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Generation of Clothing Items with Jamdani Motif Elements Using Automated Generative Adversarial Networks

Hujaifa Islam, Samiur Rahman Abir, Md. Sakibur Rahman, Hasan Mahmud, Mohammad Shafiul Alam
**Corresponding Author: Samiur Rahman Abir (samiourabir123@gmail.com)*

Department of Computer Science and Engineering, Ahsanullah University of Science and Technology, Dhaka, Bangladesh

Abstract

Clothing serves as an artistic medium for humans to express their preferences, thoughts, and cultural heritage, while the application of machine learning, particularly Generative Adversarial Networks (GANs), remains largely unexplored in the realm of clothing production and design, with designers currently relying on their imaginative skills to create diverse styles. In this article, Conditional Generative Adversarial Networks (cGAN) are used to suggest an automated approach. Neural style transfer and cGAN algorithms are employed. to create traditional clothing with distinctive patterns and a variety of styles. For this study, the Fashion MNIST and Jamdani Motif Dataset datasets were both employed. The conditional GAN model was used to produce several styles of apparel using the MNIST dataset. The Neural Style Transfer model is then used to combine the created picture with the Jamdani Motif pattern from the Jamdani Motif dataset. Using Otsu's image segmentation technique, the foreground, and background of the resulting picture are separated. Performance scores of this model are as follows: Inception Score is 1.3573909, Fréchet inception distance is 1272.222597, Kernel Inception Distance is 636200.667, Coverage Metric is 33.79799. We polled several people on our work output, and the results are detailed in a later section. Generate Jamdani clothing using single pattern and remove extra regions using image segmentation.

Contribution of the Paper: Generation of clothing items with Jamdani Motif pattern.

Keywords: CGAN, Neural Style Transfer, Jamdani Motif, Fashion Mnist, Transposed convolutional layer.

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1. INTRODUCTION

Humans have covered their bodies with clothing from the dawn of humanity. Although clothing styles and patterns may evolve over time, the value of clothing never changes. Humans have gone a long way from using leaves as clothing to having hundreds of various sorts of garments, each with thousands or millions of individual styles. Clothing reflects the human pursuit of beauty, and it has been one of the embodiments of human civilization. Bangladesh is a nation that values tradition and has a diverse culture. Different types of artwork and patterns may be used to display Bangladeshi culture and traditions. Jamdani is a vibrantly patterned, sheer cotton fabric that is traditionally produced by artisans and trainees all across Bangladesh on a handloom. Jamdani textiles combine the intricacy of design with muted or vibrant colors, and the finished garments are highly breathable. The patterns used in Jamdani Motif are very unique and vibrant. The many Jamdani patterns and motifs may make traditional clothing more appealing to us as it is no longer solely used as a covering.. patterns and designs are a part of clothing from ancient times. So designing is a very important part of every clothing item. Design is a form of art and designers use their imagination to create designs. Our main objective is to generate clothing items with Jamdani Motif patterns infused within the clothes. Artificial Intelligence (AI) [1] is the ability of a digital computer to perform tasks commonly associated with intelligent beings. Since its initial discovery in 1955, AI, and particularly machine learning, has aided in the solution of a wide variety of issues. Deep learning has seen significant usage recently in a variety of applications, including computer vision, natural language processing, stock market predictions, and intelligent systems. In recent times deep learning has been also used to generate different images. In 2014 GAN was created for this purpose[2]. Since GAN's development, it has been used to generate the actual face of a human, different music texts, images of different animals, surgical images, etc. GAN can also be used to create artistic designs. The aim is to use a variation of GAN to generate traditional clothing items. . Here [3] Different Jamdani Motif patterns have been produced using conditional GAN. The aim of the project is to develop garments using these numerous Jamdani Motif designs as a design element. The plan is to use Conditional GAN (A variation of GAN) and Neural Style Transfer algorithms [4] to infuse these Jamdani Motif patterns into blank clothing templates of clothing items [5]. Incorporating designs into furniture, creating designs for tiles and blankets, and other items are all possible with Jamdani Motif patterns. All of these concepts may be put into practice utilizing GAN or a GAN variant.

The key contributions of our paper are:

- Inspired designers to create more unique and creative modern clothes with Jamdani Motif patterns.
- Generated clothing items with Jamdani Motif pattern.
- Removed out-of-boundary region using image segmentation.
- Generated clothing items with a single pattern element.
- Used pattern expansion to create new design and its result on the outcome.

2. RELATED WORKS

The process of creating Bangladeshi traditional clothing has not yet been documented in a paper. Numerous various strategies and models have been applied in articles that are connected to our issue. Different types of GAN are introduced in [6]. The description and working procedure of GAN, Semi GAN, C GAN, BiGAN, InfoGAN, AC-GAN, SeqGAN, BEGAN are contained. Then, the real-world application [7] possible use cases of these GAN models are discussed. Finally, ends with the impact of GAN on the current AI field and the relation between GAN parallel intelligence is discussed.

