Research and Application of Vietnamese antiquities reconstructing and preserving Based on Deep Learning

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Abstract

In the strong wave of technological advancements, it's crucial to prioritize the development and preservation of history. By using modern technologies like deep learning, it becomes possible to apply them to the conservation and promotion of cultural heritage. Besides, artificial intelligence, specifically deep learning, has a great influence on the field of computer vision. Currently, deep learning techniques have developed and are capable of recovering images based on large amounts of data. This has great significance in its application to the field of historical preservation. This study focuses on the application of deep convolutional neural networks to recover ancient Vietnamese patterns using three different deep learning models Generative Image Inpainting with Contextual Attention, Image Inpainting via Generative Multi-column Convolutional Neural Networks, and Generative Image Inpainting with Image Fine-grained Inpainting and mainly focuses on completing the image data set of patterns on cobalt blue underglazed porcelains under the Nguyen Dynasty. The specific focus on recovering patterns from cobalt blue underglazed porcelains under the Nguyen Dynasty is significant as these artifacts hold historical and cultural value in Vietnam. Creating a dataset of patterns on cobalt blue underglazed porcelains, provides a valuable resource for future researchers and preservationists. We have collected 4600 images of patterns on cobalt blue underglazed porcelains under the Nguyen Dynasty. To evaluate the tested models, we quantitatively and qualitatively evaluate the results showing that the experimental model performs quite well. These promising results reinforce the effectiveness of deep convolutional neural networks in the field of historical preservation and image inpainting. The research outcomes showcase the potential of advanced technology in recovering and preserving the cultural heritage of ancient Vietnamese patterns on cobalt blue underglazed porcelains from the Nguyen Dynasty. The research has a direct impact on preserving and promoting Vietnamese cultural heritage, which is vital for maintaining a connection to the past and fostering a sense of identity among younger generations. It combines the power of modern technology with historical artifacts, ensuring that the value of these cultural treasures remains relevant and accessible in the digital era. The results have potential applications in various fields such as education, research, and tourism, contributing to raising awareness about Vietnamese history and culture in the era of advanced technology. This can enhance the understanding of Vietnamese history and culture, both within the country and among international audiences.

Index Terms

Convolutional neural networks, pattern recognition, data collection, inpainting, historical preservation

I. Introduction

As can be seen, the development of deep learning techniques is of great significance in the historical field. Vietnam possesses an extensive collection of physical cultural heritage, comprising millions of precious artifacts, antiquities, and national treasures. These valuable items are carefully preserved and exhibited across a network of 125 museums located throughout the country. The museums are strategically distributed in various regions and are particularly concentrated in major cultural and tourist hubs [1]. However, the application of deep learning techniques to restore ancient Vietnamese patterns remains largely unexplored. Vietnamese antiquities hold a significant cultural and historical value that needs to be preserved and protected. However, the historical value of Vietnam is gradually fading both physically and mentally, especially among young people. The study titled ”Educating Traditional Cultural Values in Vietnam Universities” conducted by Nguyen Sy Trung and Vu Hong Van reveals that the education of traditional cultural values has not received significant attention in Vietnamese universities for an extended period. Furthermore, the research highlights that only a limited number of universities incorporate cultural subjects into their curriculum at the university level [2]. Many artifacts have been damaged or lost over time and many people are not aware of the value and meaning of Vietnamese antiques, making it challenging to preserve them [1]. Over the years, some experts in culture and fine arts have admitted that our fields such as movies, fine art, interior decoration, graphic design, etc. are being ”Chineseized” ”. One of the important reasons pointed out is that due to the lack of resources, Vietnam currently does not have a pattern library. ancient culture to serve as an application basis for products bearing the spirit of Vietnamese culture. Meanwhile, many other countries have thousands of patterns, gathered into libraries of vector patterns, optional online.

This study focuses on the preservation and restoration of ancient Vietnamese patterns on cobalt blue underglazed porcelains the Nguyen Dynasty. By focusing primarily on assembling a comprehensive data set of pattern images of this era from various collections and archival sources. The research will contribute to the archiving and digitization of historical image data of Vietnam. This study applies and evaluates image restoration models based on deep convolutional neural networks from previous studies. Tests performed on the collected data set will shed light on the effectiveness of these models in restoring complex patterns on porcelain artifacts.

Applying Deep Learning technologies to preserve and restore Vietnam's cultural heritage is a modern and advanced method, attracting the attention of the following scientific, political, local and international communities. The importance of this study lies in the immense value of preserving and understanding cultural heritage. To effectively navigate the challenges and leverage the opportunities presented by Industry 4.0, it is essential for us to proactively develop its culture in the coming years [3]. By employing advanced deep learning techniques, the research will contribute to the growing body of knowledge in the field of computer vision, specifically in historical restoration. Furthermore, this is a special way to spread, educate and reach young people in the current era. The recovery and restoration of ancient patterns on cobalt blue underglazed porcelains will not only provide insights into the artistic traditions of the Nguyen Dynasty but also enhance our overall comprehension of Vietnamese history and culture. Furthermore, By doing so, it aims to enrich our understanding of Vietnamese cultural heritage and inspire further advancements in the field of historical preservation.

