neural network with smaller dataset such as our gathered Ankara dataset can cause the network to memorize all training examples and therefore cause the model to over-fit thereby impeding on the model performances. It could equally present a harder mapping problem for such model given the patchy or sparse sampling prints in the high dimensional input space. In order to ensure the StyleGAN model performed optimally, the noise input was then introduced during training and helped smoothened the input space and consequently resulted into a better generalization and faster training and is shown in Figure 7.

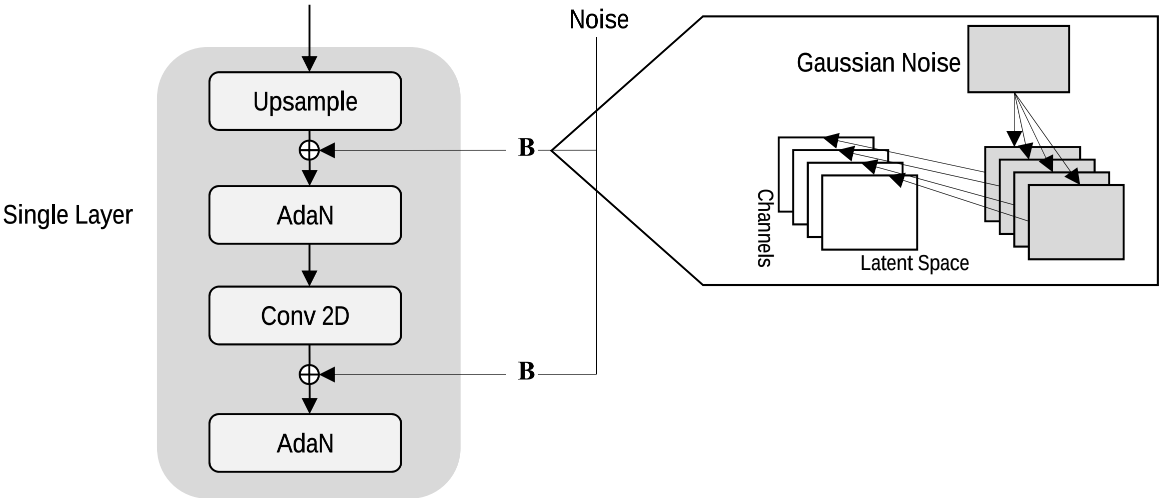

Figure 7 The application of Gaussian noise to StyleGAN model.

2.8 The StyleGAN model training

The StyleGAN model was trained on Tensorflow deep learning framework on Google Collaboratory running NVIDIA K80 GPU. For the StyleGAN model whose architecture is shown in Figure 4, the study adopted iterative training procedure which gave room for model fine-tuning and parameter adjustment till desired Ankara output was gotten from the model. The training was done in mini batches of 32 using Adam optimizer with following hyperparameters (learning rate, lr = 0.001, beta_1, β1 = 0.9, beta_2, β2 = 0.999, epsilon, ℓ = 1ℓ - 07). The metrics used for monitoring the model's' performances were loss values and accuracy at each mini-batches and epochs depending on experimental need.

2.9 Training epochs

In this research experiments, epoch connotes the number of times the learning algorithms successfully made a complete iteration through the entire Ankara dataset. One epoch therefore means that each sample or data points in the Ankara training dataset have had the opportunity of updating the internal model's parameters for a better performance result. An epoch for this research is set to 1000 i.e 1 Epoch = 1000 iterations and is represented in the x-axis of the model performances graphs in the result and discussions.

2.10 Discriminator loss functions

It is a method of quantifying or measuring how well the discriminator was able to distinguish real images from fake ones. This is done by comparing the discriminator's prediction on real images to an array of 1s and the discriminator's prediction on fake images (generated) to an array of 0s. The Binary cross entropy was used to achieve this.

2.11 Generator loss functions

It is a measurement of how well the generator was able to trick the discriminator. When the generator is performing satisfactorily well, the discriminator started classifying the fake images as real (or 1s) i.e., the generator loss valued started approaching 1 (one). The Adam optimizer was used at both the discriminator and generator network.