Old clothing designs are used to generate new clothes which have the patterns of old clothes but the design shape of a new fashion style [8]. DISCO-GAN is used which is a variation of GAN. The 6 generated clothes will be different for every client in an online shopping site and the feedback given by the clients will be given back to the model to improve the performance. The researchers ended the paper with a conclusion that using such a model in an online store can hugely increase sales and have a recommendation system [9] that can pique a client's interest. Generative Adversarial Networks for Garment Design are proposed [10]. A deep learning model, Design-AttGAN is introduced which can automatically edit garment images conditioned on certain user-defined attributes. Att-GAN is first employed for the development of clothing pictures, however as a result, its performance is seen to be subpar. To solve this issue, the design-AttGAN model is used. When learning several characteristics, the Design-AttGAN model performs better than the basic AttGAN model, and it also performs better on a smaller dataset.

It is suggested to use generative adversarial networks to design shoes in [11].First, a stable Generative Adversarial Network (GAN) trained only on sports shoes was created through the experiment using a variety of models. The dream shoe generator is the primary goal, however it can only be achieved by successfully completing the following three steps: Generation of Simple Shoes Classification of Functional Types Classification of Attributes They picture a Conditional GAN for shoe generators that accepts a vector of attributes denoting the characteristics a person wants in a shoe.

The main aim is to elucidate latent match rules considering clothing attributes under the framework of the generative adversarial network (GAN) [12]. Then, outfit comparisons are produced using these latent match criteria. An expanded version of c-GAN called attribute-GAN learns mapping from a set of clothes. A generator and two discriminators are employed in this model. One is a multitask attribute classifier network, while the other is a convolutional "PatchGAN" discriminator that may capture high-frequency structure information in small patches. A large-scale dataset of 19,081 pairs of collocation clothing images from Polyvore is compiled. 15,000 pairs were selected for model training, and 3000 pairs were used for validation and 1081 pairs were utilized for testing. Nine types of clothing attributes from a total of 93 attributes are extracted.Attribute-GAN results are compared with the state-of-the-art methods including cGAN+L1, cGAN, and Vanilla GAN. It is observed that Attribute-GAN achieves the highest scores compared to other models. A regression CNN model [13] with MAE (Mean Absolute Error) is also trained to predict the matching degree in terms of generated image pairs. After 50 epochs, the loss value was no longer descending. Their Attribute-GAN achieved the best diversity of Synthetic images and matching degrees of generated clothing outfits.

An extended working procedure is applied to fashion GAN in [14] which is an Improved version of BicycleGAN that maps the desired fabric image to a selected fashion sketch or a contour image of the garment.A two-to-one GAN-designed architecture is shown here that can produce an image with specific visual information and that may be expressed as a loss function to produce regular texture pictures, such as stripe texture. The fashion sketch or contour picture limits the final created image's form, while the fabric pattern limits the color and substance of the image. Additionally, an additional local loss module is included to regulate the texture synthesizer of the generator. FashionGAN learns a two-to-one mapping among three image domains. The architecture of FashionGAN is based on cVAE-GAN and cLR-GAN. A garment dataset of 24,000 images taken from e-commerce sites and a public garment dataset and another fabric pattern dataset by cropping a patch from each image in the garment dataset was built for the research. FashionGAN is a reliable model that functions for fabrics with a single color and a regular pattern, but it cannot map an irregular one and that's its limitation and is an end-to-end framework [15] that only needs users to input a desired fabric image and a fashion sketch. FashionGAN establishes a bijection relationship between fabric and latent vector so that the latent vector can be explained with fabric information.

Al-Muzaini et al. [16] suggested an Arabic picture captioning model. Their integrated model learns picture characteristics and captions separately. The model is three-part. First, a CNN [17] with LSTM builds a language model to encode linguistic sequences of different lengths. Second, a CNN builds an image feature extractor model [18] to extract fixed-length vector features from pictures. Third, a decoder model uses vectors from LSTM models [19] to create a final prediction. Crowdsourcing, Arabic translators, and Google translation API translated sections of the Flicker8k dataset (2261 photos) to Arabic. ClothGAN is proposed in [5]. Which is an innovative framework for designing new patterns and styles of clothes based on a generative adversarial network (GAN) and style transfer algorithm [20] which can generate e new patterns and styles of clothes with Dunhuang elements (the traditional art of China) by using the Dunduang dataset (52,908 images of Dunhuang) and the Fashion MNIST dataset [21], inspired by FashionGan, a website that allows users to input a desired clothes sketch and a photograph of a certain fabric to create a virtual clothing image. The GAN module and the style transfer module make up the two main components that make up the ClothGAN architecture. The style transfer neural network is used to add Dunhuang elements to the generated clothing, blending the old and new beauties. The GAN module (Generator and discriminator are composed of multi-layer CNN) is trained to generate new clothing patterns from Fashion MNIST images and random noise. Comparable models DCGAN and FashionGAN don't have ClothGan's average IS and HPS score.

3. PROPOSED METHOD

This section provides a method for generating clothing items with the Jamdani Motif pattern. Our process has been broken down into 7 key steps. Workflow of the proposed architecture in Fig. 1.

