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HandloomGCN: Real-time Handloom Design Generation Using Generated Cellular Network

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Abstract: Handloom design creation, deeply rooted in cultural heritage, has traditionally relied on manual craftsmanship. The individual minds are conditioned to biased and coming up with combine aesthetics of non-handloom designs with handloom designs is a tough task. This paper explores an innovative approach by fusing deep convolutional neural networks with cellular automata for generating handloom designs to automate and enhance this intricate process. Further the output is processed with a higher resolution network. The fusion network works on higher-levels of feature pyramid, managing the image layout at a texture level. We implemented the approach with different weight ratios to generate the outcomes. This method also avert over-excitation artifacts and reduces implausible feature mixtures in compare to previous approaches. It allows to generate adoptable result with increased visual effects. Unlike existing methods, the combined system can match and fit local features with considerable variability and yielding results. The outcomes shows potential of this fusion in pushing the boundaries of design innovation in the field of handloom textiles. Qualitative and quantitative experiments demonstrate the superiority of the introduced method among all other existing approaches. The work established a comprehensive benchmark for comparision and results into a new publicly accessible "HandloomGCN" dataset of handloom clothes for this research field.

Keywords: Handloom Design, Texture, Deep convolutional Neural Network, Generated cellular Network, High-Resolution Network, Weight ratio

1. INTRODUCTION

The fashion industry has been changed dramatically throughout time, reflecting changes in society and advances in technology. It governs the entire globe, producing an endless number of fascinating products every minute to meet consumer demand. Fashion has become one of the most creative industries, and fashion trends are ever-evolving. People around the world are willing to spend money on staying stylish, regardless of their socioeconomic status. User-specific fashion trends have always been determined by their preferences and likes. People of all castes, creeds, and nationalities are drawn to fabrics of different kinds and designs. The fabric sector is an evergreen sector where neither global nor national sensex can effect. In India, household looms accounted for a maximum of 61.44% of all looms, with commercial looms making up 38.56% of all looms. The Northeastern states of India hold over sixty percent of the country's handloom skills reservoir, with 16.83 lakh (60.5%) of all handloom households operating there.

In Assam alone, there are 12.41 lakh handloom families [1], which constitutes 44.6% of the total. As per the 2001 census estimate, about 2,24,381 individuals living in Assam are involved in the traditional handloom cloth production

Figure 1. Assam Traditional Handloom

[2]. The Assam traditional loom is showm in the Figure.1. Since the beginning of time, handloom weaving has played a significant role in Assamese socioeconomic life. The three most well-known and distinguished clothing types made in Assam are eri, pat, and muga as shown in Figure.2. Ethnic traditional handlooms suffer the most with the industry only functioning as a sporadic tourist attraction. The industry

also has to contend with issues like a dearth of innovation [3], lack of standards, and heightened rivalry from the mill and power loom industries. During the data collection, we consulted some potential design alternatives that could revitalize this business process, but it can be challenging to bring these variants to light, particularly by the people working currently in the industry. Our visit to Sualkuchi, a renowned silk village, we observed that a significant portion of the time nearly 1/4 is consumed in creating new custom designs. This delays the entire weaving process. The challenge lies in generating new designs that blend non-handloom styles with traditional handloom patterns, as the human mind often struggles with this complex task. Scientifically, it is difficult to quantify the integration of diverse aesthetic elements quickly. Our approach aims to address this issue by producing designs or textures from existing or randomly chosen priors, independent of both traditional and generic designs. With the growing demand for automated handloom systems capable of creating personalized designs for various handloom products, it is also crucial to manage the numerous variables involved. This challenge can be described as the ”Transfer or Generation” [4] of Texture and Geometric Artifacts in an image. ”Transfer” refers to creating a handloom design based on pre-existing generic designs, while ”Generation” involves creating something entirely new from random noise, relying on fixed feature extraction.

