PersiDani Fusion: Investigating Jamdani and Persian Motif Fusion through Image Processing, Transfer Learning, and GAN

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Abstract

Jamdani is a traditional heritage of the Indian subcontinent and holds a rich history in Bangladesh. Originally inspired by Persian patterns- the geometric forms of the Jamdanis have evolved over time by incorporating diverse natural elements like foliage, flowers, and birds leading to a shift from the old original aesthetic. This study aims to revive the traditional Persian pattern and fuse it with the current Jamdani designs. We employed a multi-faceted approach to explore the fusion of traditional Jamdani designs with Persian motifs by applying image processing, transfer learning, and generative adversarial networks (GANs). Our methodology involves leveraging image processing and neural style transfer to seamlessly merge Jamdani and Persian motifs. Additionally, we investigate StyleGAN's ability to generate fresh motifs that capture the essence of both traditions. To facilitate this fusion, we have curated a new dataset for Persian. Using conventional image processing, transfer learning, and GANs, we conducted an experiment to produce unique motifs by combining Jamdani and Persian designs, followed by a comparative analysis of the resulting images. Our results successfully generate new Jamdani motifs. Through experiments and analysis, we contribute to computer vision and textile artistry, fostering innovation in motif generation and cultural preservation. This research encourages further exploration of diverse cultural motifs in the digital realm.

Keywords: Pattern Fusion, Image Processing, Neural Style Transfer, StyleGAN

1 Introduction

Jamdani is a traditional handloom textile of Bangladesh that is highly regarded for its intricate designs and fine craftsmanship. The word 'Jamdani' came from the Persian language, combining 'Jam' and 'Dani' meaning "flower" and "Jar" respectively which means- Jar of Flowers [1]. Originally inspired by Persian motifs, Jamdani evolved over time to combine modern and local elements into distinctive patterns. Persian designs were characterized by intricate floral patterns, geometrical shapes, and stylized motifs. These motifs were skillfully woven into the fabric, reflecting the refinement and elegance associated with Persian aesthetics. As time passed, the wavers (tati) modified the Jamdani motifs with local and natural motifs like lotus, flowers, leaves, birds, swan, peacock, fish ,and animals along with some original varieties of paar, buti, techri, jaal, chhitra, etc [2]. The artisans who make these sarees, create the themes based on the knowledge of their previous experiences and knowledge passed down from their masters and the motifs are not recorded or preserved to makes each Jamdani saree a distinct piece of art. Thus, the ancient motifs have been lost over time and incorporating natural elements into their designs, causes the predominance of Persian motifs to gradually fade.

Everything in today's world is tech-based. It has greatly simplified our lives. The global textile market is expected to grow from $1.5 trillion in 2020 to roughly $2.25 trillion in 2025 [3]. The article [4] said computer-based technologies are frequently used in many areas of the textile business, including design analysis, peg planning, computerized jacquard looms, computerized knitting machines, pattern creation, software that repeats patterns on home textiles for clothing, testing, and many other areas.

Image processing technology has already started making inroads in textile fields. Investigations into fiber cross-section analysis, cotton maturity measurement, trash in cotton estimation, measurement of pore size distribution, analysis of fiber crimp, fiber blending, yarn structure, including yarn thickness, twist, and hairiness, determination of weave type, detection of fabric defects, creating patterns, etc. have all been the subject of research [5]. Over the past 20 years, artificial intelligence (AI) has gained momentum in the textile sector. Machine learning, a part of AI, has a significant impact on several tasks, including fabric purity checking, material checking, preventative maintenance, design extraction, and design and pattern generation [6–8]. By fusing the stylistic elements of a referred style image with the content aspects of a given content image, neural style transfer aims to create a new image, this principle can be used in the textile industry to generate new patterns for garments. Recently, generative adversarial networks (GANs) have become popular in fabric pattern recognition and generation [9]. GANs work well in managing the fusion of images in several fields [10] where significant aspects of two or more picture sources are extracted, and combined to provide a single image that is more useful and instructive for later applications.

In the past, Jamdani artisans wove motifs directly on the loom, but now they follow designs from catalogs created by fashion designers. New motifs are also being designed by artists and entrepreneurs, expanding beyond traditional weavers. This change raises concerns as traditional motifs may be altered, and ancient Persian designs in Jamdani motifs have nearly disappeared. There is no dataset for Persian motifs to integrate them with modern Jamdani. Creating a combined Jamdani and Persian motif requires a method that is both computationally simple and visually appealing, which could help revive the old Jamdani tradition. We made such attempts to develop an experiment that will create a new motif essence of both real Jamdani and Parsian designs by fusion. This study aims to create unique Jamdani motifs that will bridge the gap between the weavers and designers not only preserving the current Jamdani motifs from further extinction by carrying on the legacy of the surviving motifs but also bringing back the original Persian motifs once again. Objectives of our paper are:

1. We have created new datasets for Persian motifs and Jamdani motifs. The datasets are available in link. To our knowledge, there is no published dataset of Persian motifs. As a result of this contribution, generative AI will be applied to textile materials in a significant way.
2. Neural Style transfer has been applied to the dataset Persian and current Jamdani dataset and has shown significant results in terms of generating the new motif.
3. Further, we have incorporated styleGAN to generate new motifs that embody characteristics of both Jamdani and Persian motifs.
4. A comparative analysis has been conducted among conventional image processing, transfer learning, and Generative Adversarial Network (GAN) methods to generate fused or

unique motifs by combining Jamdani and Persian designs.

5. The research carried out in this study allows for further exploration and appreciation of diverse cultural motifs and helps to emerge the computer science and textile industries. In addition, it helps to maintain the national heritage and the capacity for generative AI in the practical domain.

2 Literature Review

During the past 67 years, the interest in pattern recognition and image processing has significantly increased. The study of pattern properties and the design of recognition systems are both included in the research of pattern recognition [11]. [12]. In the textile sector, the main task is quality control and manual inspection attempts are being replaced with automated visual inspection using camera and image processes [13]. [14] presents a survey of computer vision approaches for detecting fabric defects, with focus on texture analysis-based methods, including the use of Gabor filtering, histogram equalization, and Fourier analysis to detect periodic textures. It also used RGB to grayscale conversion and noise removal to improve detection scores. Different histogram-based, co-occurrence matrix-based, mathematical morphology-based, Wavelet and Fourier transform-based techniques are used for fabric defect direction [15]. Moreover image processing techniques like circular haugh transform is used to measure fabric drape [16], measure and demonstrate fabric color [17]. However, no study has worked on creating or fusing textile design the patterns using conventional image processing methods.