II. Related work

In the past, image were manually repaired using the inpainting technique to preserve the image quality. With the advent of the digital age, picture storage methods have quickly transitioned from hard copies to digitalized units in a less onerous way thanks to the use of digital tools[4]. Although the practice of picture inpainting, or the art of restoring outdated and damaged photos, has been for a while, it has lately grown in favor as a result of recent advancements in image processing technology [5]. The development of deep learning techniques has revolutionized computer vision, enabling remarkable advancements in image recognition, restoration, and analysis. Researchers have successfully applied deep convolutional neural networks to various domains, including image inpainting, where missing or damaged parts of images are intelligently reconstructed. A study "Generative Image Inpainting with Contextual Attention" by Jiahui Yu et al. presents a deep generative model-based approach for image inpainting [6]. They introduce a fully convolutional neural network that can handle images with multiple holes of varying sizes and locations during testing. The key innovation is the integration of contextual attention mechanisms, allowing the network to explicitly utilize surrounding image features as references during training. By incorporating contextual attention, the model can effectively borrow information from distant spatial locations, resulting in improved structures and textures consistent with the surrounding areas. The authors evaluate their method on various datasets, including faces, textures, and natural images, and demonstrate that it generates higher-quality inpainting results compared to existing approaches. The paper "RePaint: Inpainting Using Denoising Diffusion Probabilistic Models" presents a novel inpainting approach based on Denoising Diffusion Probabilistic Models (DDPM). RePaint demonstrates high generalization capabilities to unseen mask types and produces semantically meaningful content in missing areas. It outperforms state-of-the-art Autoregressive and GAN approaches for at least five out of six mask distributions. The method's flexibility and effectiveness make it a promising solution for inpainting tasks in computer vision applications [7]. The paper titled "FFTI: Image inpainting algorithm via features fusion and two-steps inpainting" by Yuantao Chen, Runlong Xia, Ke Zou, and Kai Yang introduces a novel image inpainting approach that overcomes the limitations of existing methods. The proposed FFTI algorithm leverages dynamic memory networks to fuse external and internal features of the incomplete image, producing an optimized map. A generation countermeasure generative network with gradient penalty constraints guides the rough repair of the incomplete image, followed by optimization based on feature coherence to obtain the final fine repair map. Experimental results demonstrate that FFTI outperforms other models in terms of visual effects and objective data, showcasing its effectiveness and potential as a promising solution for image inpainting tasks [8]. The paper "EdgeConnect: Generative Image Inpainting with Adversarial Edge Learning," was authored by Kamyar Nazeri, Eric Ng, Tony Joseph, Faisal Z. Qureshi, and Mehran Ebrahimi proposes EdgeConnect as an effective solution to this problem, leveraging generative adversarial networks (GANs) and edge information[9].

Image inpainting is a powerful technique used in various fields to restore, enhance, or manipulate images by filling in missing or damaged regions. It has found applications in computer vision, graphics, medical imaging, cultural heritage preservation, and more. In this context, recent research has explored the use of deep learning methods, such as generative adversarial networks (GANs), for inpainting tasks, leading to significant advancements in image restoration and synthesis. Ecem Sogancioglu, Shi Hu, Davide Belli, and Bram van Ginneken wrote "Chest X-ray Inpainting with Deep Generative Models" in the field of medicine. The authors point out that while generative adversarial networks (GANs) have been successfully used for inpainting in natural images, the field of medical imaging has not been properly investigated. The study examines how three inpainting models based on deep learning—context encoders, semantic picture inpainting, and the contextual attention model—perform when applied to chest X-ray images [10]. The paper titled "INCLG: Inpainting for non-cleft lip generation with a multi-task image processing network" presents a PyTorch-based image inpainting system aimed at predicting non-cleft facial images for patients with cleft lip. The software framework uses image inpainting, which allows the prediction of non-cleft facial images without requiring cleft lip images for training, thus ensuring patient privacy. The authors introduce a novel multi-task architecture that predicts both the non-cleft facial image and facial landmarks, resulting in improved performance as evaluated by surgeons. This approach facilitates the understanding, awareness, and discussion of cleft lip surgeries, benefiting both medical professionals and patients[11].

In the field of historical preservation, the integration of advanced technologies has become indispensable for safeguarding and restoring cultural artifacts. The application of cutting-edge tools, such as artificial intelligence, computer vision, and deep learning techniques, has revolutionized the way we approach the conservation and restoration of historical treasures. In "Enhanced Inpainting Model Revitalizes Historical Paintings with Vision Transformer," Xinran Duan, Chaoyong Jiang, and Yachun Fan present a deep learning architecture for restoring ancient paintings. The method utilizes an advanced edge detection model to extract crucial structure information, including texture, painting style, and overall structure, which is then employed for the restoration process. The effectiveness of the approach is validated through training and testing on diverse ancient painting datasets. By expediting and enhancing the accuracy of restoration while preserving the original artistic style, the proposed model contributes to the preservation and transmission of our historical culture, holding significant value for VR cultural heritage conservation and presentation [12]. The research paper titled "Multi-stage Progressive Reasoning for Dunhuang Murals Inpainting" introduces a novel approach, the Multi-stage Progressive Reasoning Network (MPR-Net), for digital restoration of Dunhuang murals, which suffer from extensive damage due to environmental erosion. To adaptively incorporate information from various scales of murals, a Multi-scale Feature Aggregation Module (MFA) is introduced. The proposed method mimics the process of a mural restorer, first inpainting the global structure of the damaged mural and then adding local texture details[13]. Xuhui Fu's (2021) research attempted to revive traditional Chinese designs. "Research and Application of Deep Convolutional Neural Network Based Ancient Chinese Pattern Restoration."The other two approaches are tested on the same section of the Qinghai traditional embroidery image data set as the strategy that is based on the deep convolutional neural network. With a total of 2000 images, the Qinghai embroidery image data set consists of embroidery of the Tu nationality, Guinan Tibetan embroidery, Haixi Mongol embroidery, Hehuang embroidered, and Huangzhong pile embroidery [14].

The integration of artificial intelligence, computer vision, and deep learning techniques has revolutionized the way we approach the conservation and restoration of historical artifacts, providing powerful tools for safeguarding our cultural heritage. These developments have expedited the restoration process while preserving the original artistic style and improving the accuracy of the restoration outcomes. Overall, the research in image inpainting continues to evolve, with ongoing efforts to refine existing methods and explore new approaches. The promising results achieved so far point to a bright future for image inpainting, where it will remain a powerful technique in various fields, enabling us to restore, enhance, and manipulate images with greater precision and efficiency.

III. Methodology

A. Dataset

Antique images are data of great value, especially in the field of artificial intelligence, big data contributes greatly to the success of models. However, to achieve this goal, very large datasets are needed to train and test AI models accurately and reliably. The effectiveness of algorithms depends heavily on the quality of the input data representation. A suitable representation leads to better performance compared to a poor representation [15]. The dataset collected in this study provides pattern images on cobalt blue underglazed porcelains in the Nguyen Dynasty of Vietnam that can enrich, diversify and expand the existing data sets.

1) Objectives: The data collected initially included images of cobalt blue underglazed porcelains under the Nguyen Dynasty in Vietnam. Pattern designs include dinner bowls, dinner plates, covered tureen, tea-set, offertory fruit-tray, altar flower vases, basin and flower pot, large flower vases, decorative pedestals. Decorative motifs include decorative motifs with animals, decorative motifs with vegetation, decorative motifs landscape, figure and story, decorative motifs with objects, and various forms of diaper patterns.