In digital image processing, an image’s texture is the deterministic sampling in the spatial domain of the image of a specific organisation or cluster of gradients and colour patterns. Assuming the same thing applies to the handloom work image, where the colour space offers texture and the geometric structure provides semantics, it should not be too difficult for humans to display the actual content by developing learning models that produce such a cohesive RGB combination. After being trained on a sizable dataset of handloom designs, deep learning networks can be trained to generate new designs that follow the same patterns and styles, saving time and effort. The idea of an automated handloom system is a promising application that blends cutting-edge technology and customary workmanship. We may overcome these obstacles and improve the productivity, precision, and consistency of handloom fabric manufacturing by addressing the issues with incorporating automated or assisted handloom processes, such as computer-aided systems or deep learning algorithms. With an automated design process, producers are able to uphold high standards and provide clients with outstanding, customisable handloom products. Resources like as labour, materials, and time are wasted in the manual method. Handloom designs lead to inventiveness and originality. By employing cutting-edge technology like artificial intelligence (AI), machine learning, and computer vision, manufacturers may accelerate the production cycle, simplify the design process, and require less manual labour. Meeting the rising demand for their products presents challenges for these businesses. Scalability is made possible by automation without sacrificing quality. By easing the strain of labor-intensive activities, bringing in younger generations to the business, and freeing up artists to concentrate on the creative parts of weaving, handloom automation systems can contribute to the preservation of traditional crafts. The entire scenario relies on a deep learning layered pipeline, which starts with the creation of datasets and ends with an efficient system that can generate designs, detect quality, and identify originality. Adoption of deep learning approaches that can maintain uniqueness while introducing many models that have been trained with little or no overfitting. The plan starts with the creation of a dataset and ends with a multi-model framework that uses deep learning techniques to be applied to all Handloom items. The study that was done demonstrates that this is an open-ended research issue that will enhance current understanding of the systems that are in place. Similar to a traditional handloom, the design texture varies with weight differences. Deep learning will also be used in addition to the work to generate and make available

Figure 2. Different Handloom Cloth Designs

our own dataset for handloom clothing such as muga, pure pat, nooni pat, etc.

Our proposed work will contributes :

- The approach ”HandloomGCN” is proposed to generate customised handloom designs using fusion of deep convolutional neural network with cellular automata.
- We introduce the “HandloomGCN” dataset, which will be publicly accessible dataset of handloom clothes and is labeled to support further research in this field.
- We established a more comprehensive benchmark by comparing the proposed method with other state-of-the-art methods in terms of retrieval matrices.

2. Literature Review

The ability of deep neural networks to tackle the difficult task of image generation has been shown in a number of recent studies. The idea of handloom design in this work is comparable to the transfer or generation of texture in a particular basic handloom cloth. There are three key task to be completed. Firstly, the created image's shape needs to match the entire coverage of the intended input. Second, the great accuracy of the image's local details must be preserved in the synthesised image. Thirdly, in order to limit certain texture to a particular regions in the mix-and-match style generating activity, a spatial constraint is required. Some of the recognizable works are specified in the Table I. A method for creating handloom textile designs using a deep learning model based on convolutional neural networks (CNNs) [5]. They suggest a framework, inspired from pre-existing handloom designs to learn and produce patterns. User feedback and design similarity measurements are used to assess the model's performance. In some papers [6], the fusion of CNN with single image super resolution [7] is implemented on ImageNet datasets. It worked well in case of higher content weights compared to low content weights.The problem mainly remains on texture distortion.

In a publication, a deep learning techniques is explored on generating handloom sari designs. The authors suggest a deep learning model that combines Long Short-Term Memory (LSTM) networks and Convolutional Neural Networks (CNNs) [8]. The programme can create new designs with comparable patterns and motifs after being trained on a collection of handloom sari designs. Research on applying Generative Adversarial Networks (GANs) to generate handloom patterns was conducted in 2020 [9]. The authors suggest a conditional GAN [10] architecture that creates handloom patterns conditioned on particular design features using seed input. The handloom designs dataset is used to train the model, and its visual quality and resemblance to actual designs are assessed.Further contribution leads to the development of a 500 image dataset ”Neural-Loom”. The study of Variational Autoencoders (VAEs) [11] for handloom design generation was conducted. In order to produce new designs, the authors suggest an architecture that encodes handloom designs into a lower-dimensional latent space and then decodes them. A dataset of handloom designs is used to train the model, and its output is assessed for visual quality and variety. Deep Belief Networks (DBNs) [12] are being used in certain research to generate handloom designs. A DBN-based model [13] that learns the patterns and hierarchical structure of handloom designs is proposed by the authors. After being trained on a dataset of handloom patterns, the model can sample from the learnt latent space to produce new designs. A variety of techniques are used, including the most advanced generative models available today [14] and style transfer algorithms, to monitor their effectiveness and assess it using user scores. 2018 [15] saw the creation of handloom designs as an image-to-image translation problem, in which the Mekhala dataset is the target distribution and the normal dataset needs to be converted using CycleGAN [16]. The normal saree dataset is used as the input picture. Convolutional Generative Adversarial Networks [17] conditioning an input mask that allows to form control and preserves the interior of the object's creative space. To increase originality in fashion creation, many image generating models are designed and investigated, each linked to a particular loss function.