Style Transfer is an effective technique for combining different styles into unique patterns. It allows blending of two images style while keeping the distinct features of each style. The study [18] introduced a Neural Algorithm of Artistic Style using CNNs to separate and merge content and style from images, enabling the creation of visually appealing designs by blending one image's content with another style. For better feature extraction self attention to the encoder-transfer-decoder framework can be used [19, 20]. The author [21] suggested using an autoencoder network approach to modify fused images so that style analysis tasks can be done more effectively. It enhances the robustness and quality of stylized images by resolving modifications in photographic images and enhancing details of style-shifting. VGG19 neural network is widely used in style transfer for [22, 23]. [24] proposed a style transfer technique for image synthesis that tackles frequent problems including the incorrect application of style details that result in artifacts. The architectural design of their adopted style the VGG 19-layer network serves as the foundation for the deep conventional neural network (DCNN), from which two DCNN models are extracted from certain layers to capture both global and local style elements. To transfer arbitrary visual styles to content images, the paper [25] suggests a universal style transfer method that eliminates the necessity for training on predefined styles. VGG-19 is used as a feature extractor (encoder) and a symmetric decoder is trained to invert the features of VGG-19 to the original pictures. [26] proposed a transfer model for altering medical image styles while preserving crucial details using a context-aware loss function. The approach employs adaptive instance normalization for efficient stylization, enabling multiple styles from a single input. Deep Feature Rotation (DFR), can be used in style transder which rotates features to generate diverse outputs while preserving stylization effectiveness [27]. [28] introduced a method using separate content and style encoders with a transformer decoder to capture global and local dependencies for stylized image generation. Moreover, this style transfer method can be useful for textile design to create new and fresh pattern bus blending content images and style images.

For creating creative designs, artificial intelligence is a way out. Deep learning has begun to carry out creative artistic designs. In 2014, generative adversarial networks (GANs) were proposed which is an unsupervised machine learning model where patterns in the input data can be discovered by the model. Using the given knowledge, the model can generate new data that is relatable to the original data [29–31]. GANs consist of two neural networks: a discriminator network and a generator network. The generator tries to generate fake data that is identical to the data samples present in the training dataset. The discriminator works as a binary classifier whose main objective is to accurately identify samples as real or fake by distinguishing between real data samples from the training dataset and the samples generated by the generator [32]. Unlike Boltzmann machines [33], GANs do not use Monte Carlo approximations [34] to train. Instead, it use back-propagation and do not require Markov chains [35]. GANs can be used for image to image translation([36], [37]), text-to-image translation [38], image super resolution([39], [40]), data generation and augmentation([41],[42]), etc. The authors [43] describe the versatile nature of GANs applications in computer vision, healthcare, science, Natural Language Processing, business, art and design, robotics, and sports. Conditional Generative Adversarial Networks [44] or cGANs are an extension of GANs used to generate conditional samples. GANs are widely employed in image processing, and PG-GAN has been used to create artificial images of road damage to detect patholes [45]. [46] use GAN to segment the scales of lesion area from dermoscopy images of skin lesions. Here, the GAN design comprises two interconnected modules: a segmentation module based on the skip connection and dense convolution U-Net (UNet-SCDC) and a dual discrimination (DD) module. Image-to-image translation refers to the controlled conversion of a source image to a target image. Pix2Pix GAN is one of the approaches that produces an impressive result based on the concept of conditional generative adversarial network, where based on some given conditions on the input image, a target image is generated.

Progressive GAN (PGGAN) and neural-style transfer are used to create StyleGAN. PGGAN is a specific type of GAN called Progressive GAN that adds layers throughout the training phase to guarantee high-quality and high-resolution images [47]. PGGAN enhances the training procedure to increase its speed and stability. To handle greater resolution, new layers are added to the first ProgressiveGAN layer as training progresses. The first layer has the lowest resolution (4 x 4). As a result, the final image has more realistic detail. Another study [48] emphasizes PGGAN's adaptability and shows how successful it is when compared to conventional GANs and their variants. This also shows how PGGAN may be used with different GAN frameworks. Neural style transfer is another technique in StyleGAN. Using a convolutional neural network, Neural Style Transfer (NST) creates artistic images. It can be employed in a variety of ways, such as the production of tools [49]. Color information, spatial position, and scale can all be controlled via style transfer. To maintain the content image's original color, color control is be used. Applying a distinct style to a certain area of an image guarantees that the style of smaller sections is under control. Controlling spatial size refers to managing the blending of various styles [50]. This style mixing concept is then used in StyleGAN to generate mixed images. [51] developed a StyleGAN generative architecture that used stochastic variation and unsupervised separation of high-level properties, allowing for effective control over synthesis at various scales. They performed on the human face images and for excellent quality. This method blends several characteristics of images together and outperformed the conventional StyleGAN. Different research uses StyleGAN to produce food images of superior quality [52]. In order to produce fresh, high-quality food images with a distinct style and to create new images by fusing characteristics from various meals, they alter the StyleGAN and apply it to the food dataset.

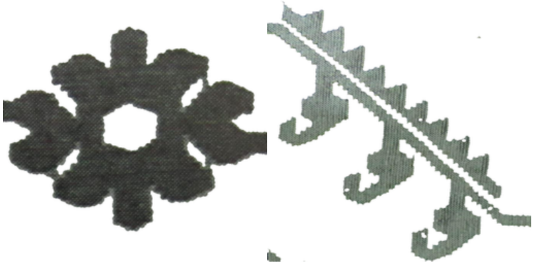
While significant advancements have been made in generative modeling and image processing, including methods like transfer learning and GANs, there is a notable gap in applying these techniques to image fusion for generating new textile designs. The origins of Jamdani motifs, are rooted in Persian styles. No prior research has explored the fusion of Persian and Jamdani motifs to generate new motifs.

3 Methodology

3.1 Dataset

3.1.1 Data Collection

As we want our model to generate new motif images combining both Jamdani and Persian motif, we prepared a dataset containing both types of images. We collected the Jamdani dataset from the study [53] consisting of 7932 different Jamdani motif images (see Fig. 1a). Since no Persian motif dataset was available, we created our own Persian motif dataset from various online sites. The collected images consists of 604 Persian Islamic patterns and rug motifs (see Fig. 1b).



(a) Jamdani motif images

(b) Persian motif images

Fig. 1: Sample example of experimental dataset

3.1.2 Data Preprocessing

Jamdani Motif Images

The collected Jamdani dataset contains 512x256 images, each split into two 256x256 parts (see Fig. 1a). The second half shows Jamdani motifs, while the first half is their skeleton representation. We extracted only the second half for our use, which were actually grayscale images, as shown in Fig. 3a. We converted all grayscale Jamdani motif images into binary images (Fig. 3b) using thresholding method. We selected a threshold of 240 after testing multiple values to achieve the best binary conversion (Fig. 2). For each pixel of the image, $f(x) = 0$ if $x \leq 240$ and $f(x) = 255$ if $x > 240$, where x is the pixel value and 0 stands for black pixel and 255 representes a white pixel.