Nguyen Dynasty: The final reign of a monarch in Vietnamese history. The Nguyen Dynasty lasted 143 years, beginning with Nguyen Anh (Gia Long)'s accession to the throne in 1802 and ending with Bao Dai's abdication in 1945.

Porcelain: The kaolin content in porcelain bone is high and the melting of porcelain bone proves that the firing temperature has exceeded 1,300oC, which is the temperature to create porcelain products in the true sense of the word.

Cobalt blue underglazed porcelains (Ordered patterned porcelains): That is sending samples to Chinese ceramic kilns to follow the orders of the orderers (the kings, mandarins and commoners of Vietnam from the Le Trung Hung period to the Nguyen Dynasty). These porcelains are made in China, but carry "Vietnamese criteria" such as:

- Vietnamese monuments including the Thien Mu Pagoda, Thuy Van Mountain, Tam Thai Mountain, Hai Van Mountain, and Thuan Hoa Market are depicted in decorative porcelain painting.

- Poetry on porcelain, poetry written in the Vietnamese-invented Nom script, which is not used in China, poetry written in Chinese but with a Vietnamese author, such as that of Lord Nguyen Phuc Chu, Dao Duy Tu, King Thieu Tri, or King Tu Duc...
- The year marks or insignia on the porcelain that corresponds to the years of the Vietnamese mission to China include names of Vietnamese rulers including Gia Long, Minh Mang, Thieu Tri, Tu Duc, and Khai Dinh.
- These porcelains are only intended for usage by Vietnamese people and are not sold on the modern Chinese market.

2) Dataset collection: Raw data sets are collected from highly reputable sources. The time to collect and annotate the images is about 3 months, starting from March 1, 2023. The raw dataset includes 723 images of various sizes. The images are in PNG format. Images are collected and archived from a variety of data sources, including Books, private collections, Youtube videos, Blogs, and Websites. The results of synthesizing the number of raw object images containing patterns from multiple sources are shown in Table 1.

TABLE I: The result aggregates the number of raw object images containing patterns from multiple sources.

Source	**Number of Images**
"Commissioned Patterned Porcelains In the Nguyen Era" - Tran Duc Anh Son	240
The collection of Record holder Dinh Cong Tuong	116
Official websites of museums	102
Khanhhoathuynga's collection Blog	95
Dai Ngan - Youtube	87
Ngoc Tinh Phung - Youtube	49
TTR Tube - Youtube	34
Total	**723**

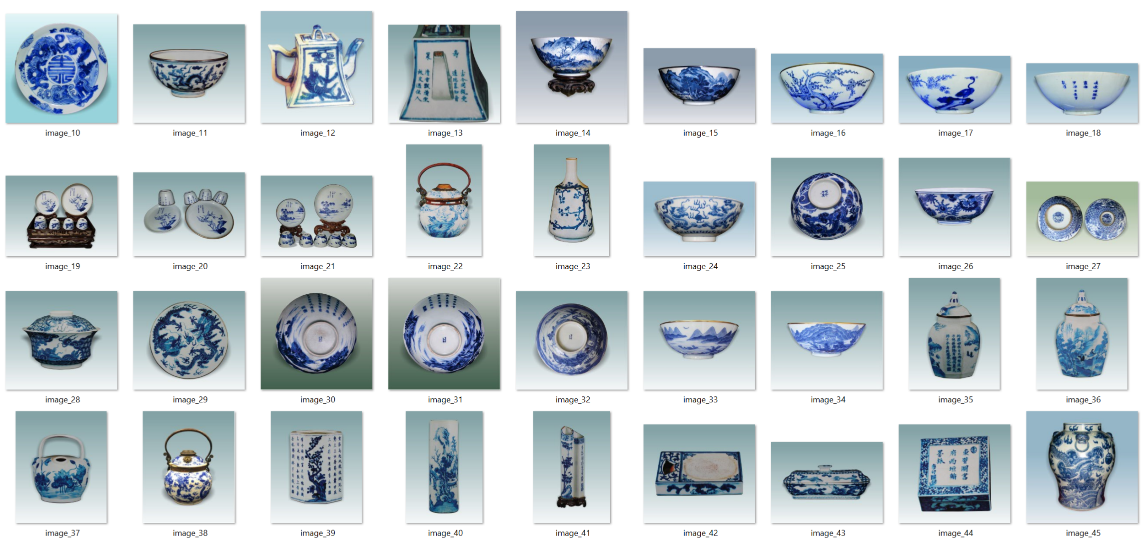

Fig. 1: Part of raw image data collected from sources.

3) Preprocessing: To process the raw data set, a number of tasks were carried out including checking and deleting duplicate images, and poor-quality images in the raw dataset. All raw images are then pattern-selectively cropped to a rectangular size of about 256*256, and unused pattern-free areas are removed from the image. Areas that do not qualify are also ignored. In the end, the number of pattern images processed was 4600.

4) Ethical considerations: Researchers are interested that Vietnamese antiques, especially those of the Nguyen Dynasty, are very rare and not easy to find and collect. Therefore, the researcher makes sure to respect the copyright of the images and videos and has also asked the owner's permission before using it. For each data source used in the study, we contacted the owner via email or cell phone and asked for permission to use the image, video, or photograph (with real artifacts). We guarantee to have all documents related to copyright issues. Furthermore, we have clarified that this is applied research on artifact images and does not make any physical changes to the artifact.

B. Block diagram of the experiment

1) Training: As the Fig 3 shows, the training framework consists of three phases: (1) data preparation, (2) prediction model preparation, and (3) evaluation. The first phase of the framework includes some preprocessing and masking operations. Since

Fig. 2: The image simulates the processing of raw data into pattern image data.

the images are collected from many different sources, the image quality, brightness and contrast will be different, so it is necessary to perform preprocessing steps to bring the data to the same distribution before training. Through the experimental process, we have drawn three preprocessing operations applied to the image including: (1) resizing the image frames to the same size, (2) reducing the noise of the data by using a Gaussian filter with kernel size 5x5 (the kernel size is derived by experimenting many times on the data), (3) and balance the brightness and contrast by converting to the original HSV color space for the return original color purpose. Next, the diagram creates a rectangular mask with a random size and position in the image frame. With three model architectures selected (see Section 3.3), after completing the training we quantitatively evaluate with 4 metrics (see Section 4.2).

