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Statistical image processing (Decorrelation Stretch) and deep learning (CycleGANs) to restore images of faded artworks

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Abstract

Cultural properties gradually fade and deteriorate over time due to various factors, including exposure to ultraviolet and infrared radiation, fluctuations in temperature and humidity that cause the degradation of organic materials, and the accumulation of dust and other contaminants on the surface. These factors diminish the visibility of the artwork, often requiring professional restoration techniques that are time-consuming, costly, and potentially irreversible. This study proposes a method to digitally restore the visual clarity of cultural properties by combining statistical image processing with deep learning. First, Decorrelation Stretch (DStretch) is applied to transform the color profile of photographed images, enhancing the visibility of faded motifs such as characters and illustrations. Next, Cycle-Consistent Generative Adversarial Networks (CycleGANs) are applied to learn the color domain transformation between the DStretch-processed (faded) images and reference images of similar, minimally faded artworks. This enables the generation of estimated prefaded images without requiring any physical intervention on the actual cultural property. The proposed method facilitates digital restoration and utilization of cultural properties, contributing to their preservation and broader public access. Furthermore, by reusing and reanalyzing processed image data, this approach fosters reproducibility in cultural heritage research, which is often susceptible to subjectivity.

Keywords: Cultural Heritage Images, Digital Restoration, Image Processing, Decorrelation Stretch (DStretch), Deep Learning, CycleGANs

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1. Introduction

The protection of cultural properties passed down through generations is a shared challenge for humanity, and today it has become an urgent issue. Many Japanese cultural properties are made from delicate materials such as washi paper and sumi ink, and once they deteriorate, restoration requires enormous costs. As deterioration progresses, the characters and designs become unclear, significantly diminishing their historical and artistic value. Furthermore, materials necessary for restoration have become increasingly difficult to obtain. The most effective way to prevent such deterioration is to limit public access to these cultural properties. However, this poses a major obstacle to academic research and hinders the pursuit of the scholarly value inherent in cultural heritage. In response to this problem, the present study has developed a method to restore deteriorated cultural properties using digital images.

2. Research objective

Cultural properties gradually fade and deteriorate over time due to exposure to ultraviolet and infrared radiation, fluctuations in temperature and humidity that cause degradation of organic materials, and the accumulation of particulate matter and other contaminants deposited on the surface (Kobayashi 1986; Fiske and Morenus 2004). These external elements obscure the original surface by physically obstructing the visible region between the surface of the artwork and the observer's naked eye. Removing such elements requires professional restoration techniques, which are both time-consuming and costly, and may risk damaging the cultural property itself (Belard 2010; Uyeda 2022).

Our research proposes a technique to recover the visibility of cultural properties to their pre-faded state using image processing and Deep Learning without any physical intervention on cultural properties.

To this end, we conducted an experimental study focusing on high-resolution and high-definition images of cultural properties held in museum collections—assets that constitute the core of museum heritage. The aim was to digitally restore images of artworks that have undergone fading, reconstructing them to their original, unfaded appearance. However, image restoration using Photoshop was influenced by the operator's subjectivity, and thus the reproducibility of the restoration could not be ensured. By advancing this research, it becomes possible to rediscover the value of works that remain unnoticed in storage without proper scholarly recognition. Furthermore, by publishing both the faded and restored images through an open-access image database, we aim to enhance the reproducibility of subjectively restored cultural heritage images. This contributes to the foundation of open science and enables broader public access to cultural heritage.

As this study is conducted by a team of six collaborators, responsibility for the research is shared collectively. The manuscript was written by Kawano on behalf of the team, with valuable advice and insights provided by the other five members.

3. Literature review

In the field of the restoration of faded images of cultural properties, 2 notable techniques—Decorrelation Stretch (DStretch) and Cycle-Consistent Generative Adversarial Networks (CycleGANs)—have emerged as effective tools in this domain.

Decorrelation Stretch, originally developed for enhancing color differences in multispectral satellite imagery (Gillespie *et al.* 1986), has been adapted for cultural heritage to emphasize subtle pigment variations and reveal lost features in murals, manuscripts, and paintings. It increases chromatic contrast, making it particularly useful in detecting faded patterns—imperceptible to the human eye—that are critical for archaeological interpretation (Figure 1) (Agapiou *et al.* 2019). These enhanced images serve as inputs to CycleGAN, improving the model's capacity to detect and learn intricate patterns such as engravings or pigment traces (Chiang *et al.* 2020).

