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. There are 12.41 lakh (44.6%) handloom families [2] in Assam alone. The three most well-known and distinguished clothing types made in Assam are eri, pat, and muga as shown in Figure.2.

Figure 1. Assam Traditional Handloom

As per the 2001 census estimate, about 2,24,381 individuals living in Assam are involved in the traditional silk clothing weaving [1] of Assam as in Figure.1. Since the beginning of time, handloom weaving has played a significant role in Assamese socioeconomic life. 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], a 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. To create a new customized design almost 1/4 th part of time is consumed. Because the human mind is biased, it becomes very difficult to come up with designs that combine non-handloom design styles with handloom designs or vice versa. In scientific words, it is challenging to quantify such a blending of taste and design aesthetic. This particular approach will therefore attempt to solve the problem of producing design or texture from existing priors or randomly chosen priors that are independent of both traditional design and the more generic designs. Another way to phrase this issue is ”Transfer or Generation” of Texture and Geometric Artifact [4] in an Image, wherein Transfer refers to basing a handloom's design on pre-existing generic designs. Generation is the process of creating something entirely novel from a suggestion provided by some random noise and remains dependent to fixed feature extraction. The demand for an automated handloom system that can produce personalized designs for a range of handloom clothes is rising due to a number of variables.

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

Figure 2. Different handloom Cloth designs

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 [18] and a generalised mutual information measure for the commonly used relative entropies, like Kullback-Leibler [19]. A review was conducted on various methods for analysing handloom texture, which were framed into four categories: structural, statistical, model-based, and transform methods [20]. Image interpreters can be trained using two sets of unlabeled photos from two different domains thanks to a revolutionary dual-GAN technique [21] that was introduced in 2017. Within the architecture [22], 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 [39], a new study was presented on the development of patterns using Wasserstein Generative Adversarial Networks Gradient Penalty (WGANs GP) [40] 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.

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

TABLE I. Handloom design generation

Methodology	Database	Limitation
Deep Belief Networks [12]	COCO Dataset	Lack in capturing fine details
Variational AutoEncoder [11]	Photographic Dataset	Lack sharpness
CNN with SISR [30]	ImageNet	Limited user control generation
Generative Adversarial Networks [9]	Neural-Loom	Prone to instability generation
Dual-GAN [22]	Own unlabeled Dataset	Limited to dissimilar textures

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.

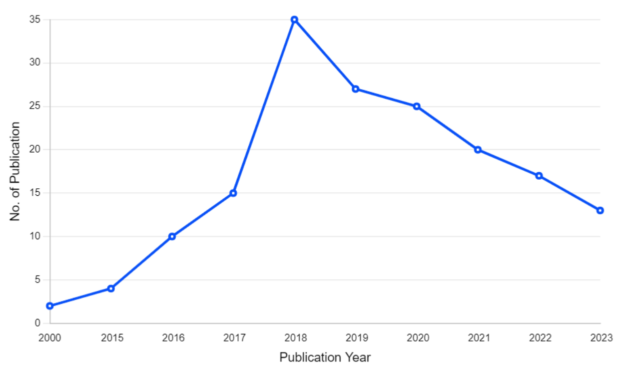


Figure 3. Publication trend during the period 2000 to 2023

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 [23], Microsoft COCO [24], 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 pictures but not enough to train our model. We also visited the silk village: Sualkuchi to gather image data of various handloom clothes, mostly muga and pat, in order to conserve our traditional handloom styles. The collected samples were artificially boosted by cropping, twisted at different angles and enhanced to high quality for more effective investigations. Finally, We produced our own dataset named ”HandloomGCN” [37] and made publicly accessible.

B. Generated Cellular Network

Our networks roughly adhere to the architectural standards as shown in Figure.4, which call for the usage of strided and fractionally strided convolutions in place of pooling layers. Five leftover blocks make up the network body. Except for the output layer, all non-residual convolutional layers are followed by spatial batch normalization and ReLU nonlinearities [25]. It guarantees that there are pixels in the range [0, 255] in the produced image. Every convolutional layer uses a 3×3 kernel except the first and last layers, which employ 9×9 kernels. Bicubic interpolation [26] can be used to the images because the networks are fully-convolutional. Fractionally-strided convolution enables the upsampling function to be jointly trained with the remaining network [27], as opposed to depending on a fixed 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. The network needs minimal computational cost. Receptive field sizes that are effective are the subject of the second advantage. Each pixel in the output has a broad effective receptive field in the input, which is useful because high-quality inputs necessitate modifying significant portions of the input in a coherent way. The effective receptive field size grows by two with each additional 3×3 convolutional layer when downsampling is not used. Each 3×3 convolution instead increases the effective receptive field size by 2D after downsampling by a factor of D, providing bigger effective receptive fields with the simmilar number of layers.