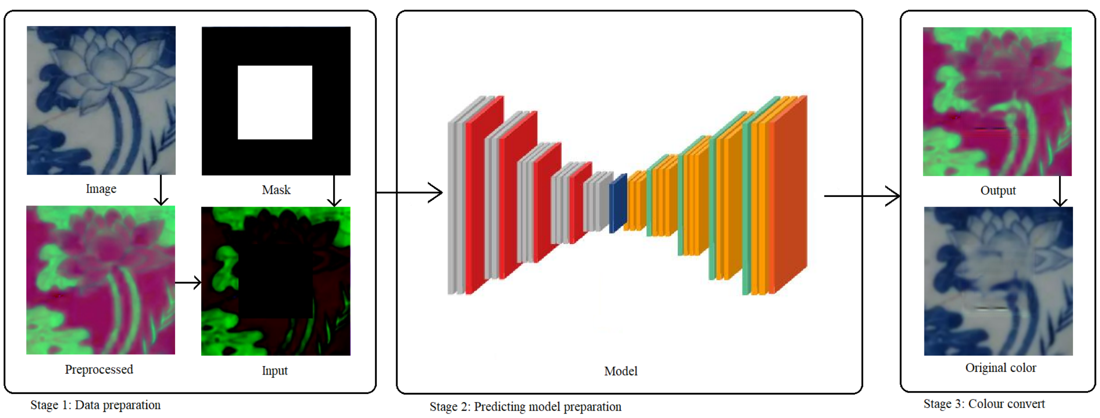

Fig. 3: Block diagram of the program image inpainting

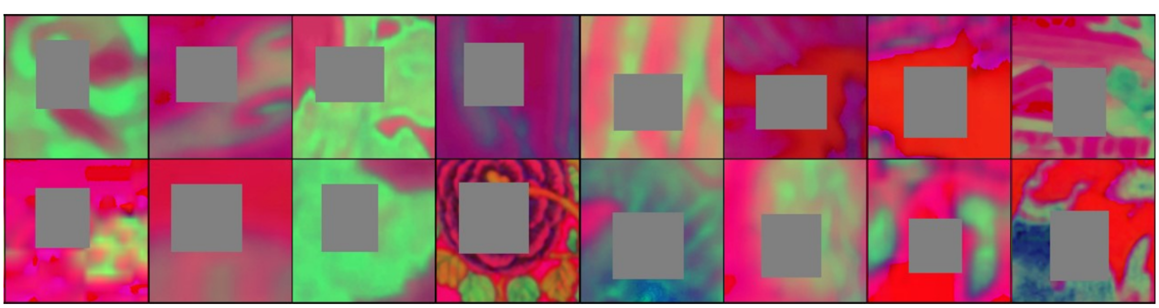

Fig. 4: Several examples of rectangle masks with varying levels of devastation

C. Model

Several computer vision jobs require the use of the image inpainting technique, which is used to replace missing or damaged portions of an incomplete image [16]. Several deep learning algorithms have been successfully used and openly reported for the inpainting job. Some popular techniques include Convolutional Neural Networks (CNNs), which are neural network architectures capable of learning the structural features of an image through the application of convolutional filters and pooling layers [17]. Encoder-Decoder Networks are another commonly used architecture, where the encoder extracts information from the original image, while the decoder network is used to reconstruct the missing regions [18]. Generative Adversarial Networks (GANs) are a type of adversarial neural network architecture, consisting of a generator network used to predict and generate pixel values for the inpainted regions, and a discriminator network used to distinguish between the original and completed images [19]. Attention Mechanisms incorporate attention mechanisms that allow the network to focus on important regions of the image and prioritize the completion of these regions first [20]. In this study, we will test three different models on the data set.

1) Generative Image Inpainting with Contextual Attention: We build on earlier work by Jiahui Yu, Zhe Lin, Jimei Yang, Xiaohui Shen, Xin Lu, and Thomas S. Huang in this paper. They created a coarse-to-fine network architecture in their paper titled ”Generative Image Inpainting with Contextual Attention” to carry out the process of adding missing pixels to an image, also known as image inpainting [14]. Here are the specific details of this model:

The model has an image-to-image structure, where one picture serves as both the input and the output. Two stages make up the model’s architecture: a coarse network and a refinement network. The Refinement Network uses the initial coarse prediction from the Coarse Network as input and produces the final detailed result.

The distorted image is fed into the coarse network, which produces a rough forecast of the missing region. To gather multi-scale contextual data, it employs a conventional encoder-decoder architecture with skip connections and dilated convolutions. 8 convolutional layers with a stride of 2 and a kernel size of 4 make up the encoder, which is followed by a fully connected layer. The decoder begins with a convolutional layer with a kernel size of 1, then 8 deconvolutional layers with a stride of 2 and a kernel size of 4. Between the encoder and decoder layers with the same spatial resolution, skip connections are inserted. With dilation rates of 2, 4, 8, and 16, the dilated convolutions are used in the middle layers of the encoder and decoder.

The distorted image and the coarse forecast are inputs into the refinement network, which produces a refined prediction of the missing region. It makes explicit use of a contextual attention module to copy or borrow data from far-off spatial regions. A softmax operation is used by the attention module to give weights to each patch after computing a similarity map between patches in the missing region and patches in the surrounding region. The missing section is then recreated using the weighted patches. Following an attention module, the refinement network has 4 convolutional layers with stride 1 and kernel size 3, then 4 more convolutional layers with stride 1 and kernel size 3.