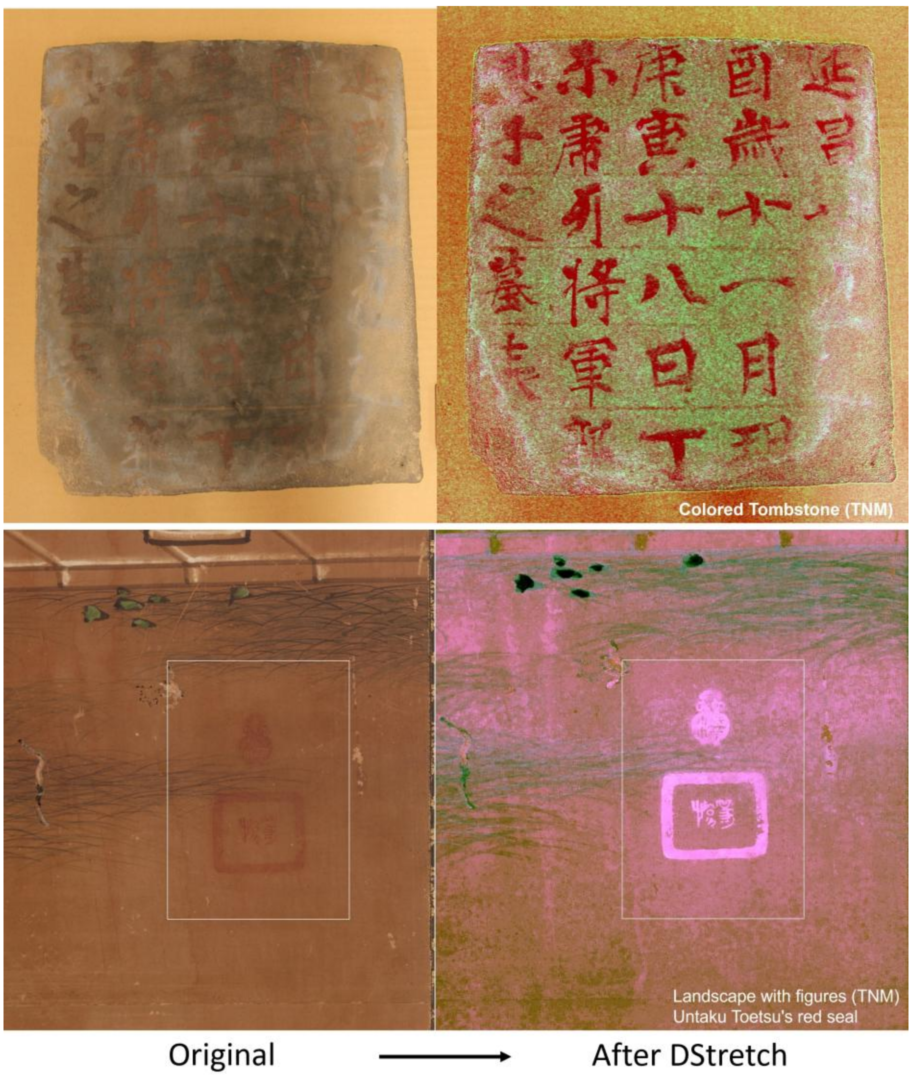

Figure 1. Figures Before (Left) and After (Right) DStretch. Epitaph on Square Tile (Above). Folding Screen with Landscape and People (Below).

CycleGANs (Zhu *et al.* 2017) introduced a breakthrough in unpaired image-to-image translation. In cultural heritage, this means degraded images can be restored by learning mappings between 'faded' and 'prefaded' images, even without paired training data. This approach is highly effective when direct examples of the original appearance are unavailable, which is often the case in archaeology and art history.

The combined use of DStretch and CycleGANs is relatively new but promising technology. DS preprocessing enhances input images by amplifying hidden features, which can then be fed into CycleGANs for more effective domain translation. This has shown improvements in restoring lost and faded colors, reconstructing damaged iconography, and virtually restoration of ancient murals. Studies by researchers have demonstrated the efficacy of using enhanced spectral data combined with deep learning networks for restoration tasks (Sun *et al.* 2022).

This intersection of traditional remote sensing techniques and modern AI represents a significant step toward the reproducible restoration of cultural heritage, especially for objects where physical intervention is impossible.

4. Research Subject

The target material for this research is a decorative Buddhist scripture called Konshi Kinji-kyo (Gold-Scripture on Indigo-dyed paper). This type of scripture was produced by dyeing paper with indigo and writing sutras with gold or silver ink, often accompanied by decorative elements such as scroll ends and cords. These scriptures were primarily created between the 8th and 13th centuries, commissioned by political leaders, nobles, and samurai families, and enshrined in temples and sutra mounds (Figure 2 Below). This was because it became a common practice to bury scriptures in the ground to preserve them for future generations. Among these scriptures were Konshi Kinji-kyō—sutras written in gold on indigo-dyed paper, depicting deities painted with gold pigment (Figure 2 Above）(Li 2017; Thumas 2022).

Figure 2: Konshi Kinji-kyo (Above) and Excavated Sutra Mound (Below)

The specific image used in our research was selected from ColBase (https://colbase.nich.go.jp/), a database with 31,212 cultural property images held by the National Institutes for Cultural Heritage:

*"**Kuyō Mokuroku*** (Memorial Service List)" (Tokyo National Museum, E-14575)

A sutra drawn in gold ink on navy-dyed paper, with border lines drawn in black ink. The scroll contains a sutra written in gold ink on dark, blue-dyed paper, the text depicting a Buddhist image, and a bronze shaft. Created in 1140 (Hōen 6, Heian period), the scroll was stored in a sutra mound. However, due to vertical tears in the cover and rainwater infiltration, the gold ink of the characters and Buddhist images became blurred and indistinct". (**Figure 3**).

This study was a case study of this ***Kuyō Mokuroku*** (Memorial Service List).

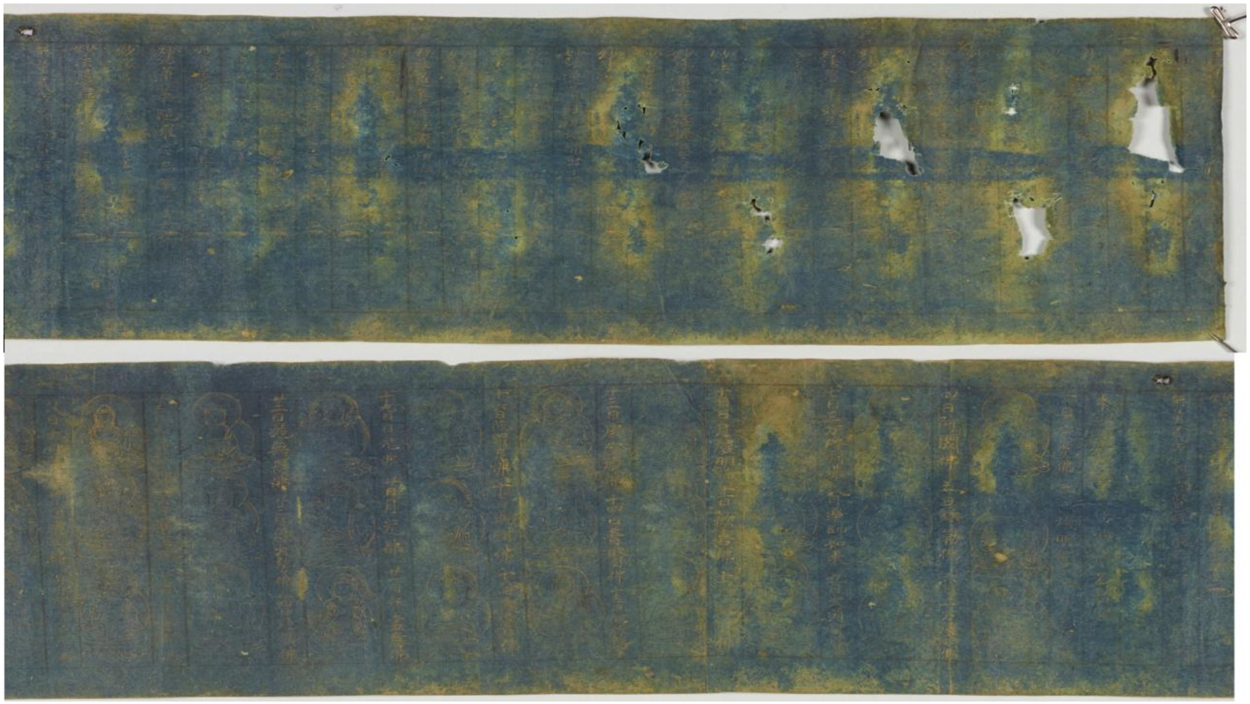

Figure 3: Faded *Kuyō Mokuroku* (Memorial Service List). Sutras written within the lines (Above) and Buddhist paintings (Below). https://colbase.nich.go.jp/collection_items/tnm/E-14575?locale=ja