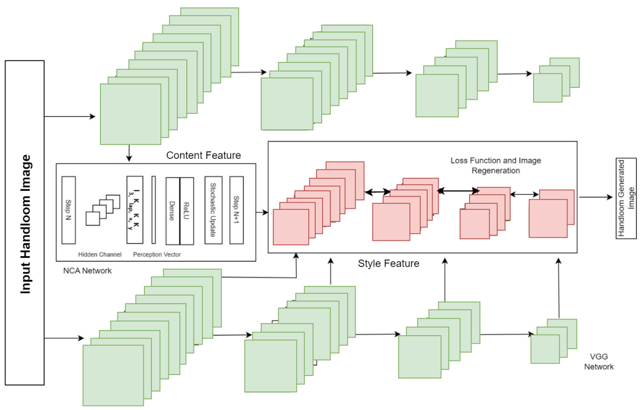


Figure 4. Generated Cellular Network

The network's usage of residual connections facilitates learning of the identify function. Each network layer often defines a non-linear filter bank, the complexity of which rises with the layer's position. 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, Gram Matrix is computed by the given Equation-1. Where i is the convolutional layer, ϕ_i(y) is the feature map of size 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 [28] 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 [29] is intended to improve the resolution and quality of the resultant image for more detailed appearance. These networks as shown in Figure.5 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 [38] 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.

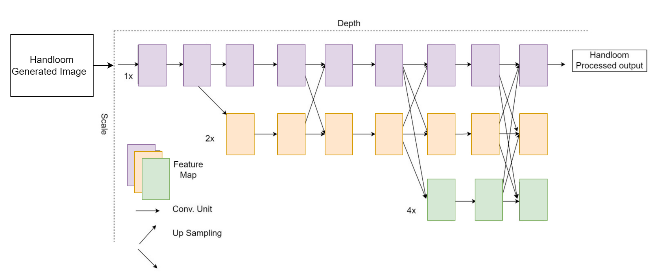


Figure 5. High Resolution Network

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 [30] 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 VGG 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) [31] 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 [32] is selected as the loss function, and the optimizer adopts Stochastic Gradient Descent (SGD) [33].

C. Experimental Results

We evaluated our proposed model with our own data, including the "Neural-Loom" Dataset and some online images. The results are showcased with different weight ratios in Figure. 6. With minimum weight ratios the structure deformation is high. However, with increase in weight ratios the deformation reduces. The experiments indicate that our approach successfully recreates the testing image's traditional structure while preserving enough style and information.

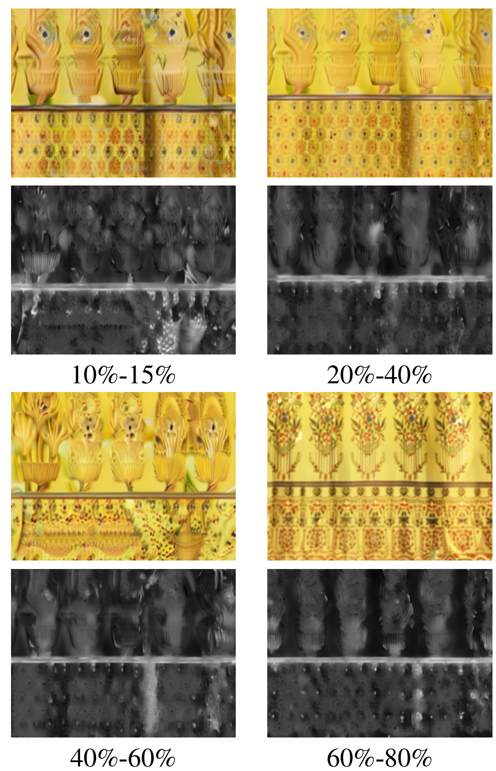
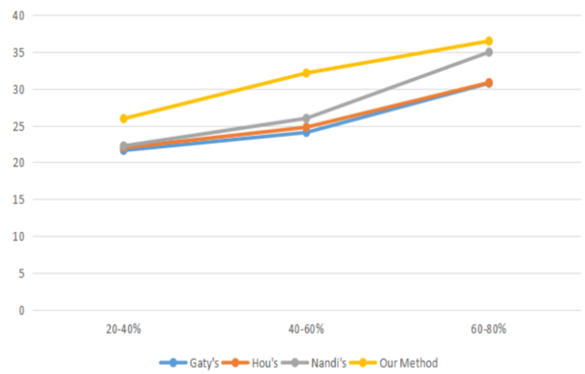