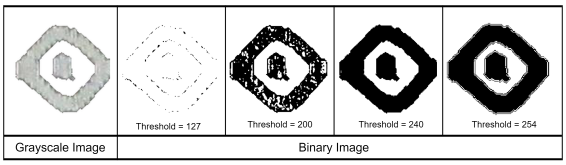
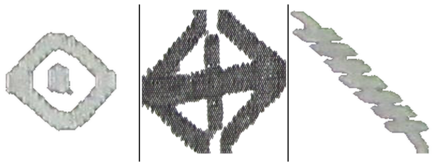
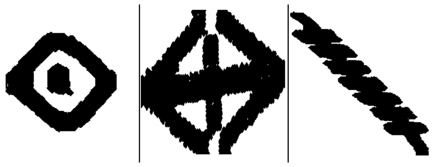


Fig. 2: Threshold selection test result



(a) Grayscale Jamdani images



(b) Binary Jamdani Images

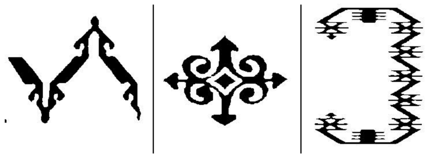
Fig. 3: Gray to binary conversion of motif

Persian Motif Images

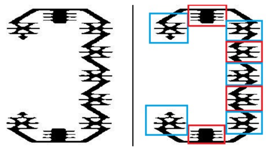
As the Persian motif images were collected from various online sites (see Fig. 1b), they were not uniform. Some were colored, while others were grayscale, and their sizes and resolutions were also different. After cropping and resizing, 604 different Persian motif images were acquired with dimensions of 256x256. Then converted into binary images using the same threshold value applied for the Jamdani Dataset (see Fig. 4a). Some images contained compound motifs, which could complicate model training, so they were removed Figure 4b shows an example of found compound motifs in the initial Persian dataset. After reprocessing, the new Persian dataset had a total of 400 different Persian motifs.

3.1.3 Data Augmentation

There was an imbalance between the Jamdani dataset, which had 7932 motifs, and the Persian dataset, which had only 400 motifs. To address this, image augmentation was applied to generate 15 new images from each original Persian motif, resulting in a total of 6400 Persian motif images (see Fig. 5). These images were shuffled and saved as our Persian dataset. Finally, the dataset consisted of 7932 Jamdani motifs and 6400 Persian motif images.



(a) Binary Persian Images



(b) Compound Persian motif

Fig. 4: Sample example of preprocessing Persian dataset

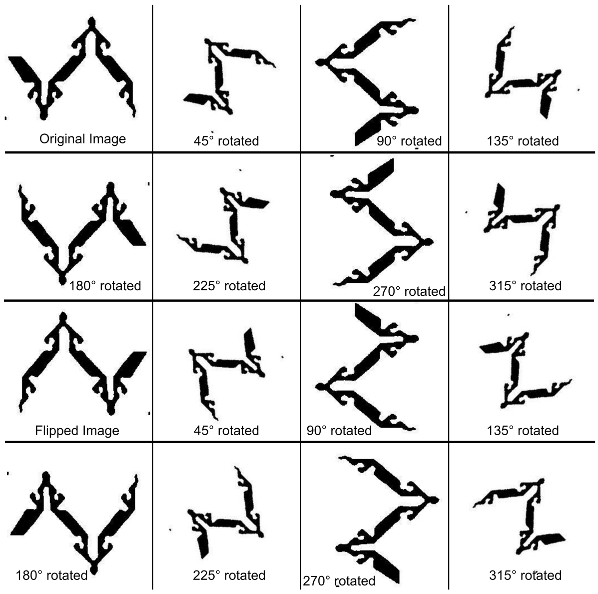


Fig. 5: Image augmentation - generated 16 images from 1 image

3.2 Module 1: Image Fusion with Image Processing

3.2.1 Approch 1: Mathematical and Bitwise Operations

We started our experiment with traditional mathematical and bitwise operation based image processing. As image are represented as a pixel matrix, first we selected a Jamdani and a Persiam image then applied basic bitwise operation on these two images to see the resulatant outcome. The basic operations included arithmetic addition $(g(x,y) = |f_1(x,y) + f_2(x,y)|)$, arithmetic subtraction $(g(x,y) = |f_1(x,y) - f_2(x,y)|)$, bitwise AND $(g(x,y) = f_1(x,y) \wedge f_2(x,y))$ and bitwise XOR $(g(x,y) = f_1(x,y) \oplus f_2(x,y))$ operation. Here $f_1(x,y)$ and $f_2(x,y)$ represents the pixel value of image one and image two and $g(x,y)$ denotes the combined pixel value after bitwise operation. Fig. 6a illustrates the steps for generating a new image using the arithmetic addition operation.

3.2.2 Approch 2: Region of Interest

Next, we applied the concept of region of interest (ROI) in combining the patterns. At first, we selected a Jamdani and a Persian image from the datasets, then considered the central part of the Jamdani and the border part of the Persian image as our regions of interest. To do so, the width and height of the images are halved as *cut.width* and *cut.height* to get the dimension of the center region (Eq 1). Then the x coordinate $(start_x)$ and y coordinate of $(start_y)$ for cropping the central part (Eq 2 and Eq 3). Then the central region is then extracted from the Jamdani motif, and border region is extracted from the Persian motif. Finally, these extarcted parts are combined to generate a new fused motif, as illustrated in Figure 6b.

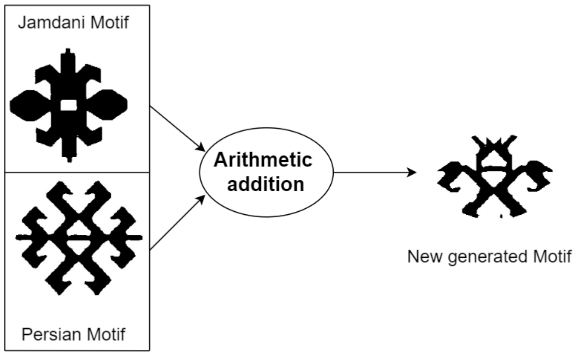
$$cut.width = width/2, cut.height = height/2 \quad (1)$$

$$start_y = (\text{height} - \text{cut.height})/2, \quad end_y = start_y + \text{cut.height} \quad (2)$$

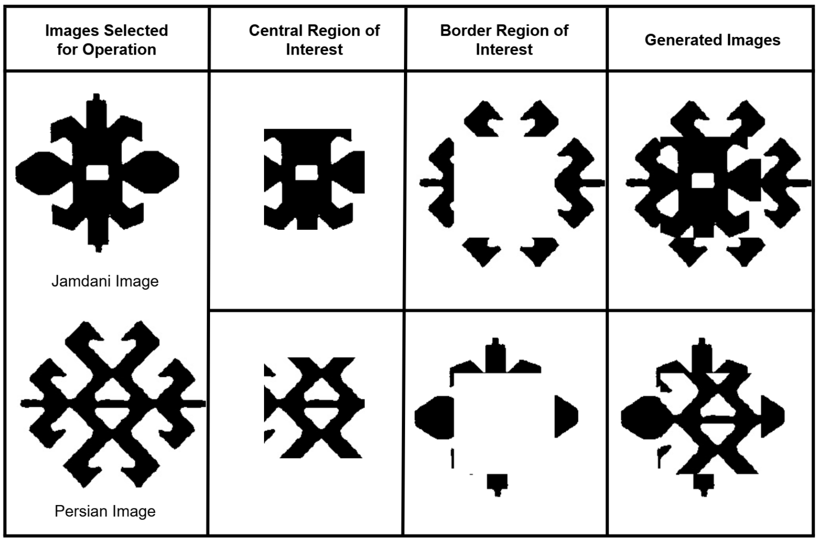
$$\text{start\_x} = (\text{width} - \text{cut.width})/2, \quad \text{end\_x} = \text{start\_x} + \text{cut.width} \quad (3)$$