5. Methodology

5.1. Theory and Practice of Decorrelation Stretch

Decorrelation Stretch is a statistical image processing technique originally used in satellite imagery and rock art analysis. Based on principal component analysis (PCA, it transforms the color space to maximize color variance, thereby enhancing visibility.

Digital images are typically composed of three highly correlated RGB components. Decorrelation Stretch applies principal component transformation to these RGB components and expands the color contrast based on the resulting components. This allows for the clear visualization of fine motifs and brushstrokes that may be invisible to the naked eye (Wei *et al.* 2023). After transformation, the color space is reverted, producing an image structurally rich in information though differing in brightness and saturation from the original.

While this method has been applied to digital restorations of rock art, its use in museum collections remains limited, partly due to concerns that artificial color transformations may compromise the aesthetic authenticity of cultural objects. In cultural heritage, even if texts or images become legible, altered colors may reduce the display or scholarly value of the artifact (**Figure 4**).

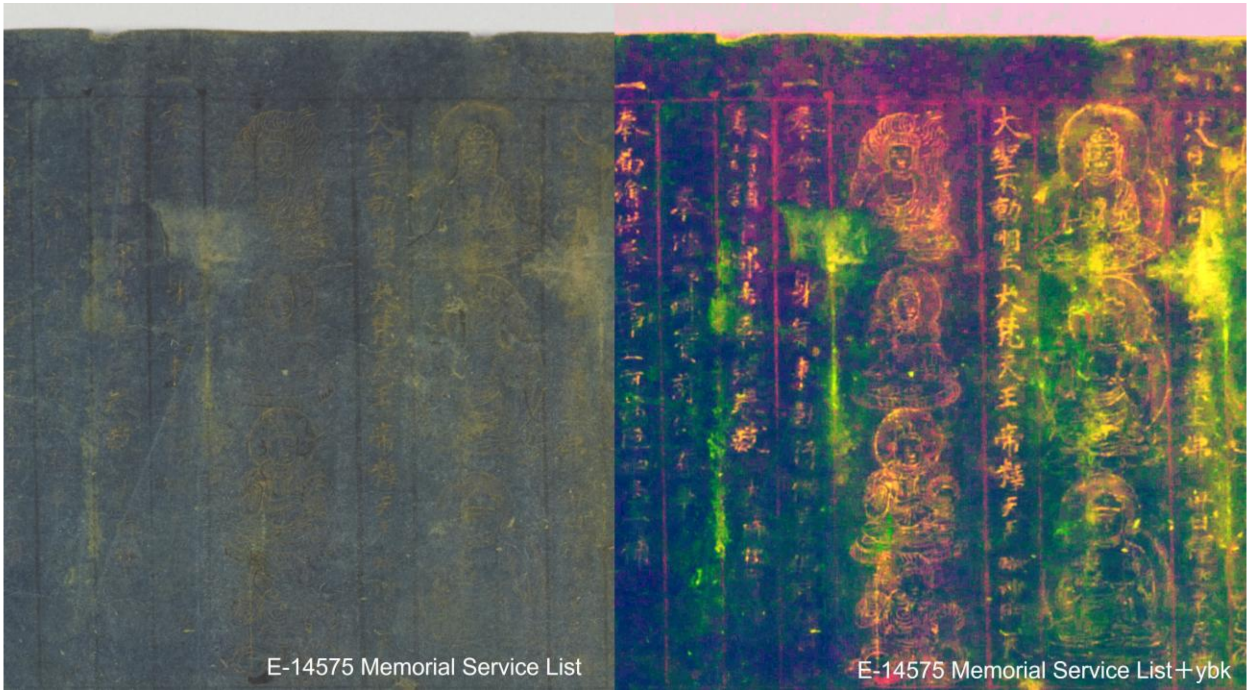

Figure 4 *Kuyō Mokuroku* (Memorial Service List) Before (Left) and After DStretch (Right)

To address this, the study employed DStretch, an application developed by Jon Harman (https://dstretch.com/), as a plugin in the ImageJ platform (https://imagej.net/). By selectively applying predefined color profile transformations to cultural property images, visibility was enhanced. DStretch offers flexibility by allowing users to choose color profiles optimized for specific targets (e.g., gold ink) (Harman 2005).

The software offers preset algorithms for decorrelation stretching that allow for customization of color space conversions. The software offers preset color spaces such as YBK, LAB, and YUV, each tailored to highlight specific color variations. The choice of color space is very important because it directly affects the visibility of certain features in an image.

The predefined color profile settings are as follows:

Black/white pigments: YBK, LAB, LBK, LWE, YWE
Red pigments: LRE, CRGB, YRD, YRE, LRD, RGB0
Yellow pigments: LDS, YDT, YYE, YBK, LYE
Other pigments: LDS, LAB, YDT, YDS, YBR, YUV

This study adopted the YBK and LDS profiles as they offered the best balance between visibility enhancement and color distortion.

Introduction and Application of CycleGANs

CycleGANs are a type of deep learning model capable of translating between two different image domains (Figure 5) (Zhu *et al.* 2017). Unlike pix2pix and other GAN models that require paired datasets (e.g., before-and-after images), CycleGANs do not rely on such pairs. This is especially important for faded cultural properties, where "pre-fade" images often do not exist due to a lack of photographic records or uncertainty about the original state.

The key feature of CycleGANs is their ability to learn transformation rules between two domains—in this case, "faded images (domain A)" and "non-faded images (domain B)"—using a mechanism called cycle-consistency loss, which ensures that translating an image to the other domain and back again results in a close approximation of the original.