Figure 6. Outputs and its roughness image of Our Proposed Methods with different weight ratio

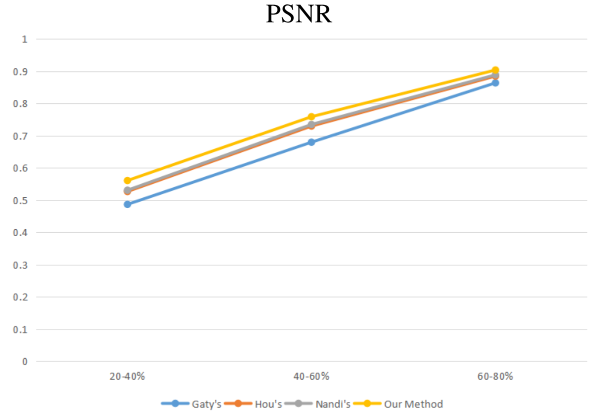
Homogenous textures (i.e., those with regular or stochastic textures) process better using our technique. Three primary metrics are used to quantitatively assess the designed method: Peak Signal to Noise Ratio (PSNR) [34], Structural Similarity (SSIM) [35] and Learned Perceptual Image Patch Similarity (LPIPS) [36]. 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.

TABLE II. Comparisions (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 [30]	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
Our Method	25.93	32.12	36.45	0.561	0.759	0.904	0.042	0.095	0.227



PSNR

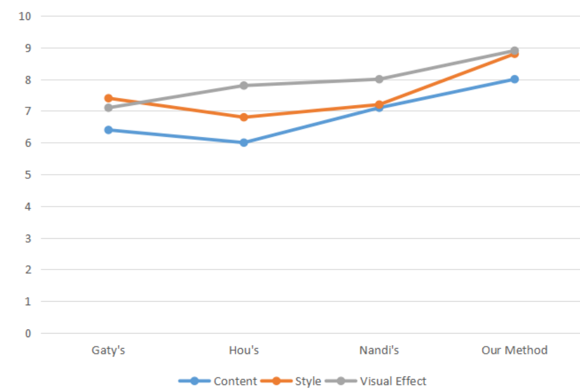


SSIM

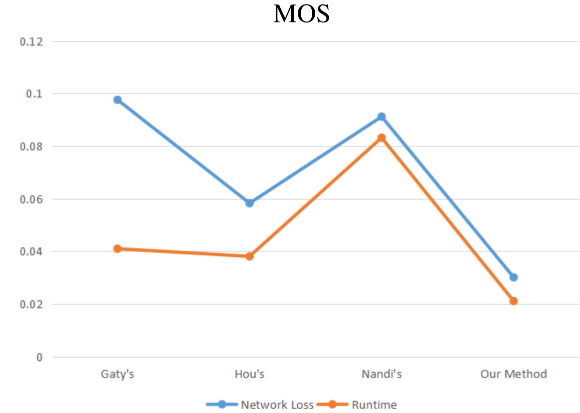
LPIPS

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

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.8. We found that our strategy outperforms the others by a significant margin, revealing that it is successful.



MOS



Loss & Runtime

Figure 8. Graphical Representation of Visual & Model performance comparisions between our approach and other methods

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

Criteria	Gaty's [30]	Hou's [11]	Nandi's [9]	Our Method
Content	6.4	6.0	7.1	7.9
Style	7.4	6.8	7.2	8.8
Visual Effect	7.1	7.8	8.0	8.9
Arbitrary	Yes	No	Yes	Yes
Loss	0.0976	0.0583	0.0912	0.0301
Runtime	0.0419	0.0381	0.8324	0.0211

5. Conclusion

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.

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