3.3 Module 2: Image Fusion with Neural Style Transfer

In computer vision and deep learning, Neural Style Transfer (NST) is a potent method that provides an innovative way to combine the content of one



(a) Addition operation of two motifs



(b) ROI operation of two motifs

Fig. 6: Pattern fusion with traditional image processing

image with the artistic style of another. This takes two images as input: one as the content image, and another one as the style image, where it transfers the style of the style image to the content image while retaining the target image's semantic content. In our experiment, the VGG19 model serves as the core architecture of Neural Style Transfer. Here, pretrained VGG19 is used for feature extraction—rather than image classification [18].

Figure 7 illustrated the our pattern fusion procedure using pretrained VGG19 architecture. here sytle image is selected from Persian motif and content image is selected form Jamdani motif dataset. Both images are then passed through the pretrained VGG19 model to extract features. The model detects content features from particular content layers, which depict the spatial organization of the content image, and style features from designated style layers, which record textures and patterns. The style loss for the generated image is determined by comparing the Gram matrices of feature maps extracted at VGG19 network levels with reference style images. This Gram matrix can be computed as follows:

$$G^l_{cd} = \frac{\sum_{ij} A^l_{ijc}(x) B^l_{ijd}(x)}{NM} \tag{4}$$

Here, G^l_{cd} represents the element at position (c, d) in the style matrix computed for layer l that captures the style correlation between feature

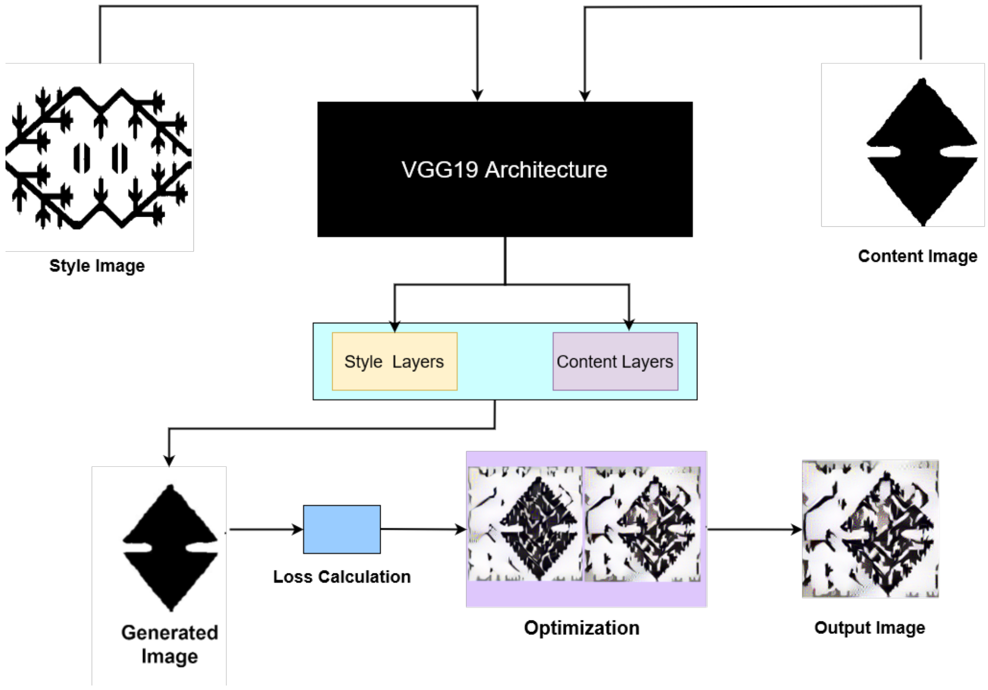


Fig. 7: Neural Style Transfer model architecture

channels c and d at that layer. $A^l_{ijc}(x)$ and $B^l_{ijd}(x)$ denotes the activation of the c^{th} and d^{th} feature channel respectively at position (i, j) in layer l of the network when processing the image x. N and M denote the number of spatial positions and the total number of feature channels in layer l, respectively. The style loss function L_{style} measures the difference in style between the generated image and the style reference image as follows:

$$L_{\text{style}} = \sum_{l=1}^{L} w_l \cdot \frac{1}{4N_l^2 M_l^2} \times \sum_{c,d} \left(G^l_{cd} - \frac{\sum_{ij} A^l_{ijc}(x) B^l_{ijd}(x)}{NM} \right)^2 \quad (5)$$

where w_l weight is assigned to the style loss at layer l. The difference in content between the original content image and the stylized image is measured by the content loss, L_{content} (Eq 6).

$$L_{\text{content}} = \frac{1}{2} \sum_{i,j} (F^l_{\text{generated},ij} - F^l_{\text{content},ij})^2 \quad (6)$$

Here,$F^l_{\text{generated}}$ and F^l_{content} denotes feature representations (activations) at layer$l$ for the generated and content images, respectively. In order to reduce the overall loss of style and content, gradual modifications are made to the image's pixel values. Automatic differentiation is used to compute the gradients of the combined loss function, which directs the update process toward configurations that more closely align with the intended style and content qualities. By repeatedly altering the input image's pixel values, the Adam optimizer minimizes the loss of style and content during the optimization process.

Training Procedure:

The training process of the model consists of several epochs, with a set number of optimization steps in each. Images were generated with 10 epochs, 100 epochs, 500 epochs, and even 1000 epochs. Different Learning rates were used for different numbers of epochs. The standard learning rate of the model was 0.02, 0.01 and 0.001. The input image is iteratively updated to minimize the combined loss function during the training process, progressively improving its appearance to more closely align with the intended style and content

3.4 Module 3: Image Fusion with StyleGAN

In our final stage, we applied StyleGAN to generate new patterns from Jamdani and Parsian motifs. StyleGAN is implemented by taking concepts from both ProGAN [41] and Style Transfer [18]. It trains the model progressively from lower resolution to higher resolution as ProGAN and uses the concept of style mixing as the style transfer to build a style-based generator architecture for GANs [51].

Dataset Preparation for StyleGAN

As we have two types of images: Jamdani motifs(7932 images) and Persian motifs (6400 images), the images must be shuffled properly after merging and before feeding them into the neural network. The process of merging and shuffling is presented in Figure 8.