A standard GAN consists of a generator (to produce realistic images) and a discriminator (to distinguish real images from fake images). These two components train adversarial to improve the quality of generated images. In CycleGANs, this setup is duplicated: two generators (AB and BA) and two discriminators (for domains A and B) are used. The model employs four types of loss functions to facilitate self-training.

Images of faded Konshi Kinji-kyo processed by DStretch were input as true samples of domain A, while minimally faded versions of the same type of scripture were input as domain B samples. The transformation from A to B and vice versa was trained using adversarial and cycle-consistency losses. The output images—A→B (restored) and B→A (simulated faded)—were then evaluated.

Because CycleGANs focus on domain characteristics (color space) rather than image content (e.g., text or motifs), they are particularly suited for datasets that are visually different but structurally similar—such as different copies of scriptures with similar techniques and materials. Thus, even without exact pairs, images of similar non-faded works can be used to generate plausible restorations.

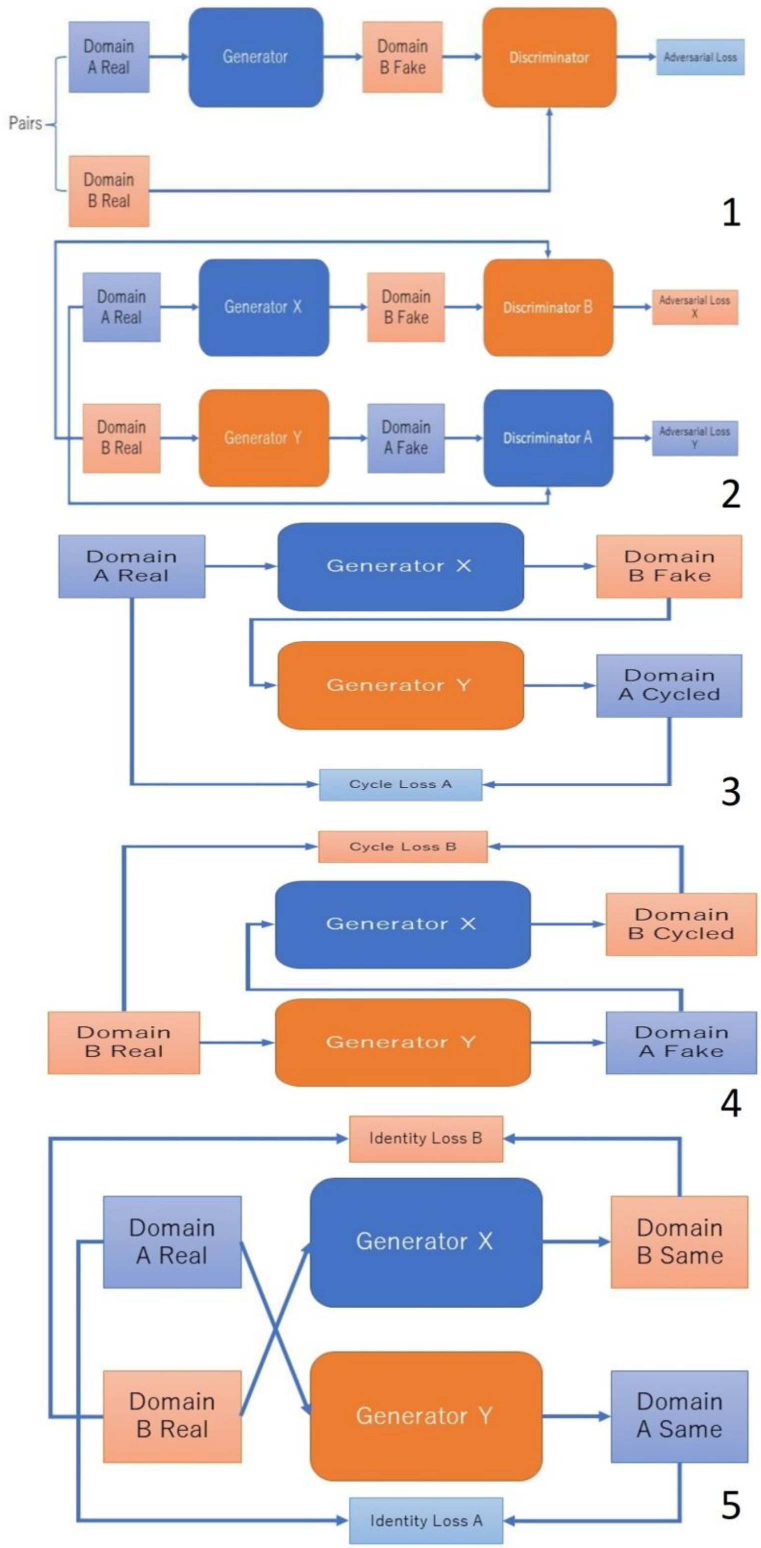

Figure 5: Identity Loss in CycleGANs Structure. (1) General GAN Structure (pix2pix), (2) Adversarial Loss in CycleGANs Structure, (3) Forward Cycle Loss in CycleGANs Structure, (4) Backward Cycle Loss in CycleGANs Structure, (5) Identity Loss in CycleGANs Structure.

Selected non-faded training images (domain B) were also obtained from ColBase, including examples from:

Table 1: Image source of non-faded Images from ColBase

Collection	Title	Object number	Image source
Nara National Museum	Dōjin Sokumukyokuhen Gekyō, scroll 2	811-4	https://colbase.nich.go.jp/collection_items/narahaku/811-4?locale=ja
	Avataṃsaka Sutra, Volume A	863-1	https://colbase.nich.go.jp/collection_items/narahaku/863-1?locale=ja
	Heart Sutra	928-0	https://colbase.nich.go.jp/collection_items/narahaku/928-0?locale=ja
	Great Perfection of Wisdom Sutra, vol. 345	1162-0	https://colbase.nich.go.jp/collection_items/narahaku/1162-0?locale=ja
	Lotus Sutra on Navy-Blue Paper with Gold Script, vols. 1–7	from 1270-1 to 1270-7	https://colbase.nich.go.jp/collection_items/narahaku/1270-1?locale=ja https://colbase.nich.go.jp/collection_items/narahaku/1270-2?locale=ja https://colbase.nich.go.jp/collection_items/narahaku/1270-3?locale=ja https://colbase.nich.go.jp/collection_items/narahaku/1270-4?locale=ja https://colbase.nich.go.jp/collection_items/narahaku/1270-5?locale=ja https://colbase.nich.go.jp/collection_items/narahaku/1270-6?locale=ja https://colbase.nich.go.jp/collect ion_items/narahaku/1270-7?locale=ja
	Great Perfection of Wisdom Sutra, vol. 52	1319-0	https://colbase.nich.go.jp/collect ion_items/narahaku/1319-0?locale=ja
Kyoto National Museum	Treatise on the Great Perfection of Wisdom	B-Kō101	https://colbase.nich.go.jp/collection_items/kyohaku/B%E7%94%B2101?locale=ja