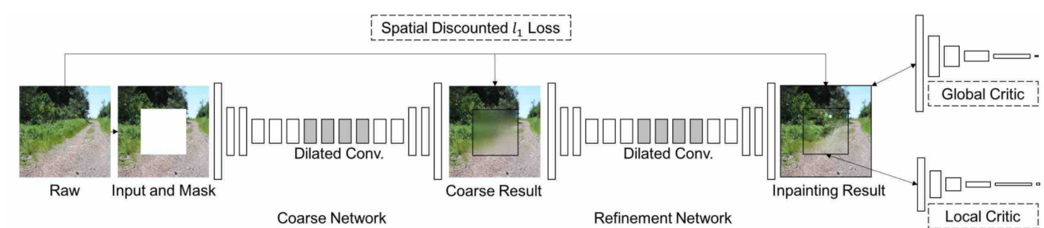

Fig. 5: Network structure of Contextual Attention [14]

The model is trained end-to-end with an adversarial loss and a reconstruction loss. The adversarial loss encourages the model to generate realistic images that can fool a discriminator network. The discriminator network has 5 convolutional layers with stride 2 and kernel size 4, followed by a fully connected layer. The reconstruction loss measures the pixel-wise difference between the generated image and the ground truth image. It consists of two terms: an L1 loss that penalizes large errors and a perceptual loss that penalizes semantic errors.

2) Image Inpainting via Generative Multi-column Convolutional Neural Networks: In this study, we inherit the previous research by Yi Wang, Xin Tao, Xiaojuan Qi, Xiaoyong Shen, and Jiaya Jia in their research titled ”Image Inpainting via Generative Multi-column Convolutional Neural Networks”. The system takes an image X and a binary region mask M as input, where M indicates unknown regions to be filled. The GMCNN consists of three sub-networks: a generator for producing results, global and local discriminators for adversarial training, and a pre-trained VGG network for calculating ID-MRF loss. The generator network has three parallel encoder-decoder branches to extract different levels of features from X with mask M. These branches capture various information with other receptive fields and spatial resolutions. The extracted feature components are up-sampled and concatenated into a feature map F, which is then transformed into the inpainted image Yˆ using a shared decoding module. The proposed GMCNN differs from conventional encoder-decoder structures and coarse-to-fine architectures. The multi-branch encoders in GMCNN address inpainting's diverse representation levels effectively, while traditional approaches may overlook this aspect. Additionally, GMCNN's parallel structures complement each other, offering improved inpainting performance compared to methods that rely solely on information inheritance.

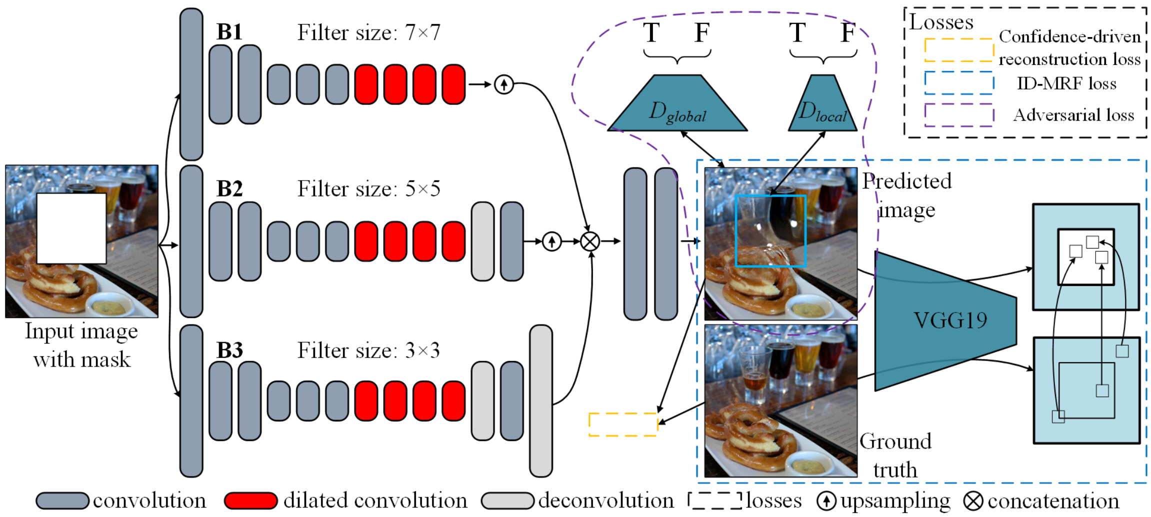

Fig. 6: Generative Multi-column Convolutional Neural Networks

3) Generative Image Inpainting with Image Fine-grained Inpainting: We build on earlier research done by Zheng Hui, Jie Li, Xiumei Wang, and Xinbo Gao in their paper titled "Image Fine-grained Inpainting" in this study. [21]. In this paper, a one-stage generative adversarial network (GAN) model for image inpainting is proposed. Earlier inpainting methods frequently created finished works with a strange structure or blurriness. The suggested model uses dense combinations of dilated convolutions to achieve larger and more effective receptive fields, addressing this issue and making it simpler to recover vast parts in an incomplete image.

The authors present a novel self-guided regression loss that concentrates on ambiguous regions and improves semantic details in order to successfully train the generator. A geometrical alignment constraint is created to align the feature center coordinates between predicted features and ground-truth ones, correcting for the pixel-based distance in addition to the widely utilized VGG feature matching loss.

To guarantee consistency in local-global contents, the model has a discriminator with local and global branches. Additionally, a discriminator feature matching technique is added to the local branch to dynamically minimize the similarity of intermediate features between artificial and real-world patches, enhancing the caliber of the images that are generated.

The suggested method's performance is evaluated on numerous open datasets and measured against cutting-edge approaches, proving its superiority.

IV. Model application results and discussion

A. Experimental Environment and Data Set

The models are experimentally conducted on the image data set of patterns on cobalt blue underglazed porcelains under the Nguyen Dynasty. Performed the pre-training steps of the data, including image format conversion, resizing, normalizing pixel values, and other processing suitable for the inpainting problem. These steps have ensured that the data is correctly prepared and suitable for model training and testing. In the process of addressing the inpainting problem, the division of image dataset into training and testing sets is an important step to ensure fairness and effective evaluation of the model. In this study, we