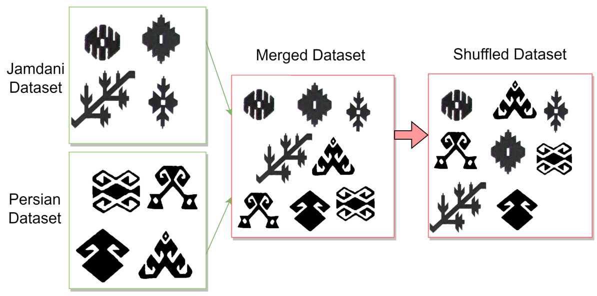
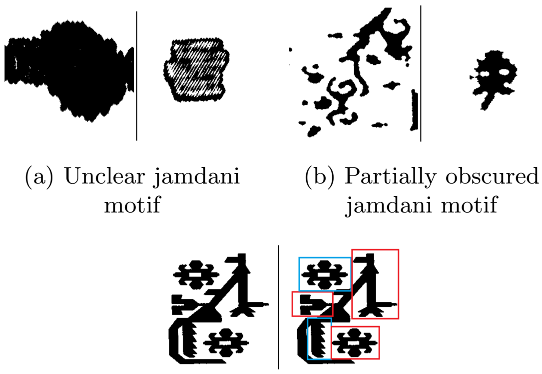


Fig. 8: Dataset preparation process for StyleGAN

If we sample the dataset randomly, the data distribution can be written as follows: pdata($jamdani$) $= \frac{7932}{7932+6400} = \frac{7932}{14332} = 0.553$ and pdata($persian$) $= \frac{6400}{7932+6400} = \frac{6400}{14332} = 0.447$. Here, the data distribution refers to the number of Jamdani and Persian motifs relative to all the motifs in the dataset. Our dataset is also a little unbalanced as *pdata(jamdani) = 0.553* and *pdata(persian) = 0.447*. To ensure the equal distribution of both motifs we tested our model on different versions of the current dataset. We trained the model on three different versions of the current datasets. These are:

1. **Current Dataset**, (*Dataset1*): It is the current version of the dataset, which contains *7932* different Jamdani motifs and *6400* different Persian motifs. We merged these two types of images and shuffled them properly.
2. **Random Selection**, (*Dataset2*): Randomly, we selected *6400* images from *7932* different Jamdani motif images. So, we had *6400* different Jamdani images and *6400* different Persian images. As *Dataset2* has the same amount of Jamdani and Persian images, a balanced data distribution has been achieved in it.
3. **Manual Selection** (*Dataset3*): This time, we selected *6400* images from the *7932* different Jamdani motif images by hand and removed those that were unclear, partially obscured, or compound motifs. Examples of unclear, partially obscured, and compound Jamdani motifs are presented in Fig 9a, Fig 9b, Fig 9c respectively.



(a) Unclear jamdani motif (b) Partially obscured jamdani motif

(c) Compound jamdani motifs

Fig. 9: Example of defective jamdani motifs.

Training model

Fig. 10 represents the whole training process of our styleGAN model. The training started with the generator generating a 4x4 resolution fake image, and the discriminator detected whether the image was fake or real. In the beginning, the generator and the discriminator had only a single block. After training in the 4x4 resolution for a while, the model added new layers for the new resolution,

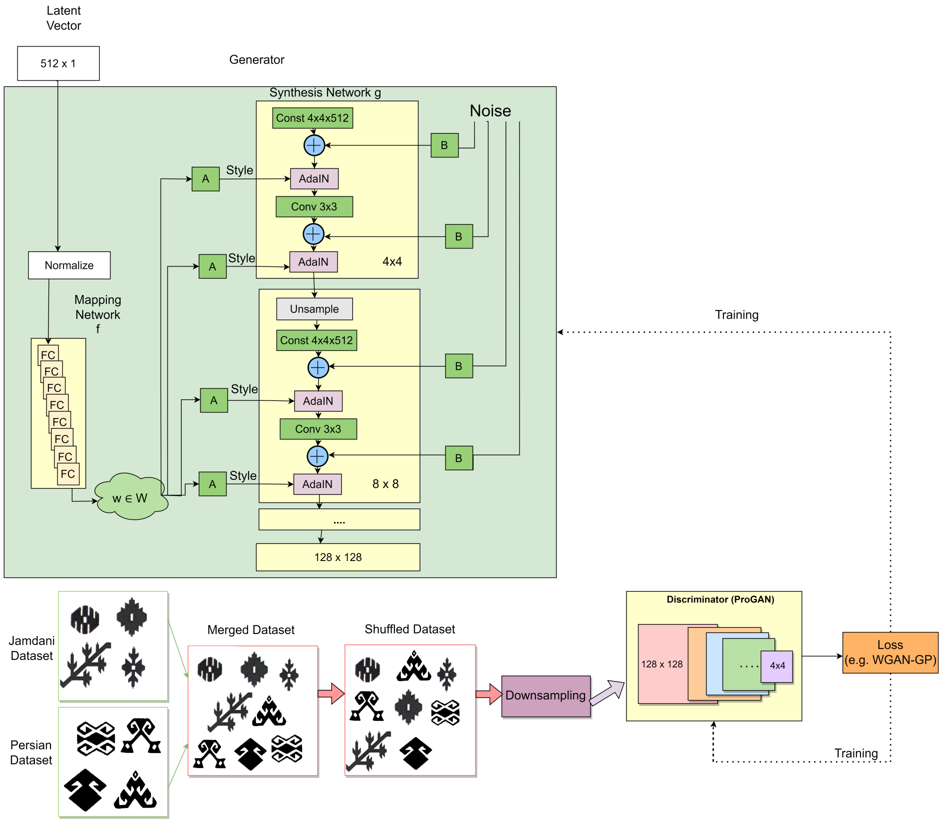


Fig. 10: Architecture and training process of the StyleGAN model

Table 1: Combination of hyperparameters of styleGAN models

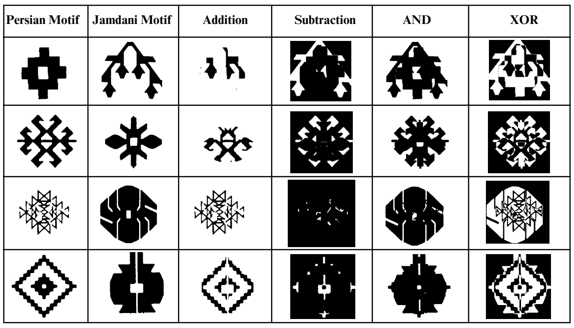
Model number	Learning rate	Optimizer	Loss function	Steps per epoch	Batch size	Dataset
M-1	0.01	Adam	Wasserstein loss, WGAN-GP loss, Drift loss	12000	16	*Dataset1*
M-2	0.001					
M-3	0.0005					
M-4	0.01					*Dataset2*
M-5	0.001					
M-6	0.0005					
M-7	0.01					*Dataset3*
M-8	0.001					
M-9	0.0005					

i.e., 8x8, and trained with it. In the study of styleGAN ([51]), this process was repeated until the model reached a resolution of 1024x1024. But in our model, the process repeated until it reached a resolution of 128x128. We trained nine versions of StyleGAN models varying different hyperparameter [54] on the three datasets- Dataset1, Dataset2, and Dataset3. There are three models per dataset, and each have a different learning rate. Table 1 represents the combination of hyperparameters for all nine styleGAN models.