2.12 Frechet Inception Distance (FID):

Frechet Inception Distance (FID) evaluate the performance of generative adversarial networks. FID represent an improvement of another metric called the Inception Score (IS) which estimates the quality of a collection of synthetic images based on how well the top performing image classification model Inception V3 classifies the images as one of the 1000 known objects. However, inception score does not capture how synthetic images are compared to real images. Conscious of this drawback, FID is chosen as a qualitative metric to evaluate this research experimental GAN models.

Just like Inception Score, FID uses the inception V3 model and is implemented at the last pooling layer of these models to capture computer-vision-specific features of imputed images. Captured activations are calculated for real and generated images and summarized as a multivariate Gausian by calculating the mean and covariance of the images. The distance between these two distributions is what is calculated using Frechet distance otherwise called Wassertein-2 distance.

In this research experiments, FID scores were calculated by loading a pre-trained Inception V3 model first. This was followed by removing the outer layer of the model and taken as activations from the last pooling layer. The outer later was made up of 1000 activations. Therefore, each image was predicted as 1000 feature vector of the images. These 1000 feature vectors are then predicted for a collection of real images from the dataset to offer insight as to how accurate the models are in representing real images. The same procedure was repeated for fake images generated by the generator which then resulted in two collections of 1000 feature vectors each for the real and generated images.

2.13 Precision

Precision metric quantifies the number of correct positive predictions a model makes. It evaluates the fraction of correct classified instances by the discriminator model among the ones classified as positive. The result of precision for a model is a value between 0.0 for a no prediction and 1.0 for a full or perfect prediction. The precision value range of 0.5 to 1.0 which represents 50% to 100% precision indicates a working model in regards to how the model effectively evaluated the fraction of instances that are correctly classified among those instances which are classified as positive. It helped in minimizing the occurrence of false – positives. This metric is represented mathematically as follows:

$$P = TP/(TP + FP) = TP/TPP \quad 1$$

where; P = Precision, TP = True Positive, FP = False Positive and TPP = Total Predicted Positive. The results of the precision score for the three models were recorded for discussion in the result section.

2.14 Recall

This metric calculates the number of true positive divided by the total number of true positives and false negatives. Just like precision, the recall value ranges between 0.0 for a no prediction and 1.0 for a full or perfect prediction. The value of recall is computed as defined as follows:

$$R = TP/(TP + FP) = TP/TAP \quad 2$$

where; R = Recall, TP = True Positive, FP = False Positive and TAP = Total Actual Positive. The recall values of all the competing models were noted for discussions.

2.15 F–Measure or F1 Score

This metric provides a yardstick for combining both the precision and recall into a single measure that captured both properties. There may be situations where a model presents an excellent precision with very terrible recall, or it has a very terrible precision but the recall is very good. F-measure, otherwise known as F1 score is simply the harmonic mean of the recall value and the precision value. Just like precision and recall, a poor F-measure is 0.0 while the best or perfect F – measure score is 1.0. It is calculated using the relationship given as:

$$FM = 2 X [(P * R)/(P + R)] \quad 3$$

where: FM = F-measure, P = Precision, R = Recall.

3. Results and discussion

The fully trained generator of the StyleGAN model was applied to generate images of Ankara patterns after the first epoch which resulted in a noisy output shown in Figure 8, the noisy output was as a result of a smaller size of the Ankara dataset used for these experiments which when compared to other available deep convolutional neural network datasets which uses around three million images which is way higher than the researcher's Ankara dataset with 3000 images.

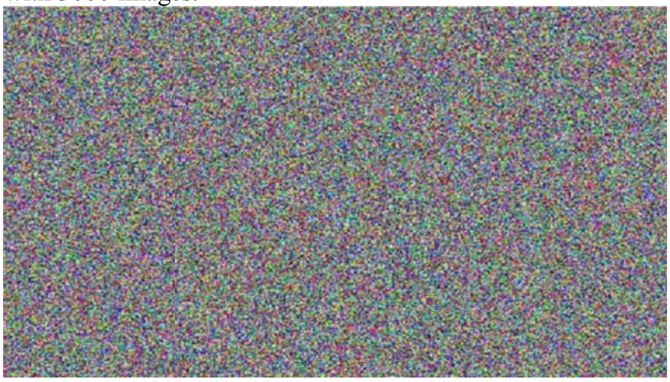

Figure 8 The screenshot of the first attempt of the StyleGAN model **to generate Ankara which resulted in a noisy output.**