3.1. Dataset Overview

Fashion Mnist Dataset Fashion-MNIST is an open-source dataset. Fashion-MNIST is a dataset of Zalando's article images consisting of 70,000 images, among them 60,000 images are training set, and 10,000 images are test set. The dataset is downloaded from Kaggle, which is very popular in terms of providing different types of datasets.

Jamdani Motif Dataset : Jamdani Motif pattern is used for this work which is generated from the Jamdani motif generator [3]. Jamdani Motif patterns are the traditional art of our country which are automatically generated from the generator [22] through machine learning using conditional GAN. So, generating of design will be according to requirements. Jamdani Motif dataset see in Table 1.

Attribute	Value
Dataset characteristics	Multivariate
Attributes characteristics	Integer
Associated Tasks	Generating
No of Attributes	28*28
No of Instances	As much as we need

Table 1: Jamdani Motif Dataset table

3.2. Dataset Description

Fashion MNIST : Fashion-MNIST is a dataset of Zalando's article images—consisting of a training set of 60,000 examples and a test set of 10,000 examples. Each example is a 28x28 grayscale image, associated with a label from 10 classes. Each image is 28 pixels in height and 28 pixels in width, for a total of 784 pixels in total. Each pixel has a single pixel value associated with it, indicating the lightness or darkness of that pixel, with higher numbers meaning darker. This pixel value is an integer between 0 and 255. The training and test data sets have 785 columns. The first column consists of the class labels. Description of the dataset and the labels are in Table II and 3 respectively.

Category	Label
T-shirt/top	0
Trouser	1
Pullover	2
Dress	3
Coat	4
Shirt	6
Snicker	7
Bag	8
Ankle Boot	9

Table 2: Fashion MNIST labels

Jamdani Motif : Jamdani Motif is the traditional art of Bangladesh, which is created based on Jamdani saree, Nokshi Katha, etc. the traditional cloth from various