6. Result

In this study, we attempted to develop a technique for image restoration using a combination of DStretch and CycleGANs. A total of 46 faded images and 52 non-faded images were used as training data under either uncompressed or minimally compressed settings (Figure 6). Figure 6-1 illustrates an example of a faded Konshi Kinji-kyo image processed using DStretch, which was employed as domain A training data. Although the brushstrokes became more distinct, the color space was altered to appear unnatural due to the application of enhanced color profiles. In contrast, Figure 6-3 shows a non-faded Konshi Kinji-kyo image used as domain B training data. These images correspond to the leftmost domain A and B in Figure 6-2 and 6-4, respectively.

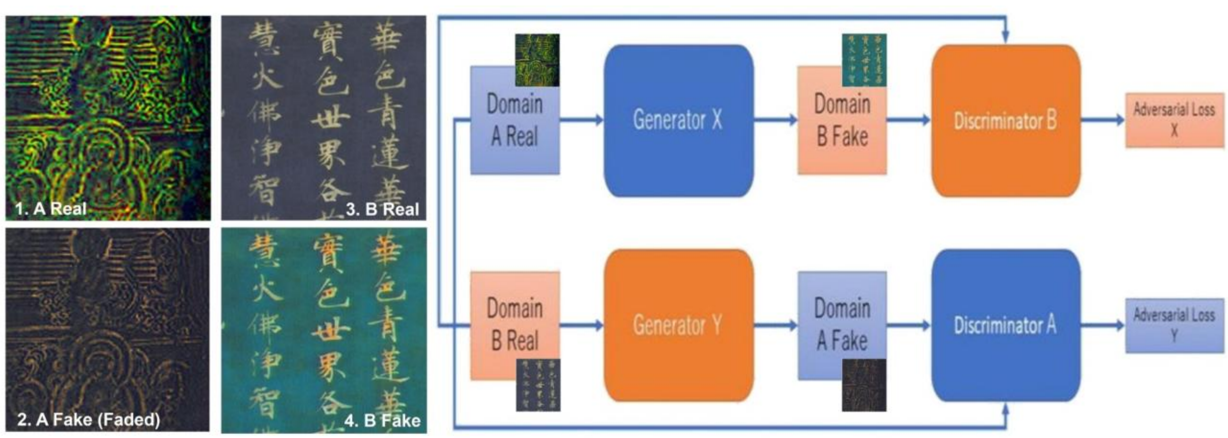

Figure 6: Real and Fake Image of CycleGANs Structure

In the CycleGAN framework, the AB generator converts the DStretch-enhanced color profile (domain A) into the original color space (domain B), while the BA generator performs the reverse transformation. As a result, the A→B and B→A images—so-called "fake" domain B and domain A images—are generated.

The A→B images represent plausible pre-faded restorations of the faded images, whereas the B→A images imitate the appearance of fading in originally non-faded images. In the field of cultural heritage, it is rare to obtain precise before-and-after image pairs due to the lack of photographic records. However, this model enables the restoration of original color schemes by learning from a large dataset of minimally faded images of similar materials and styles.

The resulting restored images showed a remarkable improvement in the legibility of scriptures and Buddhist iconography written in gold ink, which had previously been obscured by fading or staining (Figures 7 and 8). As demonstrated in Appendix A, our proposed method succeeded in first enhancing textual and pictorial features using DStretch, followed by translating the image into a color space that closely resembles non-faded cultural property images via CycleGANs. A visual comparison is shown between the original faded image and the image restored by the CycleGAN model. In particular, it is emphasized that the gold lettering in areas previously obscured by water damage has been beautifully restored. However, some artifacts, such as block tiling, remain in the restored image, especially in areas of high contrast. These results indicate that although the restoration is mostly successful, further improvement of the model architecture and learning process is needed to achieve a more seamless restoration. These outcomes indicate the effectiveness of the proposed method for restoring and enhancing visibility in images of cultural heritage artifacts(Putranti *et al.* 2025).

The software used in this experiment is available on GitHub.

https://github.com/arch-inform-kaken-group/pytorch-CycleGAN-with-Hydra-and-MLflow