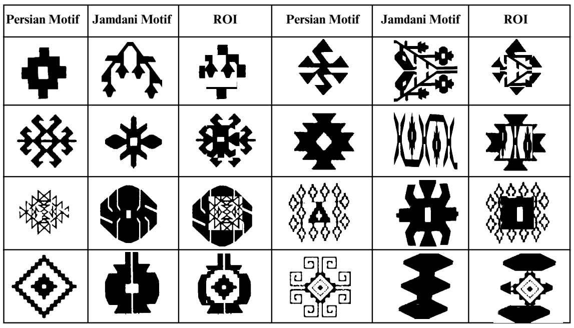
4 Result Analysis

4.1 Module 1: Image Fusion with Image Processing

Figure 11a shows the resultant image after applying mathematical operations (addition, subtraction, XOR, and AND) on Pesian motif and Jamdani motif. The result of creating new motif using the outer region of one motif and the central region of another is shown in figure 11b. We observed that the two distinct motifs do not mix in traditional image processing methods.



(a) Arithmetic Operations Result

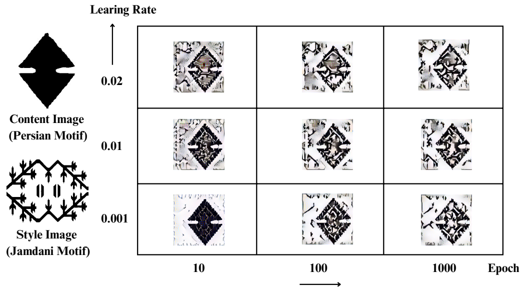


(b) ROI result

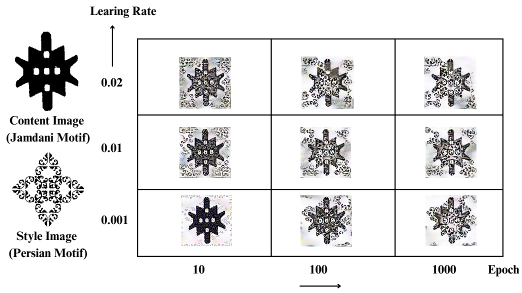
Fig. 11: Resultant image fusion using traditional image processing

4.2 Module 2: Image Fusion with Neural Style Transfer

The Persian motif image is utilized as the content image and the Jamdani motif image as the style image in the figure 12a. Additionally, figure 12b shows the result of vice-versa - the Persian motif as the style image and the Jamdani motif as the content image. The epoch is set to 10, 100, and 1000. A learning rate of 0.001, 0.01, and 0.02 has also been used. We increased the epoch rate of the design so that there is less noise in the image. As the learning rate increases, style detail increases, and image blending increases.



(a) Content Image - Persian Motif, Style Image - Jamdani Motif



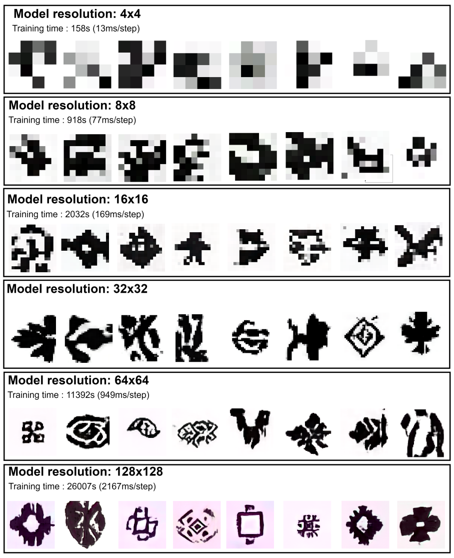
(b) Content Image - Jamdani Motif, Style Image - Persian Motif

Fig. 12: Image fusion using Style Transfer

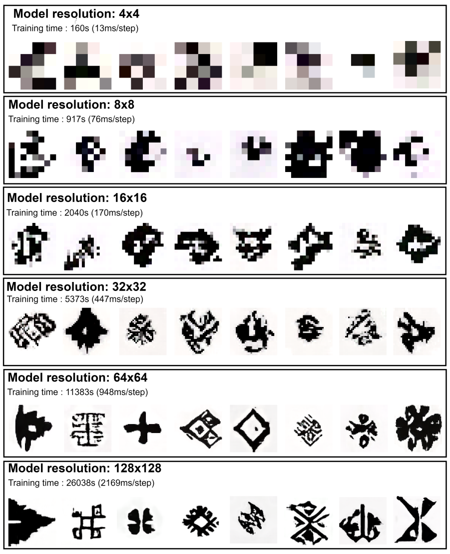
4.3 Module 3: Image Fusion with StyleGAN

We were able to successfully develop unique patterns by using StyleGAN. In our experiment, we have employed nine distinct combinations of hyperparameters to train StyleGAN models. Each model is designed to generate new motifs that embody characteristics of both Jamdani and Persian motifs. Some examples of generated motifs from Model 1 and Model 2, across all specified resolutions, are presented in Figures 13. Rest of the models result are given in Appendix A.

We employ two primary criteria in order to evaluate the models of GAN: fidelity and diversity.



(a) Model-M1 (learning rate = 0.01)



(b) Model-M2 (learning rate = 0.001

Fig. 13: Generated Motifs by Model-M1 and Model-M2

Fidelity ensures the high quality and similarity to the input data while generating images. Diversity checks whether the model is able to generate a variety of images reflecting the diversity of the training data. However, comparing images based on these criteria can be challenging due to the ambiguity of what criteria to employ for comparison. Because, when our models generate images, those are a fused version of both Jamdani and Persian motifs, and there is no ground truth to these kinds of images.

Figure 14 shows the generated images from all nine StyleGAN models at their targeted resolution of 128x128 pixels. It is observable that the generated images of model number M-8 are more visually appealing compared to the others. The reason for this enhanced visual quality is that we used Dataset3, where we manually trimmed out the compound Jamdani motifs while balancing Jamdani and Persian motifs.