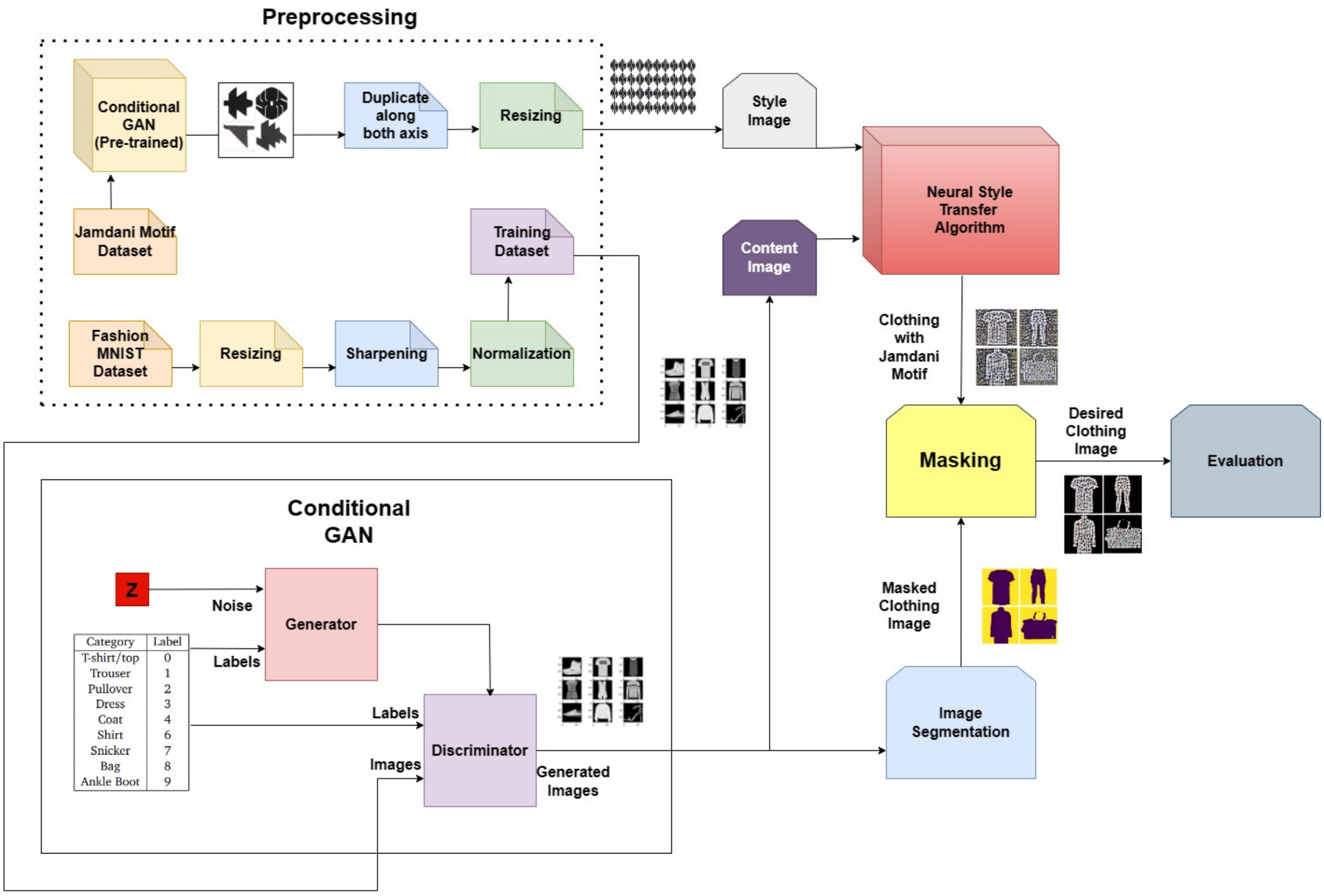

Figure 1: Workflow of the proposed architecture

Attribute	Value
Dataset characteristics	Multivariate
Attributes characteristics	Integer
Associated Tasks	Generating
No of Attributes	28*28
No of Instances	70,000

Table 3: Fashion MNIST

Bangladeshi Brands and also from the historical place of Bangladesh. At first, pictures are taken, and then processed the pattern. So, it is a generator that is constructed by conditional GAN. So, the generation of the pattern will be according to the requirements [23]. All the patterns or designs are 28x28 grayscale images. Each image is 28 pixels in height and 28 pixels in width, for a total of 784 pixels in total. Each pixel has a single pixel value associated with it, indicating the lightness or darkness of that pixel, with higher numbers meaning darker [24]. This pixel value is an integer between 0 and 255.

Data pre-processing : "More data beats clever algorithms, but better data beats more data." So, the data is preprocessed, and it is easy to perform for the model. Pixel values are taken as input, so none of the attributes are empty or null which is an advantage for calling it better data. But to perform the model, the image size is 28x28 pixels. But not every image size will be that size. As the input value is the pixel, every larger image is converted into 28x28 pixels, and generated all the motif patterns into 28x28 pixels also. The pixel value or the intensity is an integer between 0 to 255. But the intensity is divided by 255 to process it because if the value is between 0 to 1 then it is easier to compute the model or can say the model can compute the process smartly.

3.3. Conditional GAN with Fashion MNIST

Conditional GAN is a variation of GAN model. Here are dataset is Fashion MNIST. We have resized the images to 112X112 and normalized them before passing them through the model. The detailed architecture of our model is depicted in Fig. 2. The hyperparameters of Conditional GAN in Table IV.

An image and numeric label help the discriminator identify fake photos. The label (1 x 50) is embedded and concatenated with the image after a thick, reshaping layer. Leaky ReLu activates two 3 x 3 convolution layer blocks. Forecasting employs large layers after flattening and dropout. Generators utilise random noise, whereas discriminators use pictures. After concatenating noise and label embedding, it passes through 3 transpose convolution layers (4 x 4, 4 x 4, 7 x 7 filters) with Leaky ReLu and TanH activation. The transpose convolution layers increase the image to 28 x 28 x 1. Training and testing data included 70,000 Fashion MNIST labelled pictures. A batch of 128 generator weights was frozen. Latent dimension (noise) and labels yield images. The generator's weights are updated using

Attribute	**Our Model**	**ClothGAN**	**DCGAN**
Number of filters in the convolution layer	128	16	1024,512,256,128
Filter Shape	Generator (4.4), Discriminator(3.3)	Generator (3.3), Discriminator(3.3)	Generator (4.4), Discriminator(3.3)
Activation function (both generator and discriminator)	Recky ReLu, Tanh	Recky ReLu, Tanh	ReLu
Optimizer	Adam	Adam	mini-batch stochastic gradient descent
Number of filters in the transpose Convolution layer	128	16	1024,512,256,128
Loss	Binary Crossentropy	Binary Crossentropy	Binary Crossentropy
Number of Epoch	100	1000	5
Batch size	128	-	128
Latent Dimension	100	-	100
Learning Rate	0.0002	0.01	0.0002
Alpha and Beta	0.2, 0.5	0.717, 0.283	0.2, 0.5

Table 4: Hyper-parameters comparison

discriminator and generator losses to improve clothing images. Discriminator is trained 100 times while generator is fixed, then generator is trained. As the discriminator becomes better at spotting fake clothes, the generator gets better at making credible photos. After label training, the generator can make real clothes.

3.4. Jamdani Motif generation using Conditional GAN

The conditional GAN generates Jamdani pattern. A neural style transfer picture uses this design. CGANs are used to generate Jamdani motifs. Handwoven jamdani contains exquisite designs. Researchers preprocessed photographs after collecting Jamdani patterns. After training a CGAN network, they created Jamdani patterns resembling the dataset. The CGAN conditional component let