The dimensions comprise various architectures of Generative Adversarial Networks that generate fashion items based on noise vectors, loss functions that promote novelty and are inspired by Sharma-Mittal divergence [22] and a generalised mutual information measure for the commonly used relative entropies, like Kullback-Leibler [23]. A review was conducted on various methods for analysing handloom texture, which were framed into four categories: structural, statistical, model-based, and transform methods [24]. Image interpreters can be trained using two sets of unlabeled photos from two different domains thanks to a revolutionary dual-GAN technique [25] that was introduced in 2017. Within the architecture [19], the dual GAN learns to reverse the job, whereas the primal GAN learns to convert images from domain U to those in domain V. Images from either domain can be translated and then reassembled thanks to the closed loop created by the primal and dual tasks. Therefore, the translators can be trained using a loss function that takes into consideration the reconstruction error of images. Tests conducted on numerous picture translation tasks using unlabeled data demonstrate DualGAN's significant performance improvement over a single GAN. DualGAN can even perform comparably or marginally better than conditional GAN trained on specific tasks in fully labeled data. In 2020 [26], a new study was presented on the development of patterns using Wasserstein Generative Adversarial Networks Gradient Penalty (WGANs GP) [27] for each class independently. The models are assessed based on their initial score. The approach is further expanded to generate multiple designs, leading to the creation of increasingly intricate appeals. The outcomes are efficient for unsupervised clustering patterns in the latent space.

TABLE I. Some existing Handloom design generation Methods

Methodology	Database	Limitation
Deep Belief Networks [12]	COCO Dataset	Struggle to capture the fine details due to their inherent complexity in modeling intricate patterns accurately.
Variational AutoEncoder [11]	Photographic Dataset	Generate images of lacking sharpness
CNN with SISR [18]	ImageNet	Offers limited user control generation in case of precise customization
Generative Adversarial Networks [9]	Neural-Loom	Prone to instability generation which can result in inconsistent and unpredictable outputs.
Dual-GAN [19]	Own unlabeled Dataset	Struggle to create designs that feature dissimilar textures.
Semantic-guided Conditional Texture Generator (CTGAN) [20]	ShapeNet car Dataset	Struggles with complex geometry or self-occlusion problems at edges of different views
Panoramic Feature Aggregation Network (PFAN) [21]	CelebA-HQ	Sensitive to the size and shape of the masks.

The entertainment industry heavily relies on 3D visual content, but creating textured 3D models traditionally is slow and subjective. In some work the Semantic-guided Conditional Texture Generator (CTGAN) [20] is introduced, which produces high-quality textures for 3D shapes that are angle-consistent and respect shape semantics. CTGAN leverages StyleGAN's latent code manipulation for precise control over texture style and structure, enhanced by a coarse-to-fine encoder architecture. In some recent advancements, the image inpainting using deep learning also have shown impressive results, particularly with texture generation. However, high-resolution texture filling remains challenging, especially for large-scale masks. To address this, the Panoramic Feature Aggregation Network (PFAN) [21] is introduced, featuring a Euclidean Attention Mechanism (EAM) for low-resolution structure restoration and a Feature Aggregation Synthesis Block (FASB) for high-resolution texture filling, achieving superior results on datasets like CelebA-HQ, Paris Street View, and FFHQ.

During the investigation of an automated handloom system less works are addressed in this field. For deep learning models to learn and generalise patterns efficiently, a large amount of labelled data is required. The lack of publicly accessible datasets containing appropriately labelled photos of handloom designs, however, presents a challenge to the component that generates handloom designs. Because of this, it is difficult to train deep learning models that produce the designs with accuracy. Handloom designs feature a wide range of complex colours, textures, and patterns. Less accuracy may result from current deep learning models inability to fully comprehend the diversity and complexity of handloom designs. Research are still needed to create a deep learning network that can accurately learn and represent the many handloom designs. Mainly the importance of implementation by our handloom worker required to be focused. Standardised assessment metrics are essential for contrasting and evaluating various automated handloom design generating techniques. At the moment, there is a lack of agreement on assessment measures, which makes it challenging to assess deep learning models functionality impartially. It is necessary to construct commonly accepted evaluation metrics that includes both the fundamental elements and particular, unique traits, such as similarity and customisation.