In order to remedy the model anomaly, some measures were immediately implemented and they included the addition of Gaussian noise at random intervals to the generator. This helped to smooth the input space and eventually resulted in a better model generalization and faster learning. Adaptive Instance Normalization (AdaIN) was applied to each convolutional layers of the synthesis network as depicted in Figure 6 which aligned the mean and variance of the content features with those of the style (patterns) features of the StyleGAN model. As a result of the modifications on the model, subsequent epochs generated images that showed understandable patterns of Ankara with full colours detailing appealing and unique patterns of African heritage in the Ankara prints which are displayed according to the epoch and Frechet Inception Distance (FID) values corresponding to the epoch that generated the Print. The screenshot in Figure 9 is for Ankara prints generated by StyleGAN model after epoch 1, Figure 10 is for Ankara prints generated by StyleGAN model after epoch 2, Figure 11 is for Ankara prints generated by StyleGAN model after epoch 3 and Figure 12 is for Ankara prints generated by StyleGAN model after epoch 4.

Figure 9 Ankara prints generated by StyleGAN model after epoch 1 with 78.894 FID value.

Figure 10 Ankara prints generated by StyleGAN model after epoch 2 with 75.149 FID value.

Figure 11 Ankara prints generated by StyleGAN model after epoch 3 with 74.269 FID value.

Figure 12 Ankara prints generated by StyleGAN model after epoch 4 with 72.314 FID value.

During training, one of the matrices used in monitoring the model performances was the loss values of both the generator and discriminator. As depicted in Figure 13, around the 100^{th} iteration, the loss value of the discriminator had already dropped to about 0.5 which is an acceptable metric value for the discriminator loss. The early reduction in the discriminator loss value was due to the fact that the discriminator was saddled with a lesser job of identifying the images which are real (from case study dataset) or fake (generated). Meanwhile, it took the generator a lengthy amount of time before it succeeded in fooling the discriminator by generating images with a near perfect look as the real samples from the dataset. During training, what offered insight to when to print and save an output from the model was through the observation of generator loss values. The model output in this context represents the overall image output from the trained model and includes the background of the imputed Ankara samples.

As shown in Figure 13, the discriminator loss value went as high as 8.2 within the 50^{th} training iteration showing that at the start the learning process of the model was quite slow but got improved after more iterative training which got the loss value gradually reduced and steady around the 130^{th} training iteration for the generator. At this point, the model had started learning useful patterns and colours from the imputed data samples from the dataset. At the completion of a training epoch (1000 iterations), the model was used to generate images which shows wonderful and colourful samples of Unique Ankara designs which are subjected to quantitative analysis.