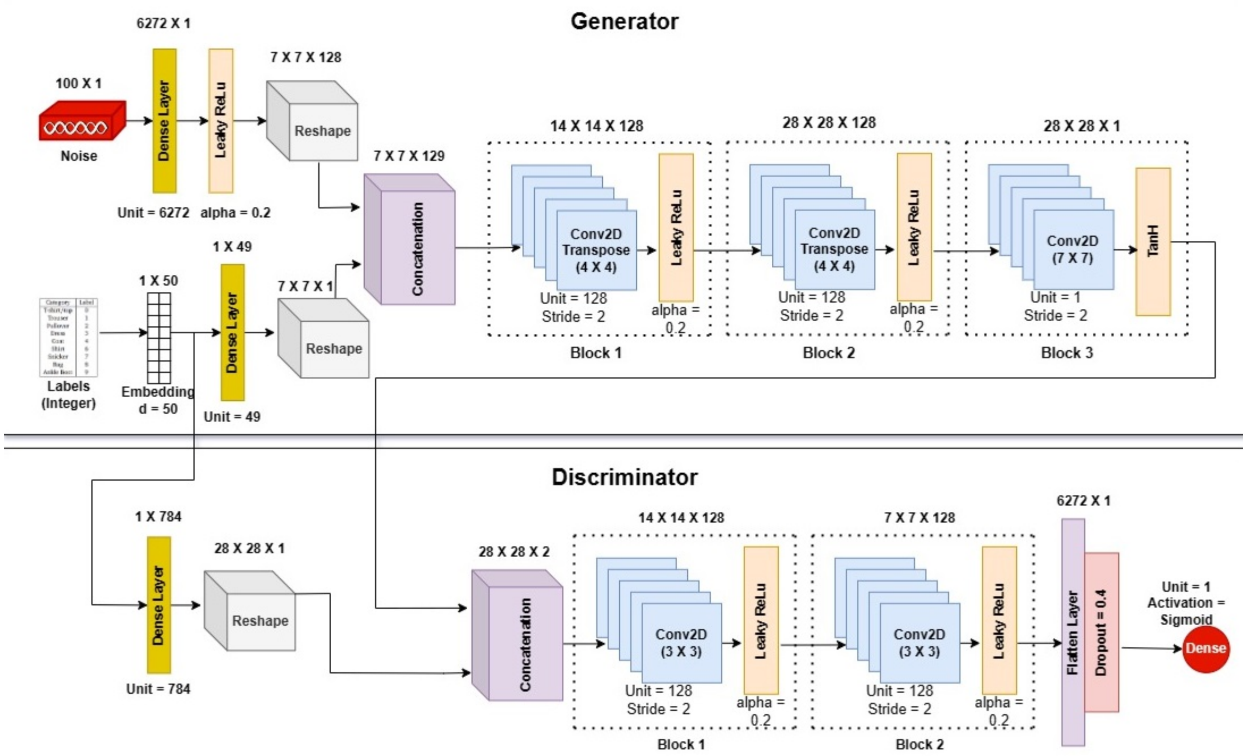

Figure 2: Architecture of Conditional GAN with Fashion MNIST

developers set motif complexity and style input requirements. Researchers preprocessed photographs after collecting Jamdani patterns. After training a CGAN network, they created Jamdani patterns resembling the dataset. Developers may control motif complexity and style using CGAN conditional component input conditions. FID, KID, and visual examination assessed the authors' technique. Their method produced pleasing Jamdani designs like the dataset. The created motifs statistically matched the dataset according to FID and KID scores. This illustrates that CGANs can make intricate textile designs like Jamdani motifs. The method may develop novel textile materials and designs. Jamdani patterns are used for neural style transfer model images.

3.5. Jamdani Motif pattern expansion

The Jamdani patterns generated from [3] is a single pattern element that is not suitable as an input for the Neural Style Transfer model. So the pattern has been duplicated N*M times (N and M are hyper-parameters and they represent a number of columns and rows used for duplicated patterns) and then that image is used as an input. The single pattern is used multiple times for making duplicate images. In the duplicate image, there are 8 rows and 20 columns are presented in the Fig. 3.

3.6. Neural Style Transfer

Neural Style Transfer is a type of convolutional neural network. Here VGG 19 model has been used as a transfer

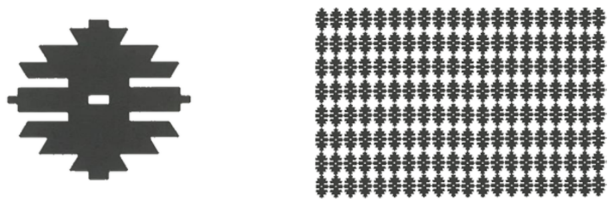

Figure 3: Jamdani pattern extension

Attribute	Value
Number of Rows	8
Number of Columns	20

Table 5: Expended pattern rows and columns

learning to create the neural style transfer model. Uses of Blocks from VGG19 model in Table 6. Hyper-parameters Used for Neural Style Transfer in Table 7.

After training this model can merge content images (generated clothing item) and style images (generated Jamdani Motif pattern) together to create clothing items with the Jamdani Motif pattern.