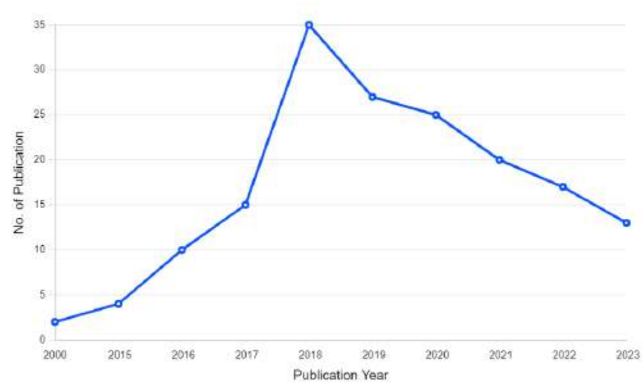


Figure 3. Publication trend during the period 2000 to 2023

Several investigations on automated design creation have been carried out globally. We found that hardly many noteworthy works in this field were published between 2000 and 2015. Nonetheless, it has progressively gained acceptance among scholars from 2015 to 2021. The era of 2017-2019 saw the highest amount of publications ever made. Figure.3 shows a graph that illustrates the publication pattern from 2000 to 2023. Based on observations, research on traditional loom clothing has been conducted most frequently in India. Majority of the work is done on everyday clothing, such as sarees and powerlooms. Thailand, Malaysia, Australia, Pakistan, Canada, Japan, Columbia, Indonesia, Bangladesh, and South Korea are among the other countries with less research in this field. Since book chapters make up the least amount of all papers, we have prioritised journal and IEEE articles here, which are the most commonly accessible types of publications.

3. Methodology

A. Data Collection

To train a generated network for the image-to-image translation an appropriate dataset was needed. For that many researchers recommended ImageNet [28], Microsoft COCO [29], and complicated embroidery datasets but the results were less successful. We identified that all available datasets are of low count,low-quality and low-resolution images. Both locally made textiles and intricately designed textiles from multiple authors were also considered. Some researchers generated images of conventional and regional handlooms mainly of sarees that make up the "Neural-Loom" [9] dataset. That dataset contains only 350+ images which is very less in number to train a network. Thus, the creation of a handloom dataset becomes a priority work as there isn't anyone of this kind. By scraping the internet and e-commerce sites for photos, we gathered some high-resolution images but not enough to train our model. After that, we visited the silk village: Sualkuchi to gather more image data of various handloom samples consisting of Pure Pat, Kesa Pat, Nuni Pat, Pure Muga, Toss Muga, and Dry Toss Muga in order to conserve our traditional handloom styles. Firstly, as shown in Figure.4 we have collected 300 samples using two smartphone models (iPhone 11 and OnePlus Nord CE 3) to account for sample variance. During image capture, factors such as focus, illumination, and distortion were carefully controlled, maintaining a 5-10 cm distance between the camera and the fabric while adhering to detailed camera specifications. Secondly, the collected samples were artificially boosted by cropping into three equal sections: the top-left, bottom-right, and center corners for introducing varied perspective and effective investigations. Additionally, image augmentation techniques were applied to enhance model generalization and diversity and resized to 500×500 pixels. Finally, this process resulted into our own dataset named as "HandloomGCN" [30] comprising of 3000 and made publicly accessible.

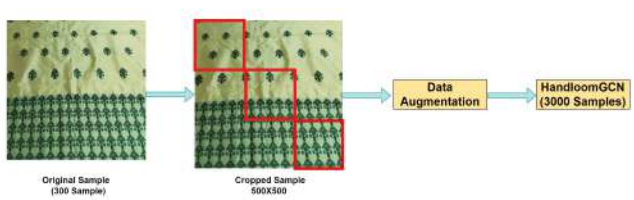


Figure 4. Our dataset "HandloomGCN" preparation process

B. Generated Cellular Network

Our network architecture largely follows the design principles of a deep convolutional neural network, specifically resembling VGG16 as illustrated in Figure.5. It employs strided and fractionally strided convolutions instead of pooling layers. The network consists of five residual blocks, and apart from the output layer, all non-residual convolutional layers are paired with spatial batch normalization and ReLU activations [31]. This setup ensures that the generated images have pixel values within the [0, 255] range. Each convolutional layer, except the first and last ones, uses a 3 × 3 kernel, while the first and last layers utilize 9 × 9 kernels. The network is fully convolutional, allowing the use of bicubic interpolation [32] for image processing. Fractionally strided convolution facilitates joint training of the upsampling function with the rest of the network [33], unlike relying on a predefined upsampling function. Our network employs two stride-2 convolutions to downsample the input, many residual blocks, and two stride 1/2 convolutional layers for upsampling in order to preserve the texture. This architecture is computationally efficient. An additional benefit of our network is the effective receptive field sizes. Each pixel in the output has a large receptive field in the input, which is crucial for high-quality inputs that require coherent modifications across significant portions of the input. Without downsampling, the effective receptive field size doubles with each additional 3 × 3 convolutional layer. After downsampling by a factor of D, each 3 × 3 convolution increases the effective receptive field size by 2D, providing larger effective receptive fields with a similar number of layers.