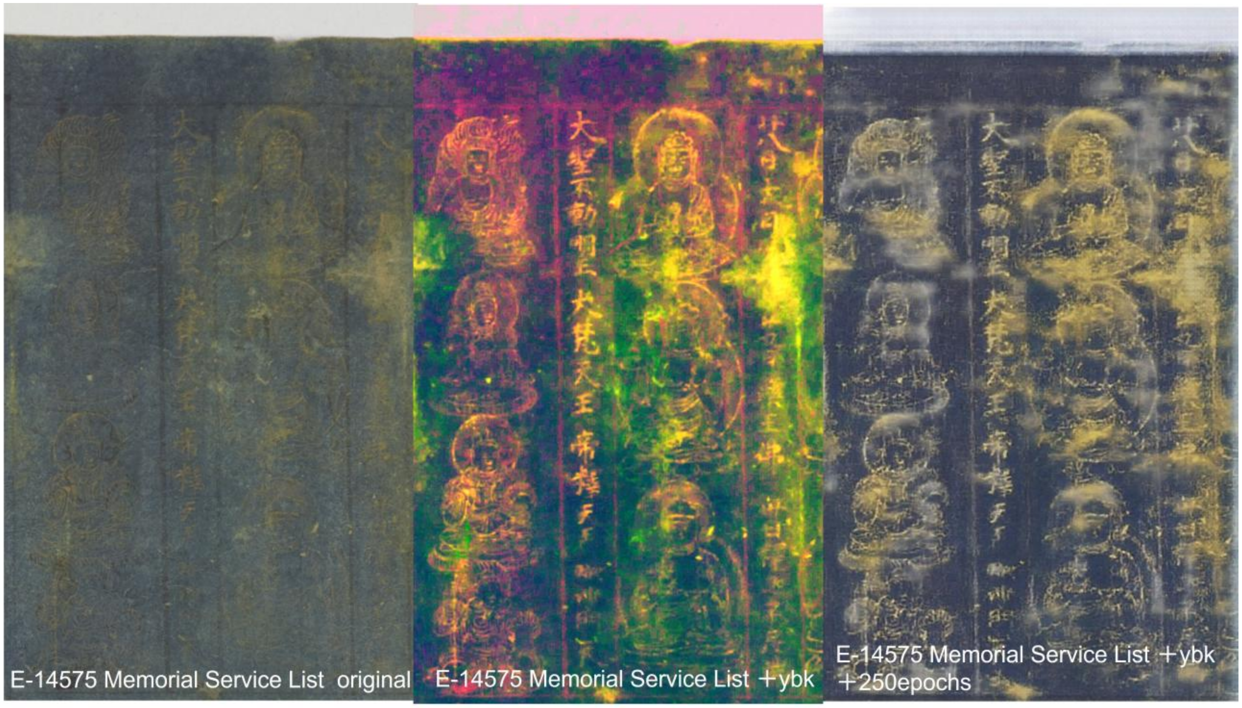

Figure 7: Comparing the Images: Original Image (Left) and applied DStretch(Center) and applied CycleGANs (Right)

Figure 8: Comparison of the Original Image (Left) and the Restored Image (Right)

7. Discussion

During CycleGANs training, it was confirmed that setting a lower learning rate for the discriminator than for the generator helped stabilize learning. However, several technical issues also emerged:

7.1. Tile Artifacts in DStretch

When color or brightness correction was applied during DStretch processing, block-like tile artifacts occasionally appeared (Figure 9). This was particularly pronounced in low-resolution or highly compressed JPEG images, where color enhancement also amplified image noise.

Figure 9: Comparison of the the Original Image with (Left) and without (Right) Flatten Image Correction applied

7.2. Artifacts in CycleGANs Output

During training, some restored images showed unnatural features likely due to overfitting or training bias:

・White cloud-like patterns appeared in the background.

・Margins not present in the input image emerged at the top and bottom.

・Regular grid patterns became visible.

These phenomena may be due to the tendency of the loss function in CycleGANs to reduce loss when generated images approach white, resulting in unintended "whitening" of the outputs. To suppress this, the parameter λ in the loss function was increased from 10 to 100, which helped reduce the whitening tendency (**Figure 10**).

Furthermore, when there were significant visual differences between faded input images and prefaded reference images (e.g., in text density or layout), CycleGANs outputs became unstable. This could be a serious issue in constructing a general-purpose model.

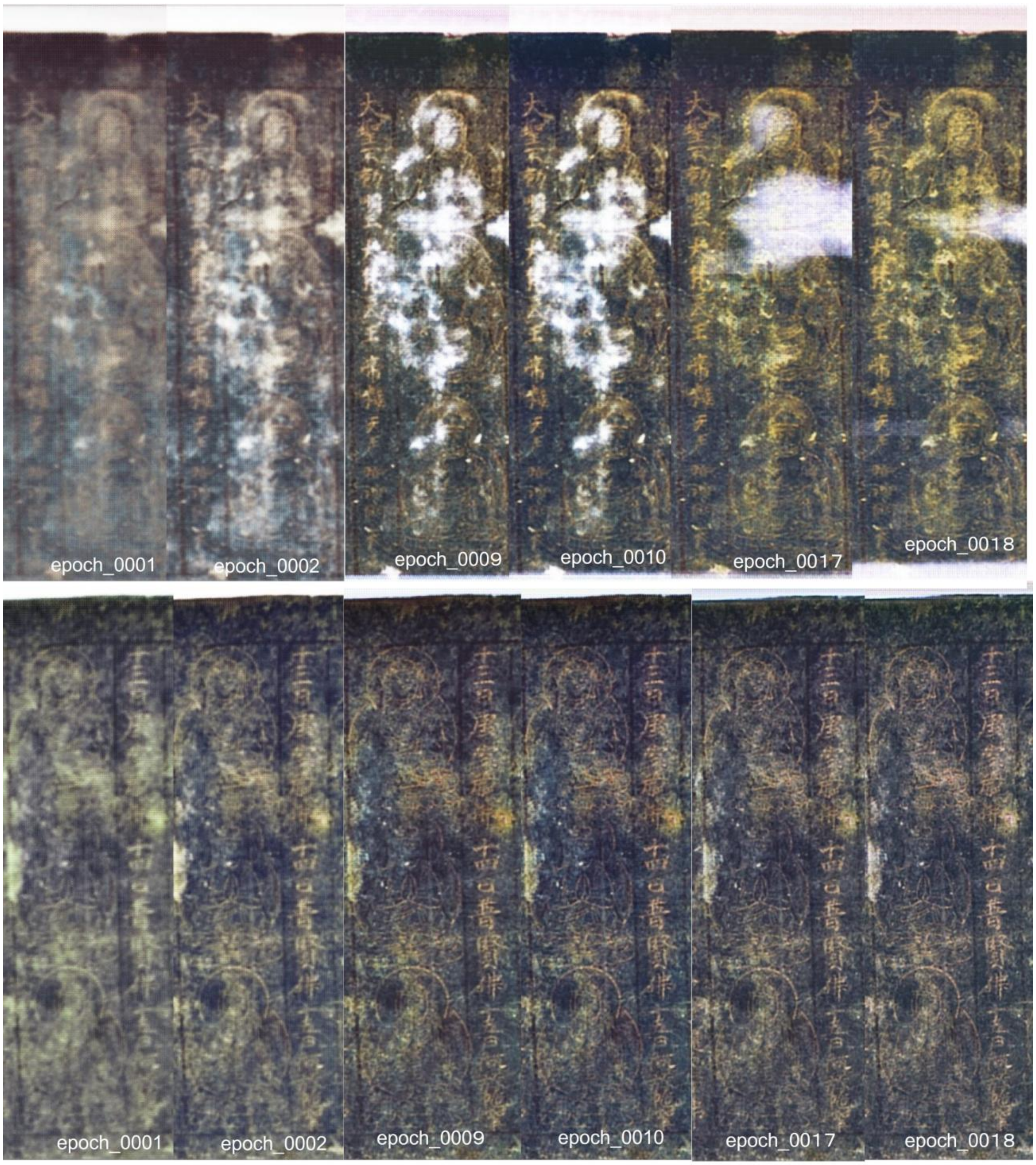

Figure 10: Comparison of hyperparameters: λ of 10 (Above) and 100 (Below) during training