3.7. Image Segmentation

The output of Neural Style Transfer model has a problem. The pattern gets printed outside the boundary of the clothing item. To solve this issue image segmentation has been done on the content image (generated image from conditional GAN). Otsu's image segmentation has been used

Content Layer	style layer
Block5_Conv13	Block1_Conv1
Block5_Conv14	Block2_Conv3
	Block3_Conv6
	Block4_Conv9
	Block5_Conv13

Table 6: Uses of Blocks from VGG19 model

Attribute	Value
Learning rate	0.02
Optimizer	Adam(Beta=0.99,epsilon=0.1)
Style weight	6
Content weight	-2
Total Variation weight	30
Epoch	10
Steps per epoch	10

Table 7: Hyper-parameters Used for Neural Style Transfer

to separate the foreground and background, is depicted in Fig. 4.

Figure 4: Image segmentation

3.8. Masking

Finally, Ostu's image segmentation's masked picture removes the output's backdrop. The foreground pixels have remained intact and the background pixels have been set to 0, which is presented in the Fig. 5.

4. Empirical Evaluation

Usually, the machine learning model's performance is evaluated using the accuracy/recall/f1 score [25]. But the actual label of the dataset is needed to calculate these things. Since GAN models often produce things, a dataset for a GAN model lacks any real labels. The effectiveness of a generative model is often assessed in two ways.

4.1. Quantitative measure

Generative Adversarial Networks (GANs) efficacy is measured quantitatively. These metrics provide impartial evaluations of the produced data and the GAN model's ability to duplicate the training set's distribution [26]. This

Figure 5: Masking

research uses quantitative measures, including Fréchet Inception Distance (FID), Inception Score (IS), Kernel Inception Distance (KID), and Coverage Metric to assess the Conditional GAN model. Results from these measures are in the Table 8.

Attribute	Value
Inception Score	1.3573909
Fréchet inception distance	1272.222597
Kernel Inception Distance	636200.667
Coverage Metric	33.79799

Table 8: Quantitative measure

4.2. Qualitative measure

Qualitative measures are subjective methods used to evaluate the performance of Generative Adversarial Networks (GANs) based on visual inspection of the generated data [27].These metrics are frequently used to supplement quantitative metrics and offer a more thorough assessment of the GAN model.Visually viewing the created pictures and evaluating their general quality, realism, and diversity are considered qualitative measurements. Here, the qualitative assessment of the mode is obtained using the Human Perception Score (HPS). A series of different questions have been asked to various kinds of people to evaluate the performance of the model. The result of the survey is given below.

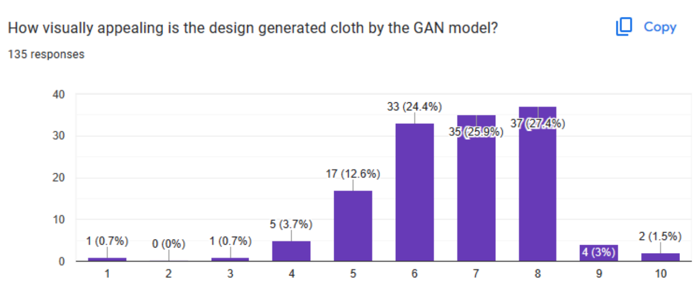

Figure 6: Human Evaluation Q&A 1

According to the Fig. 6, the highest rating received is 8, receiving 27.4% of the vote, which indicates the design has great visual appeal.

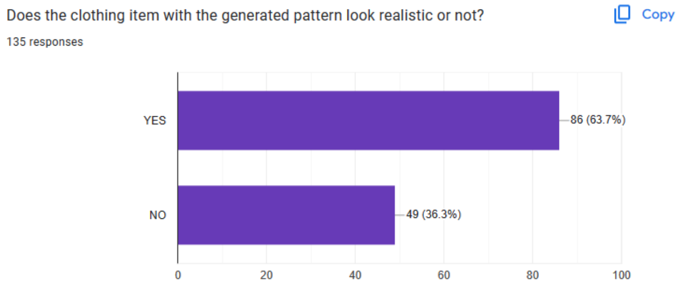

Figure 7: Human Evaluation Q&A 2

According to this Fig. 7, a small proportion of respondents disagreed that Jamdani's textile patterns seem realistic.

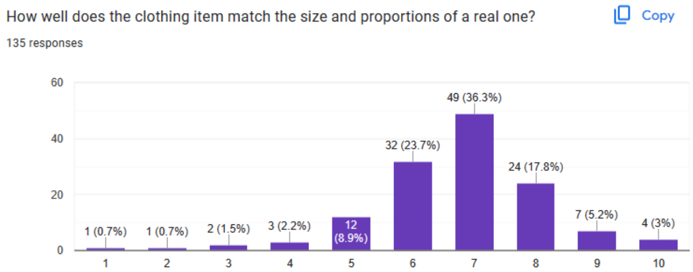

Figure 8: Human Evaluation Q&A 3

On a scale of 1–10, of Fig. 8, voters decided whether the clothing item matched the genuine one in terms of size and proportion. Rating six received the most votes from the general public, with a percentage of 28.6%.