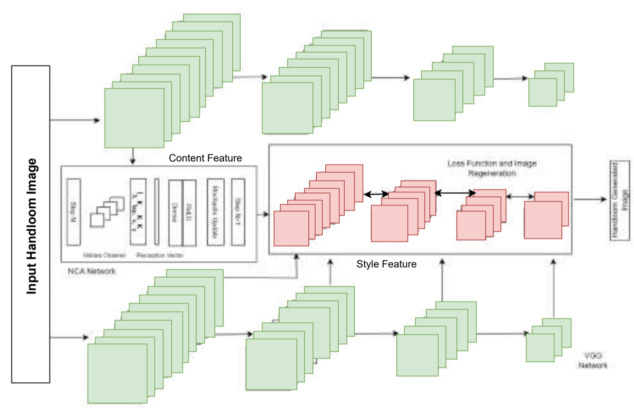


Figure 5. Generated Cellular Network

The use of residual connections in our network facilitates the learning of identity functions. Each layer in the network acts as a non-linear filter bank, with complexity increasing deeper into the network. A representation of the image that becomes more explicit about object information as it moves up the processing hierarchy is created during training. The network's hierarchy depicts the image's texture while becoming mostly insensitive to its exact look. Therefore, higher layers in the network do not oblige the precise reconstruction pixel values, but they do express the high-level information of textures and their positioning in the input image. The bottom layers, in contrast, only duplicate the original images precise pixel values. Thus this network refers to the feature retaliation in higher layers of the network as the original representation. Feature correlations of multiple layers, we obtain a stationary, multi-scale representation of the input image, which grab its texture details using gradient descent that minimizes the mean-squared distance between the entries of the Gram matrices. Mathematically, the Gram Matrix is computed as given in Equation-1, where i is the convolutional layer, and ϕ_i(y) is the feature map of shape $C_i \times H_i \times W_i$.

$$G_i^{\phi}(y)_{c,\hat{c}} = \frac{1}{C_i, H_i, W_i} \sum_{h=1}^{H_i} \sum_{w=1}^{W_i} \phi_i(y)_{h,w,c} \phi_i(y)_{h,w,\hat{c}} \qquad (1)$$

The cellular automata [34] states are initialized as vectors of features, iterated for a random number of steps, and the resulting state is fed into the observer network. A loss is enforced to match the values of the gram matrices when the target texture and the output are fed to the observer network, respectively. Using a typical backpropagation throughput time, we backpropagate this loss to the network parameters. Created a cellular automata grid with initial states where each cell represents a different area of the image and changes throughout time. The cellular automaton's starting state was encoded with information regarding feature correlations through the use of the Gram matrix. This is accomplished by mapping the Gram matrix values to the initial cell states. The cellular automaton's rules are applied across a number of iterations. A cell's present state and the states of the cells around it determine its state at any given iteration. The cellular automaton uses the encoded Gram matrix representation to produce dynamic patterns as it develops. The progress of the patterns is influenced by the relationships among the features, producing output that is visually appealing. To get the desired visual output, the process is iteratively improved by changing the Gram matrix, cellular automaton rules, or parameters. The image generation $\hat{y}$ using our proposed network is shown in the Equation-2. Where $S_{t+1}(i, j)$ is the state of the cell at position(i,j) in the next step. f is the activation function with W as weight matrix. $G_i^{\phi}(S_t)_{c,\hat{c}}$ represents the Gram matrix of extracted features from the current state. $neighborhood(S_t, i, j)$ is the local neighborhood around cell (i,j) with b as bias.

$$S_{t+1}(i, j) = f(W.concat(G_i^{\phi}(S_t)_{c,\hat{c}}, neighborhood(S_t, i, j))+b) \qquad (2)$$

C. High Resolution Network

A deep learning architecture [35] is intended to improve the resolution and quality of the resultant image for more detailed appearance. These networks as shown in Figure.6 use sophisticated interpolation techniques and convolutional neural networks (CNNs) to produce high-resolution copies of the low-resolution input images. The enhancement of the overall visual quality by retrieving textures and fine-grained information that could be distorted during the generation process. It enable to sustain the semantic knowledge during the feature reconstruction. Since larger factors demand more semantic reasoning about the input, the focus is on ×4 and ×8 output. It runs on the premise of additive Gaussian noise [36] and is based on small changes between pixels. This network will be helpful for upscaling photos to make them look better on high-resolution displays, boosting the clarity, and even raising the caliber of surveillance.