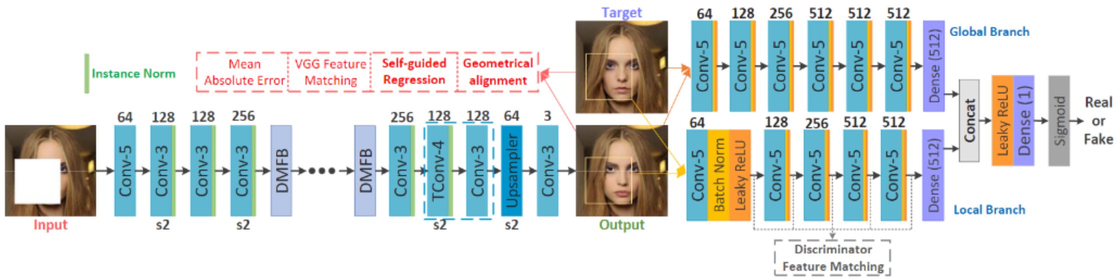

Fig. 7: Network structure of Image Fine-grained Inpainting [21]

utilized a dataset comprising 4600 images and performed the data split following a 9:1 ratio, resulting in 4140 images for training and 460 images for testing. The random selection of images for each set was carried out with considerations for randomness and fairness, ensuring that the generated datasets are representative of the original data. Part of the data set of patterns on cobalt blue underglazed porcelains under the Nguyen Dynasty is shown in Fig 8.

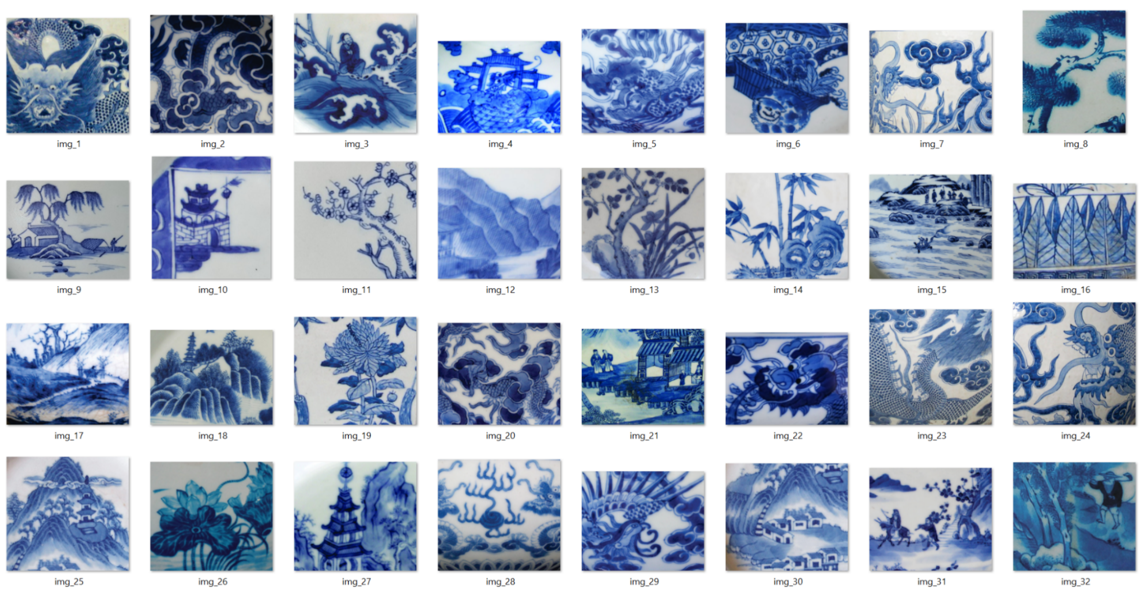

Fig. 8: Part of the data set of patterns on cobalt blue underglazed porcelains under the Nguyen Dynasty.

B. Evaluation Index

In order to more comprehensively evaluate the results of different models in experimenting on the above data set. We use the following 4 metrics:

L1 Loss: Mean absolute error (MAE), measures the average absolute difference between the predicted and ground truth pixel values. It provides a measure of how much the model's predictions deviate from the true values.

$$L1Loss = \frac{\sum |x^f - x^r|}{\sum_{i \in \omega} x_i^f} \tag{1}$$

L2 Loss: The average squared difference between the predicted and actual pixel values is measured by the mean squared error (MSE). Greater errors are amplified by it than by L1 loss.

$$L2Loss = \frac{\sum (x^f - x^r)^2}{\sum_{i \in \omega} (x_i^f)^2} \tag{2}$$

Peak Signal-to-Noise Ratio, or PSNR, is a widely used statistic to rate the quality of an image. It calculates the difference between the maximum power of a signal and the strength of the noise that degrades the signal's fidelity. Better image quality is indicated by higher PSNR values.

$$PSNR = 20 * \log_{10}\left(\frac{MAX_1}{\sqrt{MSE}}\right) \tag{3}$$

$$MSE = \frac{1}{m*n}\sum_{i=1}^{m-1}\sum_{j=1}^{n-1}\left(x_{i,j}^{f} - x_{i,j}^{r}\right)^2 \tag{4}$$

Total Variation Loss (TV Loss): TV loss is a regularization term that encourages smoothness in the image by penalizing rapid changes in pixel values. It helps in reducing noise and producing visually pleasing results. Lower TV loss indicates smoother image reconstruction.

$$R_{V^\beta}(f) = \int_\Omega \left(\left(\frac{\partial f}{\partial u}(u,v)\right)^2 + \left(\frac{\partial f}{\partial v}(u,v)\right)^2\right)^{\frac{\beta}{2}} dx \tag{5}$$

$$R_{V^\beta}(x) = \sum_{i,j}\left((x_{i,j+1} - x_{i,j})^2 + (x_{i+1,j} - x_{i,j})^2\right)^{\frac{\beta}{2}} \tag{6}$$

By considering these evaluation indicators together, the research aims to provide a comprehensive assessment of the performance differences between the models. Each indicator contributes a different aspect of image quality, such as absolute difference, squared difference, image fidelity, and smoothness.

C. Experimental Results

1) Quantitative results: Table 2 displays the comparison outcomes of image restoration on portions of data image patterns on cobalt blue underglazed porcelains produced during the Nguyen Dynasty. According to Table 2, the third technique in this study work performs better than the other two methods in terms of a number of different indices, including L1 loss, L2 loss, PSNR, and VT loss.