8. Conclusion

This study proposes a new framework that integrates statistical image processing (DStretch) with deep learning (CycleGANs) to recover the visual clarity of cultural heritage image. The combination of conventional image enhancement techniques and deep learning has significantly advanced the field of digital restoration in archaeology. In addition to DStretch, other classical techniques such as contrast adjustment, when integrated with deep models like CycleGAN, have proven effective in restoring degraded visual information while preserving authenticity.

The case studies conducted in this study yielded the following key findings. Although this is only a preliminary experiment, it raises both possibilities and challenges for image restoration of cultural properties. The three outcomes are as follows:

1. In the case of *Konshi Kinji-kyō*, specific DStretch profiles such as YBK and LDS proved particularly effective for enhancing gold ink inscriptions and Buddhist paintings. This finding underscores the importance of selecting appropriate color space configurations within DStretch and suggests the possibility of developing systematic profiles for red, yellow and other colors. The challenge for future research will be to determine whether a generic color space can be identified or whether customization is essential.

2. While DStretch enhances visibility, it may also introduce artifacts when applied to low-resolution or heavily compressed JPEG images. Therefore, careful selection of input images and thoughtful pre-processing design are essential for achieving optimal results. In future research, we would like to examine whether it is possible to develop a decorrelation algorithm that is less sensitive to image quality.

3. When training CycleGANs with visually distinct datasets—such as faded versus prefaded images—the model exhibited unstable. Building a more generalizable model will require datasets that control for structural attributes such as brushstroke patterns, and character density. This limitation affects the generalization goals of the model and requires further improvement in learning methods to handle such differences.

The framework proposed in this research can be applied to the virtual reconstruction of pottery, mural fragments, manuscripts, and carved objects. For instance, CycleGANs has been employed to digitally restore ceramic sherds by reconstructing missing patterns and edges.

Despite its promise, this approach presents several challenges. A primary concern is the risk of generating historically inaccurate content—so-called "hallucinations"—that do not correspond to the original artifact. To mitigate this risk, researchers are incorporating constraints and emphasizing ethical guidelines to ensure transparency and accountability in AI-driven restoration (Tolosana *et al.* 2020).

In conclusion, the integration of image processing techniques and CycleGANs constitutes a foundational technology for the digital preservation and utilization of cultural heritage. This approach not only facilitates preservation but also broadens public access. Future research will expand the range of applicable heritage objects and support heritage documentation, academic research, and museum outreach (Pietroni and Ferdani 2021).

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・Organized for the study entitled "Making Digital Archive of Decorated Tumulus by Using VR Techniques" Grant-in-Aid for Scientific Research (A), JSPS (Japan Society for the Promotion of Science), 2007-2010

・Organized for the study entitled "Basic Studies on the decorated tumuli in Pasema highland area in Indonesia" Grant-in-Aid for Scientific Research (C), JSPS, 2017-2020

・Organized for the study entitled " Establishment of research base for preservation and public utilization of prehistoric mural paintings as human heritage." Fund for the Promotion of Joint International Research (Fostering Joint International Research (B)), JSPS,2019-2024

・Organized for the study entitled "Establishing a technical basis for statistical image processing and deep learning for the digital restoration of cultural heritage." Grant-in-Aid for Challenging Research (Exploratory), JSPS, 2022-2025

・Organized for the study entitled "Creation of the foundation for digital restoration technology for cultural properties using a combination of statistical image processing and machine learning" Grant-in-Aid for Scientific Research (Ｂ), JSPS, 2022-2026

・Organized for the study entitled "Building the Digital Twin Platform for the Preservation and Open Access of Prehistoric Decorated Tombs in Europe" Fund for the Promotion of Joint International Research (International Collaborative Research), JSPS, 2024-

Data Availability Statement.

This paper is available at the following link.

https://zenodo.org/records/16888802

The software is available at the following location.

https://github.com/arch-inform-kaken-group/pytorch-CycleGAN-with-Hydra-and-MLflow

Conflicts of Interest

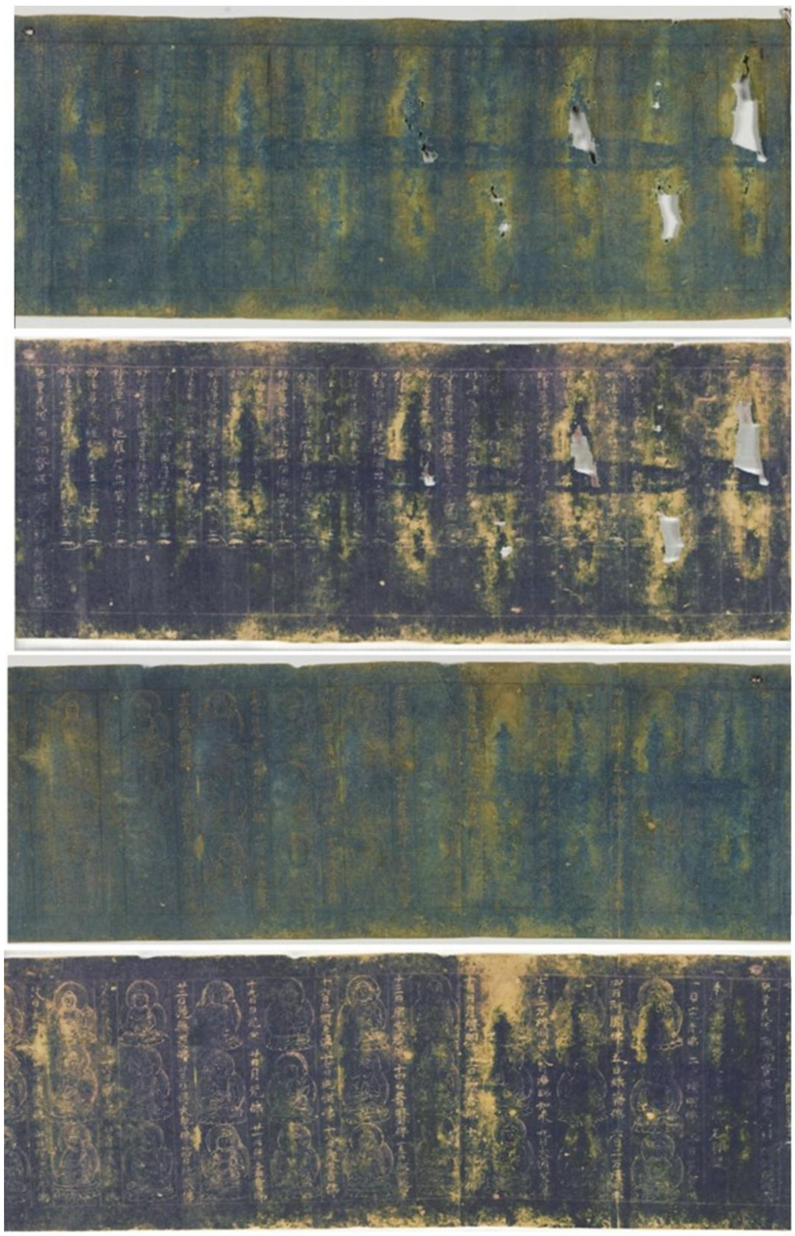
The authors declare that they have no conflicts of interest relating to the content of this article. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