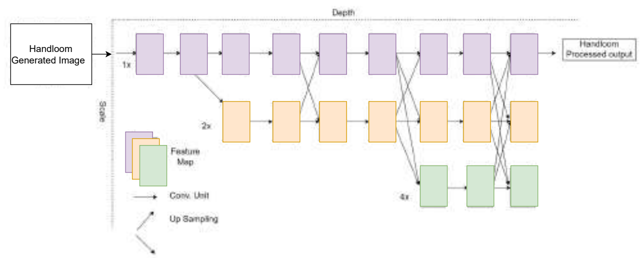


Figure 6. High Resolution Network

4. Experimental Results

A. Baseline methods

1) Handloom design generation using GAN

Handloom design generation using Generative Adversarial Networks (GANs) [9] is a captivating synergy of artistry and artificial intelligence. GANs consisting of a generator and discriminator network, engage in a creative dance where the generator learns to produce intricate handloom patterns inspired by historical designs. The discriminator, on the other hand, sharpens its ability to distinguish between real and generated patterns. Through this adversarial training process, GANs gradually produce high-quality, novel handloom designs that capture the essence of traditional craftsmanship. These AI-generated designs offer a fresh perspective on textile artistry, providing a wellspring of inspiration for artisans and designers. With the power to blend tradition with innovation, handloom design generation using GANs is at the forefront of the revitalization of handloom textiles, paving the way for a harmonious union of heritage and modernity in the textile industry.

2) Texture synthesis using Neural Style Transfer

The concept of Neural Style Transfer (NST) [5] is a fascinating exploration of merging styles with the rich heritage of craftsmanship. NST leverages convolutional neural network [18] to transfer the stylistic characteristics of one image typically a famous artwork onto the texture's design. In this context, it enables artisans and designers to infuse textiles with the aesthetics of renowned artistic styles, creating a fusion of art and tradition. The process involves separating the content and style of an image and then recombining them in a visually harmonious way. This approach not only adds a layer of creativity to textile design but also preserves and honors the cultural and artistic traditions associated with various textures. Design generation through NST breathes new life into traditional textiles, offering a contemporary perspective while celebrating the time-honored craftsmanship that defines these unique textures.

B. Experimental Setup

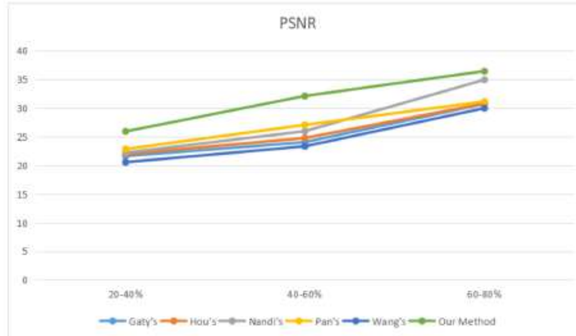
The NVIDIA Geforce GTX 1650 Max-Q GPU is employed for the duration of the investigation. The input images are of resolution of 500x500x3. We proposed a network, fusing VGG16 model as the backbone for fine feature extraction with cellular network to capture spatial dependencies and generate handloom designs. This method will demonstrate the convergence of computer creativity and textile skill. Additionally, a high-resolution network is loaded in order to achieve high-resolution output. With multiprocess computation, the proposed network took minimum hours to train the model, and the Average feature extraction time (AFE) [37] is 13 microseconds per image. The comparision benchmark of hand-crafted works and deep learned feature methods is established. The following parameters are used in the comparison process. The batch size is set to 60, the epoch is set to 70, the dropout is set to 0.5, the random horizontal flip is set to 0.5, the learning rate is set to 0.05 and programmed to decay once the number of iterations proceeds to 2/3 to 1/10 of its initial value. Cross-Entropy [38] is selected as the loss function, and the optimizer adopts Stochastic Gradient Descent (SGD) [39].

C. Experimental Results

We evaluated our proposed model using our own data, including the "Neural-Loom" dataset and a selection of online images. The results, displayed in Figure.8, illustrate various weight ratios. At lower weight ratios, the structural deformation is significant. However, as the weight ratios increase, the deformation diminishes. These experiments demonstrate that our approach effectively reconstructs the traditional structure of the test images while retaining sufficient style and detail.

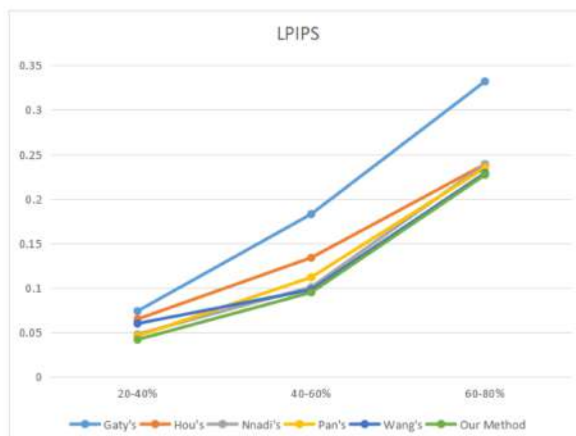
Homogenous textures (i.e., those with regular or stochastic textures) process better using our technique. Three primary metrics are used to quantitatively assess the designed method: Peak Signal to Noise Ratio (PSNR) [40], Structural Similarity (SSIM) [41] and Learned Perceptual Image Patch Similarity (LPIPS) [42]. The results are compared to those of the state-of-the-art counterparts with weight ratios of 20–40%, 40–60%, and 60–80%. The suggested method's performance exceeds the other strategies, proving its efficacy beyond uncertainty. By comparing the outputs with the arranging order of the diversity in weights, the Table II illustrates the quality of the generated image and also represented in graphical form in Figure.7.