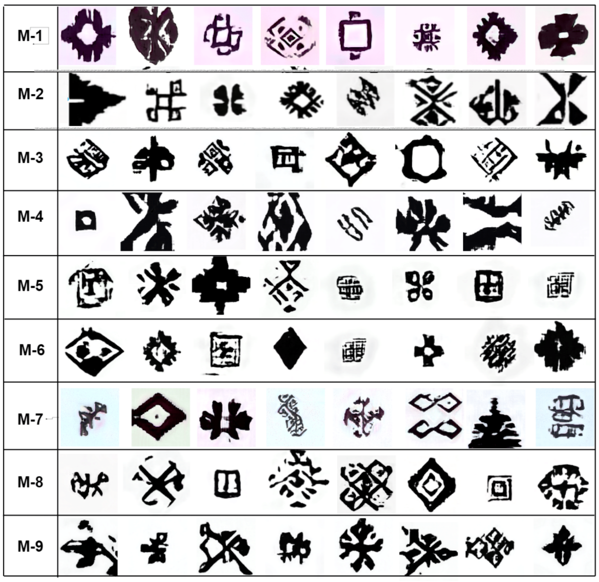
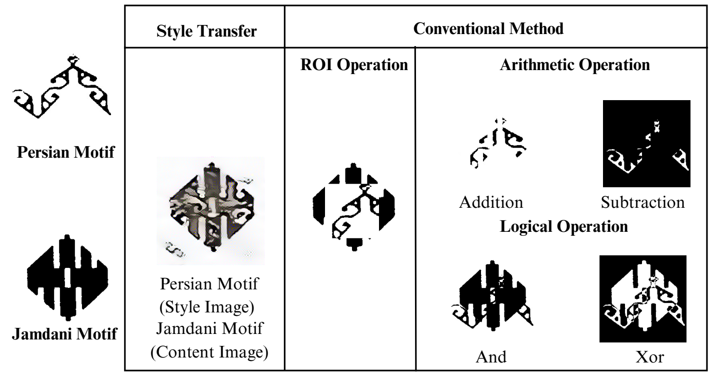


Fig. 14: Generated unique motifs by StyleGan model

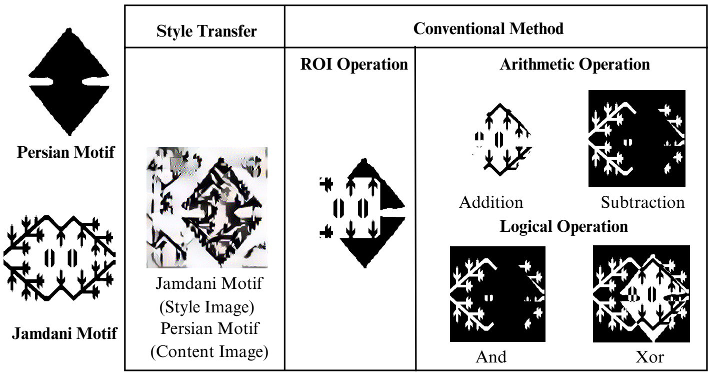
5 Comparative Result Analys

5.1 Image Processing VS Style Transfer

In this section, we conducted a comparative analysis between the fusion result of the traditional method and the style transfer method. We selected two experiments- **Experiment 1:** where Style image - Persian Motif and Content image - Jamdani Motif (Figure 15a) and **Experiment 2:** where Style image - Jamdani Motif and Content



(a) Experiment 1



(b) Experiment 2

Fig. 15: Comparison between Style Transfer method and Conventional method

Table 2: Comparative evaluation of image processing and style transfer methods

	Evaluation Metrics	Style Transfer Method	Conventional Image Processing Method		
			Region of Interest (ROI)	Arithmetic Op. (ADD)	Logical Op. (AND)
Experiment 1	SSIM	0.22	0.73	0.28	0.95
	FSIM	0.88	0.69	0.60	0.68
	PSNR	8.21	9.36	2.89	16.69
Experiment 2	SSIM	0.49	0.75	0.28	0.95
	FSIM	0.83	0.69	0.69	0.68
	PSNR	8.86	8.77	9.32	5.41

image - Persian Motif (Figure 15b). The evaluation matrices for the Style Transfer and Conventional approaches are displayed in the table 2. Since image subtraction and image XOR operations result in an inverted image, we did not employ them in this instance. Peak Signal-to-Noise Ratio (PSNR), Structure Similarity Index Measure (SSIM), and Feature Similarity Index Measure (FSIM) have all been computed. The study showed that the FSIM score consistently yields the greatest results for Style Transfer, while the SSIM score typically performed better for the Region of Interest. The PSNR scores for the image processing approach and style transfer were nearly identical.

For Artistic purposes, the FSIM score is more important so Style Transfer is preferable where on the othere hand Image Processing is a more manual process. Instead of using ROI or mathematical image processes, the Style Transfer method's blending of two motifs is more suitable. ROI may provide a high score in evaluation matrices, however improper picture selection may cause issues.

5.2 Style Transfer VS StyleGAN

To address our primary objective of generating images blending Jamdani and Persian motifs, we tried three different methods. Style transfer needs two input images—a style image and a content image—while StyleGAN works independently after a one-time training process. For this comparative study with style transfer, we choose our best styleGAN model M-8. Figures 16 shows examples of generated images using style transfer and styleGAN. Style transfer blends Jamdani and Persian motifs well, but the shapes mostly match the content image. It applies the style image onto the content, creating a derivative result. In contrast, StyleGAN generates completely new shapes, combining features from the training data. Its outputs are of impressive quality.

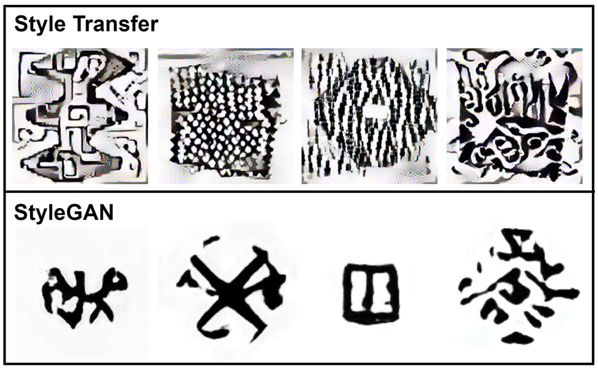


Fig. 16: Example images generated using Style Transfer and StyleGAN

Nevertheless, one major challenge associated with StyleGAN is its training complexity, which demands substantial computational resources. In our case, due to these limitations, we could only train our model up to a resolution of 128x128, requiring nearly 13 hours of training time. However, this training is a one-time process, and once completed, the trained model can generate images instantly. On the other hand, style transfer does not necessitate pretraining, as it relies on a pre-trained model. Each output generation with style transfer requires approximately 11 minutes on our machine. Hence, the choice between the two methods depends on the availability of computational resources and the specific requirements of the task.

6 Future scope and Conclusion

In this study, new motifs were generated by combining existing Jamdani and Persian motifs in three different ways: image processing, neural style transfer, and StyleGAN. After that, a comparative analysis was conducted among these three approaches. From the comparative study, it was found that, between image processing and neural style transfer, images generated using neural style transfer achieved a higher FSIM score, but the SSIS score was better for traditional image processing. As for artistic purposes, the FSIM score is more important, so style transfer is preferable. The comparative analysis between style transfer and StyleGAN shows that, for style transfer, it is necessary to select a style image and a content image from the dataset manually. Then, the neural style transfer model takes several minutes to generate the fused image. Additionally, the shape of the generated image mostly matches the content image. In contrast, StyleGAN generates completely new shapes every time with more impressive image quality. Also, once the model is trained, images can be generated instantly. Therefore, it can be concluded that, among these three approaches, StyleGAN generates more impressive fused images. The contributions made through the research are as follows:

i) Two datasets were generated: the Jamdani motif dataset and the Persian motif dataset. The datasets are available here: link.

ii) Three motif generation techniques were presented, each incorporating characteristics from current Jamdani motifs and their predecessor Persian motifs. The trained StyleGAN model is also available at the above link.

iii) A comparative analysis was conducted among the three approaches to motif generation, demonstrating why StyleGAN is a better option for generating new motifs.