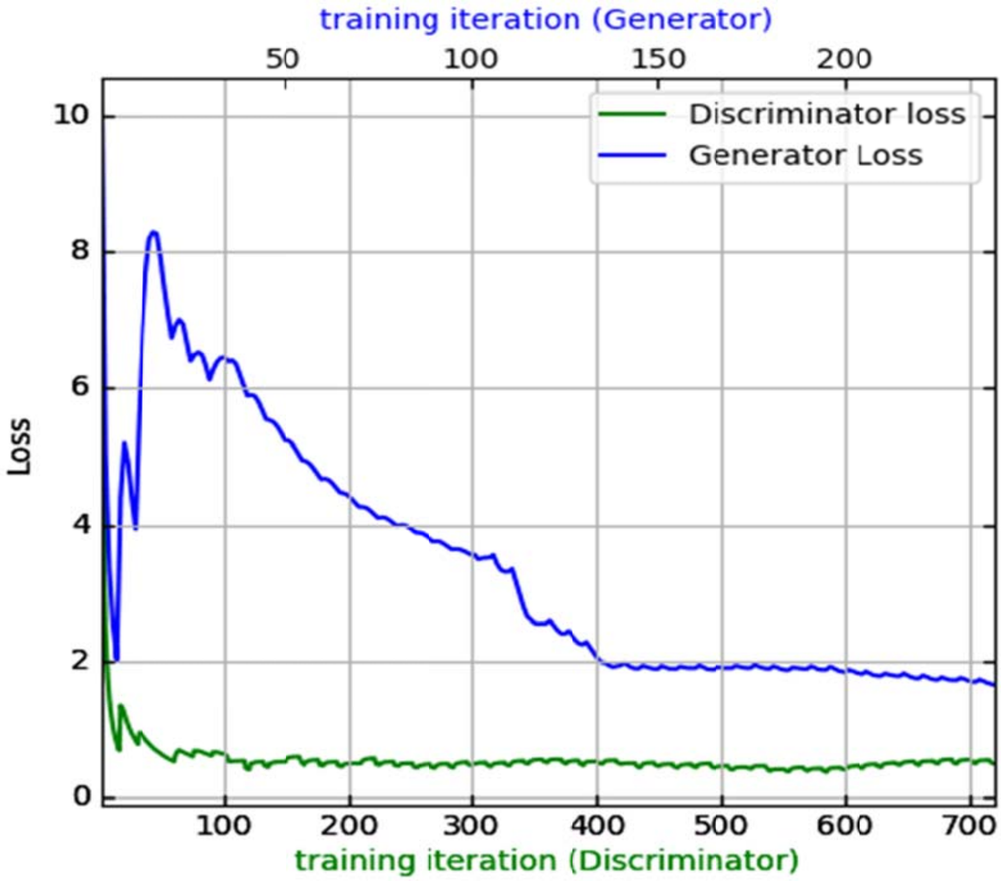

Figure 13 Graph of the generator vs discriminator losses during training

The results of the StyleGAN FID metric score is presented in Table 1 and Figure 14. The results indicate that the FID metric scores for the StyleGAN model for all the epochs are acceptable , as they are below the threshold value of 100 and the FID metric score is also increasing steadily (decreasing) with increase in the epoch.

The recall, precision and F-measure metrics scores for the StyleGAN model are as shown in Table 2 and Figure 15 which show that StyleGAN model has acceptable scores (above 50 %) in all the three metrics.

Table 1 StyleGAN FID metric score versus model **training epochs**

SAGAN Model Training Epochs	SAGAN Model FID metric score
1	78.894
2	75.149
3	74.269
4	72.312

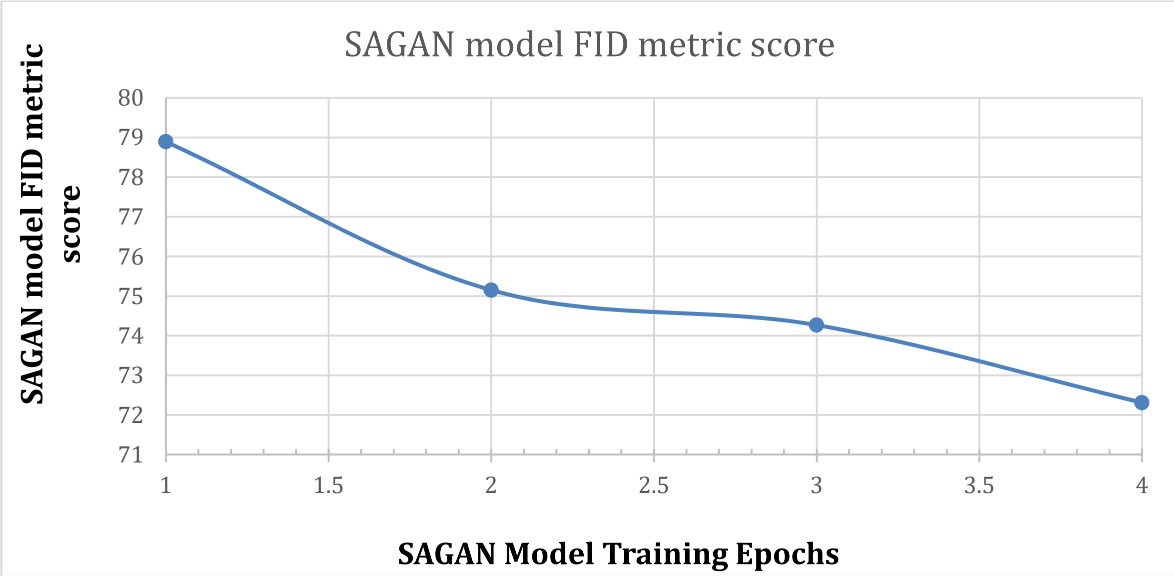

Figure 14 StyleGAN FID metric score versus model training epochs

Table 2 The Recall, Precision and F- Measure metrics scores of the StyleGAN

Recall (%) score for the StyleGAN	Precision (%)score for the StyleGAN	F-measure (%)score for the StyleGAN
58.1	62	56