We performed an introspective user research for qualitative evaluation. In this evaluation, 30 volunteers with experience in image processing are taking part. From those regenerated outputs by the suggested method and the representative state-of-the-art approaches, they are requested to select the most realistic image. Each participant is given 10 questions in total, chosen at random from the dataset. We compile the average vote and framed in the Table III of results along with the performance loss and runtime of the methods for a clear comparative view. The results are also represented in graphical form in Figure.9. We found that our strategy outperforms the others by a significant margin, revealing that it is successful.



PSNR

SSIM



LPIPS

Figure 7. Graphical Representation of comparisions (PSNR, SSIM, LPIPS) between our approach and other methods

The designed network also offers a promising advancement by addressing the limitations of existing methods. The VGG16 network, renowned for their deep convolutional

TABLE II. Comparisons (PSNR, SSIM, LPIPS) between our approach and other methods

Method	PSNR			SSIM			LPIPS		
	20-40%	40-60%	60-80%	20-40%	40-60%	60-80%	20-40%	40-60%	60-80%
Gaty's [18]	21.63	24.06	30.74	0.487	0.680	0.864	0.074	0.183	0.332
Hou's [11]	21.99	24.77	30.81	0.527	0.730	0.885	0.065	0.134	0.283
Nandi's [9]	22.23	25.97	34.05	0.531	0.735	0889	0.048	0.101	0.239
Pan's [20]	22.85	27.07	31.15	0.525	0.741	0890	0.046	0.112	0.235
Wang's [21]	20.55	23.34	29.99	0.510	0.725	0898	0.060	0.098	0.229
Our Method	25.93	32.12	36.45	0.561	0.759	0.904	0.042	0.095	0.227

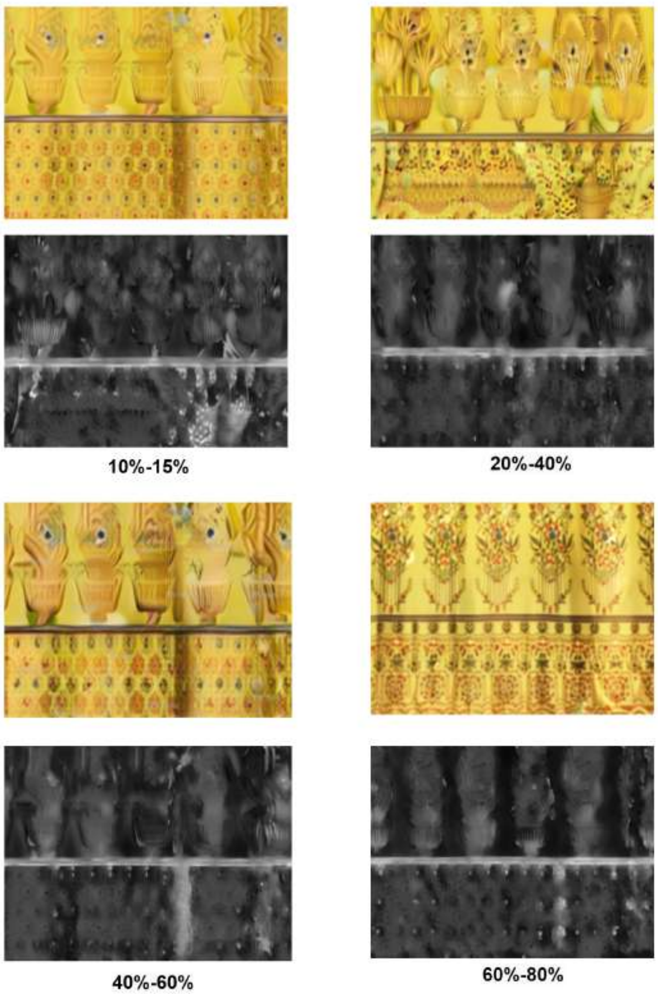
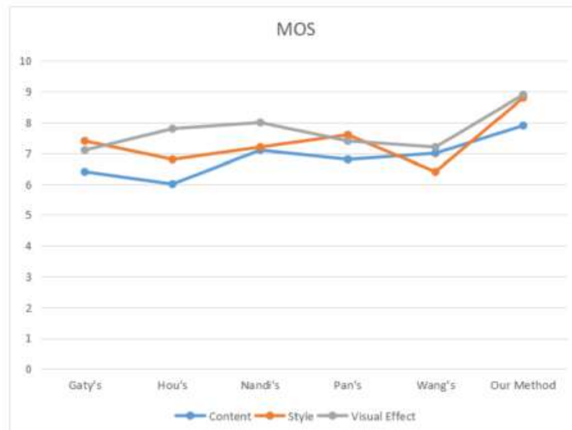
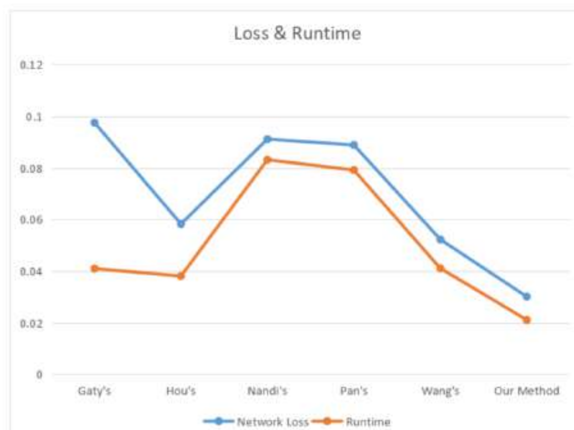