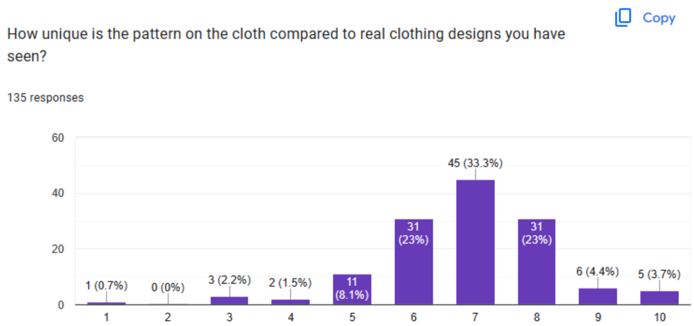

Figure 9: Human Evaluation Q&A 4

Voters awarded the fabric's pattern an excellent rating according to Fig. 9 when compared to other real garment patterns they had seen (figure reflects the vote participation %).

According to the data of Fig. 10, respondents responded well when it came to the design seeming appropriate for use on apparel. About 60% of the participants believed that the design was significantly better.

Figure 10: Human Evaluation Q&A 5

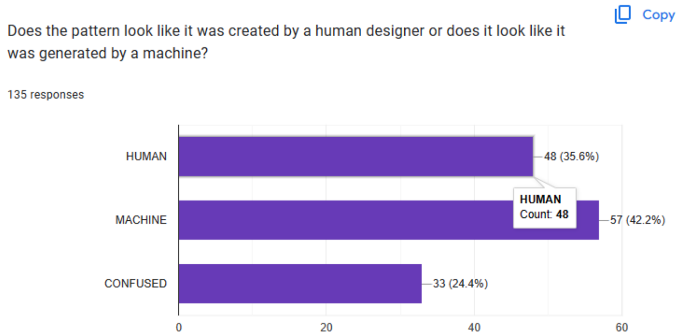

Figure 11: Human Evaluation Q&A 6

When asked whether a human or a machine looked to have created the pattern in the Fig. 11, the majority of voters (42.2%) decided to favor the Machine. This shows that there are still a lot of scopes for improvement in order to make this design more precise, accurate, and acceptable as a human design.

5. CONCLUSION

Researchers often find it difficult to find the perfect balance between form and function when designing clothing. It's also challenging to train a machine learning model to understand creative work. This study presents a methodology for making garments that may demonstrate artistic and creative ability. Jamdani Motif adorned garments are possible with this style. The findings demonstrate that the produced pictures from the model might serve as a resource for, or provide inspiration for, creative clothing designers. It may serve as a useful tool for recreating Bengali clothing's historic and cultural elements. Although the Jamdani Motif is most often associated with traditional garments like the saree and the panjabi, this model is able to successfully transfer the design to more contemporary articles of apparel like t-shirts, purses, pants, etc. This kind may wear modern and traditional clothes. The model creates basic outfits and low-resolution photographs. Flaws and future development, including this model, are noted. Machine learning transforms art and creativity. Arts, music, film creation, architecture, clothing design, etc. benefit from new technology. However, human creativity and ideas should not be neglected. Combine machine learning and modern technology with human minds to create something beautiful and unique that may brighten humanity's future.

References

[1] K. M. Hasib, M. R. Islam, S. Sakib, M. A. Akbar, I. Razzak, M. S. Alam, Depression detection from social networks data based on machine learning and deep learning techniques: An interrogative survey, IEEE Transactions on Computational Social Systems 10 (4) (2023) 1568–1586. doi:10.1109/TCSS.2023.3263128.

[2] Q. Li, X. Wang, B. Ma, X. Wang, C. Wang, S. Gao, Y. Shi, Concealed attack for robust watermarking based on generative model and perceptual loss, IEEE Transactions on Circuits and Systems for Video Technology 32 (8) (2021) 5695–5706.

[3] M. T. R. Shawon, R. Tanvir, H. F. Shifa, S. Kar, M. I. Jubair, Jamdani motif generation using conditional gan, in: 2020 23rd International Conference on Computer and Information Technology (ICCIT), IEEE, 2020, pp. 1–6.

[4] K. A. Lima, K. Md Hasib, S. Azam, A. Karim, S. Montaha, S. R. H. Noori, M. Jonkman, A novel data and model centric artificial intelligence based approach in developing high-performance named entity recognition for bengali language, PLOS ONE 18 (9) (2023) 1–36. doi:10.1371/journal.pone.0287818.
URL https://doi.org/10.1371/journal.pone.0287818

[5] Q. Wu, B. Zhu, B. Yong, Y. Wei, X. Jiang, R. Zhou, Q. Zhou, Clothgan: generation of fashionable dunhuang clothes using generative adversarial networks, Connection Science 33 (2) (2021) 341–358.

[6] K. Wang, C. Gou, Y. Duan, Y. Lin, X. Zheng, F.-Y. Wang, Generative adversarial networks: introduction and outlook, IEEE/CAA Journal of Automatica Sinica 4 (4) (2017) 588–598.