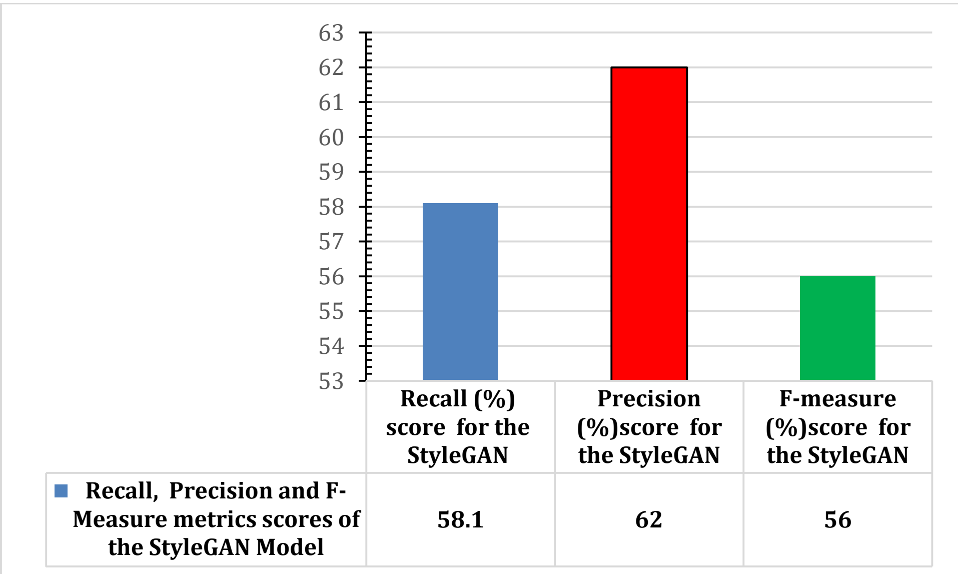

Figure 15 The bar chart of Recall, Precision and F- Measure metrics scores of the StyleGAN Model

3.1 Comparison of the StyleGAN model with some already published models

The study in [33] proposed an automatic colouring model for ethnic costume sketches using generative adversarial networks. The GAN model used adopted smooth loss during training in order to increase stability with a fully connected layer in the output layer to reduce human intervention on parameters. The model successfully transforms hand-drawed ethnic costumes into coloured costumes but lacks in aesthetics. The chosen styleGAN model for this research however uses stochastic noise for stability of training and is capable of generating Ankara prints reflecting unique patterns peculiar to Africans and reflecting aesthetics through its uniquely decorative patterns.

In a similar research, [34] proposed ClothGAN, a Generative Adversarial Network model for generating fashionable Dunhuang clothes blending old and new beauty of the print though with poorly designed garment styles. StyleGAN used for this research demonstrate an unequal capability of generating Ankara with unique African prints. Whereas generated Dunhuang clothe were evaluated using Inception Scores (IS), Ankara generated by StyleGAN model for this research were evaluated using Frechet Inception Distance (FID) which is an improvement of [34].

The study in [35] gave a consolidated backing for AI generated products when their research "Artificial Intelligence in the fashion industry: consumer responses to Generative Adversarial Networks (GAN) technology assessed the customer's willingness to purchase AI generated fashion items. Ankara prints generated through this research using StyleGAN if properly approved could solve the bottleneck posed by the traditional batik mode of producing Ankara with limited supply of unique Ankara in the market to meet the massive demand and usage.

4. Conclusion

The paper presented the Style Generative Adversarial Network (StyleGAN) model development, training and application in generating new and unique African Ankara designs from set of existing Ankara designs fed into the model as input dataset. The model performance was performance was quantified in terms of Frechet Inception Distance (FID) score, Precision, Recall, and –measure or F1 Score. The StyleGAN model was trained on Tensorflow deep learning framework on Google Collaboratory running NVIDIA K80 GPU. The model was trained using a 3000 image dataset locally sourced African Ankara design patterns. The result that the StyleGAN model performed well in all the performance metrics used. Also, when compared with some published research results, the StyleGAN presented in this paper performed better than those other models examined.

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