Figure 8. Outputs and its roughness image of Our Proposed Methods with different weight ratio



MOS



Loss & Runtime

Figure 9. Graphical Representation of Visual & Model performance comparisions between our approach and other methods

layers, adeptly capture intricate details and textures in images, effectively overcoming the complexity challenges faced by Deep Belief Networks. When combined with Cellular Automata, which draws inspiration from the self-organizing behavior, this approach enables iterative refinement of designs, achieving photographic-level sharpness and detail, thus resolving the shortcomings of Variational AutoEncoders. This hybrid model also provides enhanced user control and customization capabilities, surpassing the constraints of CNN with Single Image Super-Resolution (SISR). Additionally, the stability inherent in generative cellular network reduces the instability and unpredictability often associated with Generative Adversarial Networks (GANs). Utilizing the innate parallelism and dynamic functionality of cellular automata, our approach operates on a grid-based structure where the state of each cell evolves over time through interactions with nearby cells. This mechanism allows for the nuanced replication of patterns and textures typical in handloom designs. Furthermore, by integrating semantic guidance, our model adeptly tackles challenges such as complex geometries and self-occlusion, while also enabling robust feature aggregation, as evidenced by previous works like the Semantic-guided Conditional Texture Generator and the Panoramic Feature Aggregation Network (PFAN). This fusion of two different structures offers a robust, stable, and highly customizable framework for generating intricate and varied handloom designs.

5. Conclusion and Future Work

This paper has raised a pioneering approach to handloom design generation through the fusion of deep convolutional networks with cellular automata, further enhanced by post-processing with a high-resolution network. The integration of these advanced computational method offers a transformative way for automating and elevating the intricate process of handloom design creation. The trained network effectively captures intricate design features and aesthetics from the dataset, while the cellular automata injects dynamic and evolving elements, enriching the designs with a harmonious blend of tradition and innovation. Moreover, the incorporation of a high-resolution network in the post-processing stage refines and enhances the generated designs, ensuring a level of detail and quality that meets the standards of high-resolution output. The comprehensive fusion methodology outputs demonstrate the capacity to produce culturally rich and aesthetically pleasing handloom designs that seamlessly combine traditional craftsmanship with cutting-edge computational creativity. The experimental results also shows the excellence in outcomes compared to other existing approaches. Some exceptions occurred in unsymmetric textures, images of strong perspective or structure difference that can be explored in future. Additionally, researchers can explore advanced techniques like integration of multi-scale features and adaptive learning algorithms that may offer promising results with diverse textile patterns.

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TABLE III. Visual & Model performance comparisons between our approach and other methods

Criteria	Gaty's [18]	Hou's [11]	Nandi's [9]	Pan's [20]	Wang's [21]	Our Method
Content	6.4	6.0	7.1	6.8	7.0	7.9
Style	7.4	6.8	7.2	7.6	6.4	8.8
Visual Effect	7.1	7.8	8.0	7.4	7.2	8.9
Arbitrary	Yes	No	Yes	Yes	Yes	Yes
Loss	0.0976	0.0583	0.0912	0.0889	0.0523	0.0301
Runtime	0.0419	0.0381	0.0832	0.0792	0.0411	0.0211

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