[7] K. M. Hasib, S. Azam, A. Karim, A. A. Marouf, F. M. J. M. Shamrat, S. Montaha, K. C. Yeo, M. Jonkman, R. Alhajj, J. G. Rokne, Mcnn-lstm: Combining cnn and lstm to classify multi-class text in imbalanced news data, IEEE Access 11 (2023) 93048–93063. doi:10.1109/ACCESS.2023.3309697.

[8] M. Singh, U. Bajpai, V. V, S. Prasath, Generation of fashionable clothes using generative adversarial networks: A preliminary feasibility study, International Journal of Clothing Science and Technology 32 (2) (2020) 177–187.

[9] K. M. Hasib, M. A. Habib, N. A. Towhid, M. I. H. Showrov, A novel deep learning based sentiment analysis of twitter data for us airline service, in: 2021 International Conference on Information and Communication Technology for Sustainable Development (ICICT4SD), IEEE, 2021, pp. 450–455.

[10] C. Yuan, M. Moghaddam, Garment design with generative adversarial networks, arXiv preprint arXiv:2007.10947.

[11] J. Deverall, J. Lee, M. Ayala, Using generative adversarial networks to design shoes: the preliminary steps, CS231n in Stanford.

[12] L. Liu, H. Zhang, Y. Ji, Q. J. Wu, Toward ai fashion design: An attribute-gan model for clothing match, Neurocomputing 341 (2019) 156–167.

[13] K. M. Hasib, N. A. Towhid, K. O. Faruk, J. Al Mahmud, M. Mridha, Strategies for enhancing the performance of news article classification in bangla: Handling imbalance and interpretation, Engineering Applications of Artificial Intelligence 125 (2023) 106688. doi:https://doi.org/10.1016/j.engappai.2023.106688.
URL https://www.sciencedirect.com/science/article/pii/S0952197623008722

[14] Y. R. Cui, Q. Liu, C. Y. Gao, Z. Su, Fashiongan: display your fashion design using conditional generative adversarial nets, in: Computer Graphics Forum, Vol. 37, Wiley Online Library, 2018, pp. 109–119.

[15] R. Jani, M. S. I. Shanto, B. C. Das, K. M. Hasib, Machine learning-based social media news popularity prediction, in: International Conference on Hybrid Intelligent Systems, Springer, 2022, pp. 714–725.

[16] H. A. Al-Muzaini, T. N. Al-Yahya, H. Benhidour, Automatic arabic image captioning using rnn-lstm-based language model and cnn, International Journal of Advanced Computer Science and Applications 9 (6).

[17] K. M. Hasib, A. Tanzim, J. Shin, K. O. Faruk, J. Al Mahmud, M. Mridha, Bmnet-5: A novel approach of neural network to classify the genre of bengali music based on audio features, IEEE Access 10 (2022) 108545–108563.

[18] W. Zhang, Y. Liu, C. Dong, Y. Qiao, Ranksrgan: Generative adversarial networks with ranker for image super-resolution, in: Proceedings of the IEEE/CVF International Conference on Computer Vision, 2019, pp. 3096–3105.

[19] K. M. Hasib, N. A. Towhid, M. R. Islam, Hsdlm: a hybrid sampling with deep learning method for imbalanced data classification, International Journal of Cloud Applications and Computing (IJCAC) 11 (4) (2021) 1–13.

[20] K. C. Chan, X. Wang, X. Xu, J. Gu, C. C. Loy, Glean: Generative latent bank for large-factor image super-resolution, in: Proceedings of the IEEE/CVF conference on computer vision and pattern recognition, 2021, pp. 14245–14254.

[21] A. Karim, P. Ghosh, A. A. Anjum, M. S. Junayed, Z. H. Md, K. M. Hasib, A. N. Bin Emran, A comparative study of different deep learning model for recognition of handwriting digits.

[22] P. Behjati, P. Rodriguez, A. Mehri, I. Hupont, C. F. Tena, J. Gonzalez, Overnet: Lightweight multi-scale super-resolution with overscaling network, in: Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision, 2021, pp. 2694–2703.

[23] K. M. Hasib, M. S. Iqbal, F. M. Shah, J. A. Mahmud, M. H. Popel, M. I. H. Showrov, S. Ahmed, O. Rahman, A survey of methods for managing the classification and solution of data imbalance problem, arXiv preprint arXiv:2012.11870.

[24] R. M. Umer, G. L. Foresti, C. Micheloni, Deep generative adversarial residual convolutional networks for real-world super-resolution, in: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops, 2020, pp. 438–439.

[25] K. M. Hasib, F. Rahman, R. Hasnat, M. G. R. Alam, A machine learning and explainable ai approach for predicting secondary school student performance, in: 2022 IEEE 12th Annual Computing and Communication Workshop and Conference (CCWC), IEEE, 2022, pp. 0399–0405.

[26] E. Lu, X. Hu, Image super-resolution via channel attention and spatial attention, Applied Intelligence 52 (2) (2022) 2260–2268.

[27] G. Kim, J. Park, K. Lee, J. Lee, J. Min, B. Lee, D. K. Han, H. Ko, Unsupervised real-world super resolution with cycle generative adversarial network and domain discriminator, in: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops, 2020, pp. 456–457.