TABLE II: Evaluation Index of Three Different Methods

Method	L1 loss (%)	L2 loss (%)	PSNR	TV loss (%)
Method 1	3.8	1.7	40.34	62.66
Method 2	22.32	10.87	37.95	26.78
Method 3	3.5	1.09	20.41	38.74

2) Qualitative results: The Nguyen Dynasty pattern design dataset's conventional pattern images were restored using all three procedures, namely methods 1, 2, and 3. The results that followed were attained. In Figures 9-11, (a) displays the original designs on cobalt blue underglazed porcelains from the Nguyen Dynasty. Pattern image (b) is the result of method 1 repair. Pattern image (c) is the result of method 2 repair. Pattern image (d) is the result of method 3 repair.

All traditional pattern images requiring restoration in this study have their central image pattern concealed, resulting in the majority of image information being masked. The restoration findings show that procedure 2 has the least effective restoration. The typical pattern image has illogical geometric elements and texture information because the repaired area is dark and highly impacted by irrelevant backdrop colors. Method 3 performs better, with the restored image's geometric information aligning more closely with human perception of traditional patterns. However, method 3 struggles to produce satisfactory texture effects. On the other hand, the first method proposed in this paper achieves superior restoration results compared to the other two methods. In order to do a more logical picture restoration based on the surrounding information of the missing area, it successfully learns the geometric structure and texture information of the pattern.

The results of the experiments conducted on the Nguyen Dynasty pattern design dataset demonstrate the superiority of the approach described in this paper for assessing the efficacy of restoring conventional pattern pictures. It is difficult to recover the geometric and texture details of the missing sections using technique 2 because background pixel information can interfere with traditional needlework images' sophisticated information structures. Method 1 is less effective at recovering texture information even though it can better restore geometric structure information. In comparison, the restoration outcomes from the third method

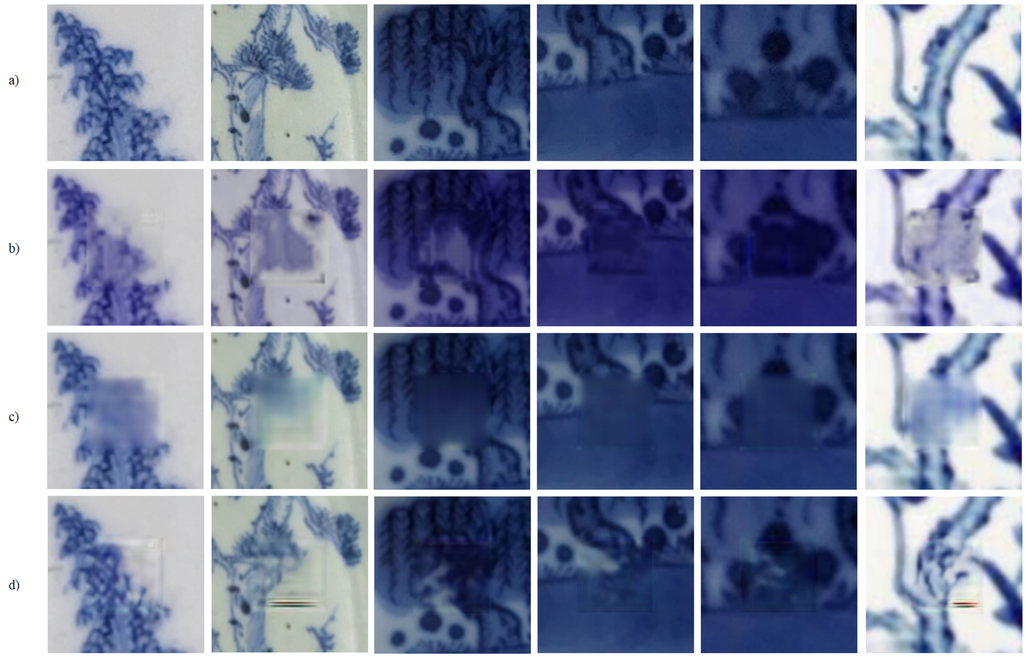

Fig. 9: Results of several mending techniques are compared. a) The original picture. b) The outcome of Repair Method 1. c) The outcome of Method 2 repair. d) The repair outcome of Method 3.

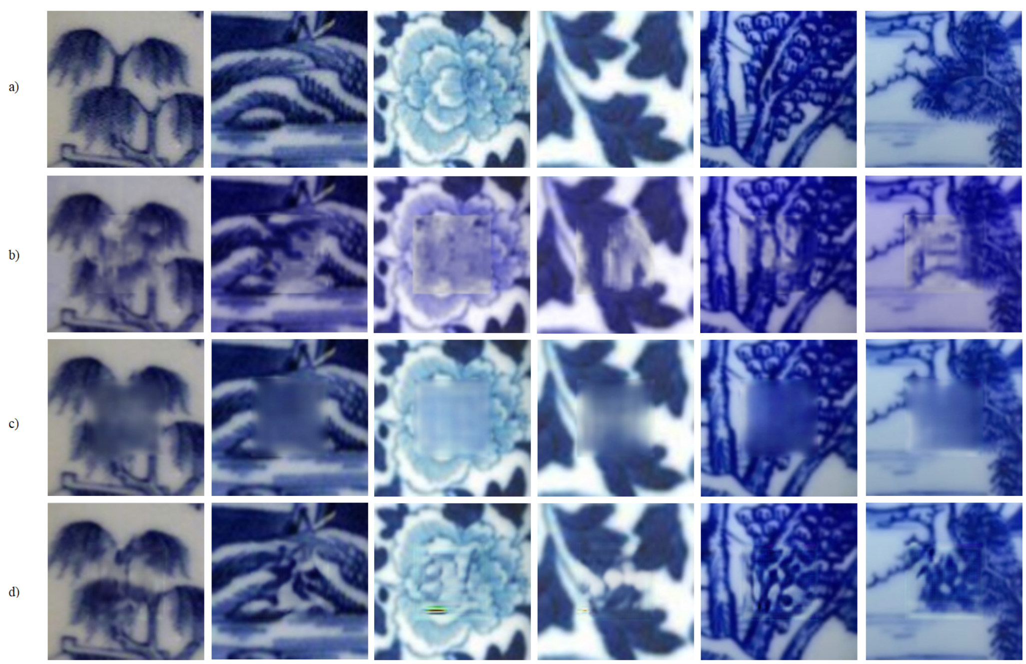

Fig. 10: Results of several mending techniques are compared. a) The original picture. b) The outcome of Repair Method 1. c) The outcome of Method 2 repair. d) The repair outcome of Method 3.

show more logical geometric structures and pattern information. In order to successfully restore information, the third model proposed in this paper generates a logical conventional pattern picture structure and texture information for the missing areas based on the information qualities surrounding those areas.