The study has a few limitations. The dataset contains a limited number of images. Since GANs perform better with larger datasets, increasing the number of images in the dataset could improve the quality of the generated images. The dataset contained only binary images, so the generated images were also binary. Incorporating multicolored images into the dataset is recommended to achieve a higher aesthetic appeal with vibrant visuals. Due to GPU memory limitations, it was not possible to generate images larger than 128x128 pixels. Improved hardware is required for this type of study. This approach can also be applied to other similar problems, such as enriching patterns for Benaroshi, Nakshi Katha, Manipuri, and so on. Additionally, their diverse cultural aspects can be combined to create hybrid motifs, demonstrating how innovative traditional art forms can be. Finally, carrying out user research and surveys will yield important information about people's acceptance of the generated motifs.

Declarations

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Conflict of Interest The authors declare that they have no conflict of interest.
Availability of data and materials: Not applicable.
Code availability: Not applicable.
Authors' contributions: Authors wrote the main manuscript text and performed the experiment's. All authors reviewed the manuscript.
Ethical Approval: There are no studies by any of the authors in this article that used humans or animals as subjects.
Consent for publication: all authors agreed to publish.
Consent to participate: Consent to publish.
Competing interests: The authors have no relevant financial or non-financial interests to disclose.

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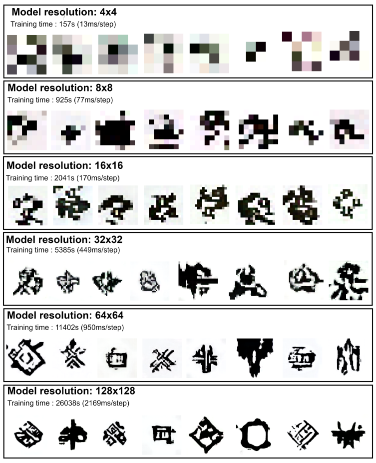
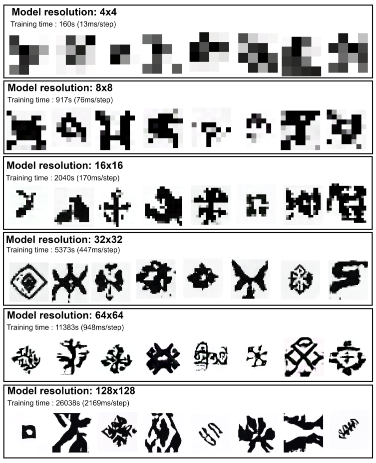
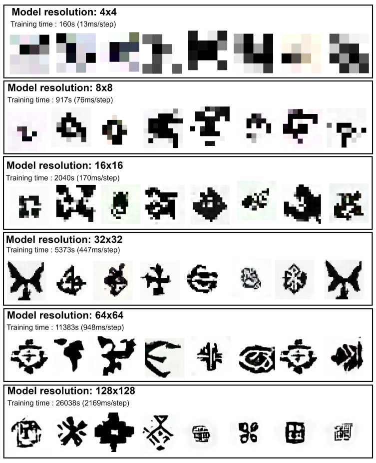
Appendix A Result of image fusion using StyleGAN



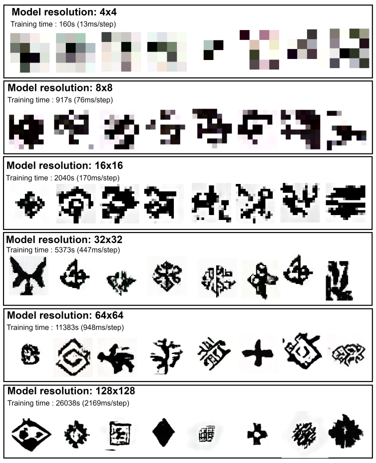
(a)



(b)

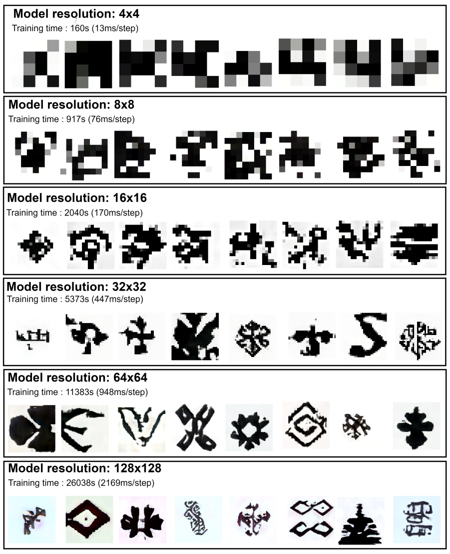


(c)

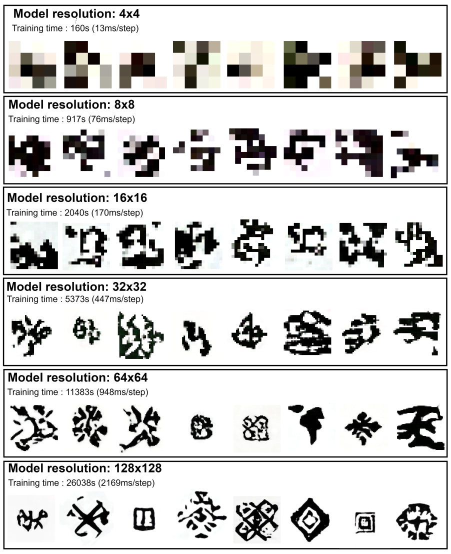


(d)

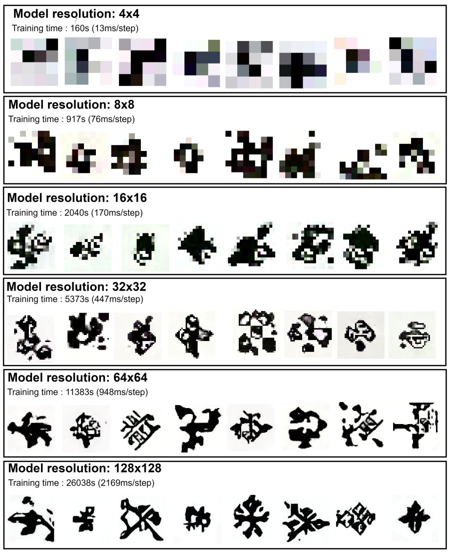
Fig. A1: Generated Motifs by Model Number - (a) M3 (Dataset1, lr = 0.0005), (b) M4 (Dataset2, lr = 0.01), (c) M5 (Dataset2, lr = 0.001), (d) M6 (Dataset2, lr = 0.0005)



(a)



(b)



(c)

Fig. A2: Generated Motifs by Model Number - (a) M7 (Dataset3, lr = 0.01), (b) M8 (Dataset3, lr = 0.001), (c) M9 (Dataset3, lr = 0.0005)