3) Deploy: The model was created, after which it was made available to everyone. We have created an application with a straightforward user interface that anyone may use to retrieve pattern images in the domain using the model. The results of the inpainting will be represented by two output images corresponding to the results of the two better models that is models

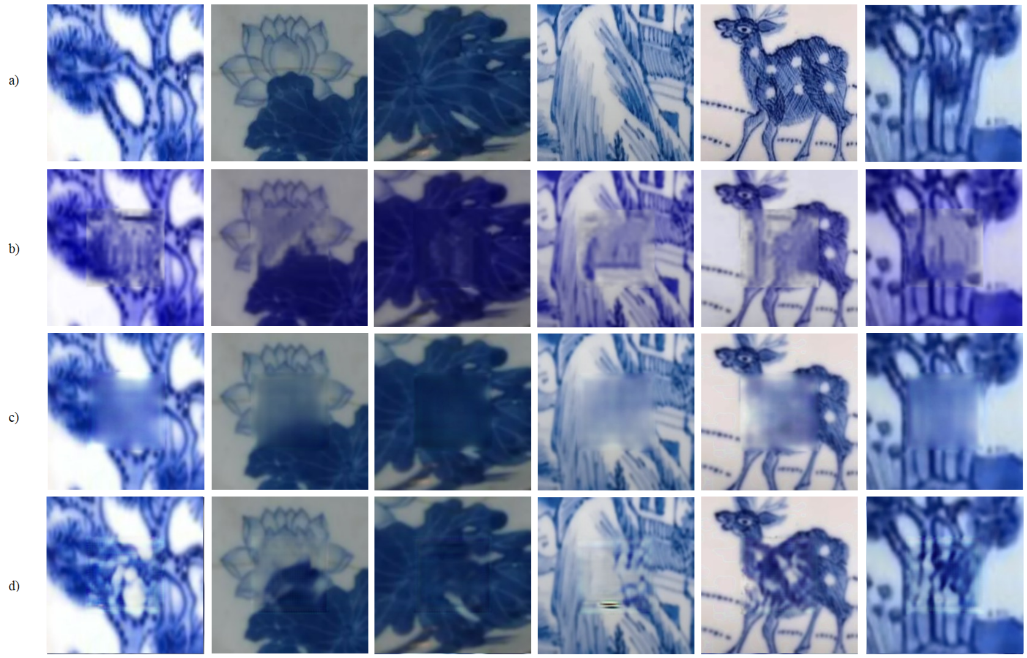

Fig. 11: Results of several mending techniques are compared. a) The original picture. b) The outcome of Repair Method 1. c) The outcome of Method 2 repair. d) The repair outcome of Method 3.

1 and 3. Figure 12 shows a screenshot of the produced application's desktop version.

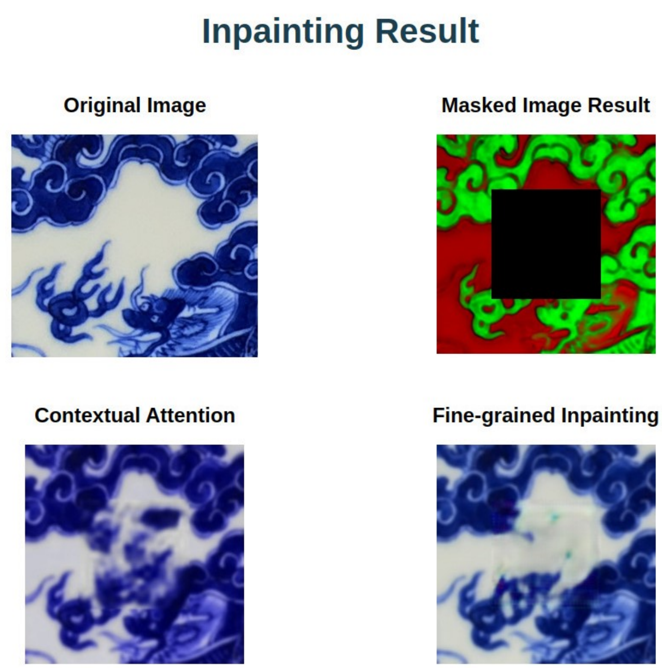

Fig. 12: A screenshot of the software used for image inpainting

V. Conclusion

This research aims to contribute to the archiving and digitization of historical image data of Vietnam by assembling a comprehensive data set of pattern images from various collections and sources. By applying and evaluating image restoration models based on deep convolutional neural networks, the study seeks to restore complex patterns on porcelain artifacts and shed light on the effectiveness of these models. We have successfully compiled a dataset of photos of patterns on cobalt blue underglazed Nguyen Dynasty porcelains in this research. It includes 4600 images of patterns, each of which was assembled from different data sources and put through a number of processing procedures. Three experiments using pattern datasets from well-known CNN architectures are also presented. The creation of a comprehensive dataset and the implementation of various image restoration models have shown promising outcomes in recovering and reconstructing the intricate patterns on historical artifacts.

Although the application of deep learning techniques in historical conservation has shown significant progress, the restoration of ancient Vietnamese patterns remains largely unexplored. In our research, the quantity of photos is still well below what is required to create a reliable and effective system. Consequently, we intend to expand the dataset above with more data in the future. We also want to broaden the scope of the inquiry into all ancient and cultural artifacts with historical significance for Vietnam in terms of their content, geography, time period, culture, etc. This study's focus on the cobalt blue glazed porcelain pattern under the Nguyen dynasty can serve as a reference for the development of other image datasets.

The importance of this study lies in the preservation and understanding of Vietnam's cultural heritage. The restoration of ancient patterns on cobalt blue underglazed porcelains will provide insights into the artistic traditions of the Nguyen Dynasty and enhance our overall comprehension of Vietnamese history and culture. The application and bringing of new technologies such as artificial intelligence to solving historical problems brings a fresh approach to history for young people. Ultimately, this research aims to enrich our understanding of Vietnamese cultural heritage and inspire further advancements in the field of historical preservation.

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