Author Contributions

This research was undertaken by a six-member research team, and responsibilities for individual tasks were distributed as follows. Conceptualization, Kazutaka Kawano; methodology, Haruhiro Fujita and Masatoshi Itagaki; software, Masatoshi Itagaki; validation, Masatoshi Itagaki; investigation, Ryo Yamamoto and Toshiki Takeuchi; resources, Haruhiko Ochiai; data curation, Kazutaka Kawano and Haruhiro Fujita; writing, Kazutaka Kawano; project administration, Kazutaka

Kawano and Haruhiro Fujita; funding acquisition, Kazutaka Kawano. All authors have read and agreed to the published version of the manuscript.

Appendix A



Kuyō Mokuroku (Memorial Service List) No.1

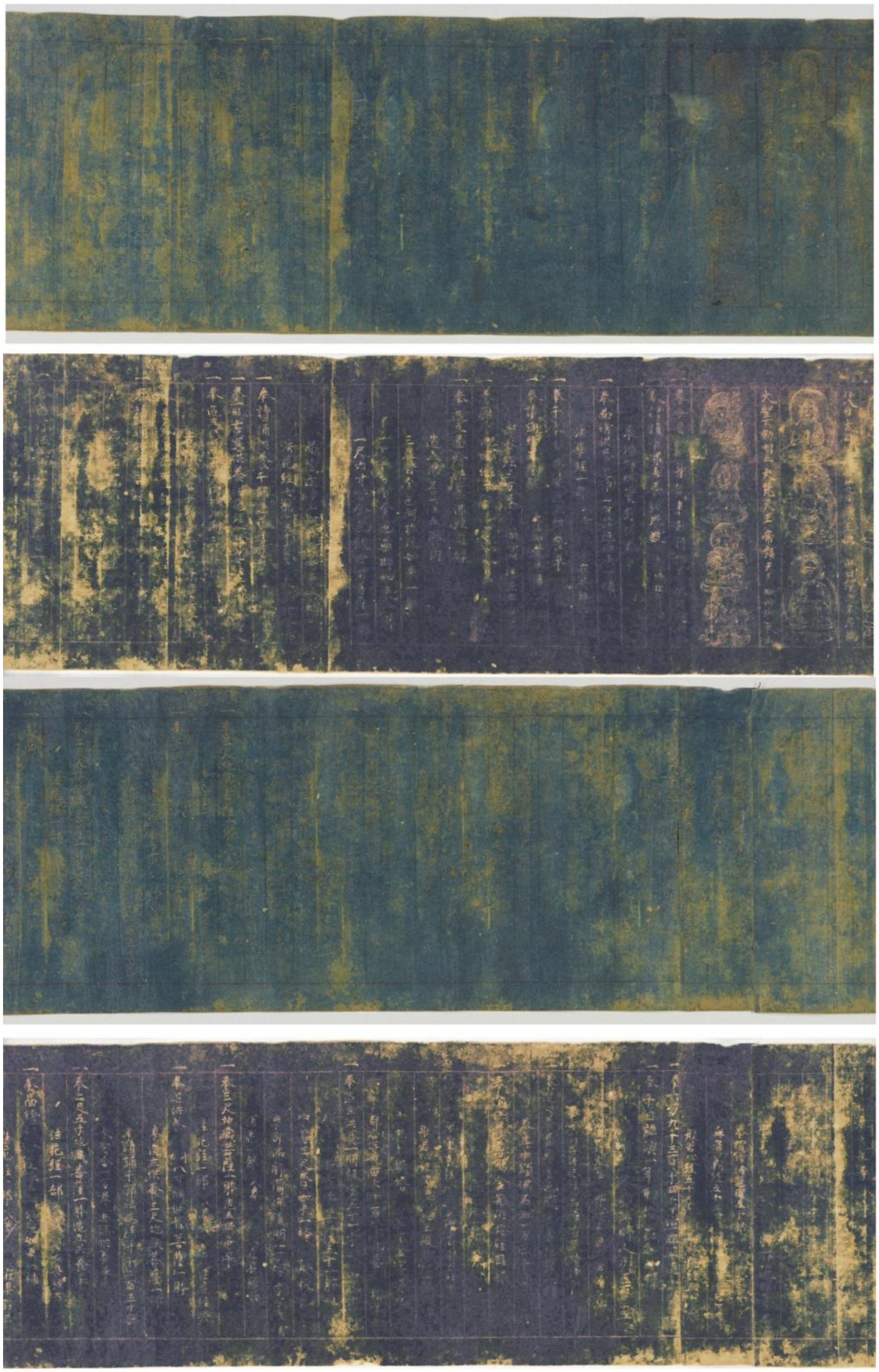
Original

Restored

Original

Restored

Figure A-1: Comparison of the original image and the restored image of Kuyō Mokuroku (Memorial Service List)



Kuyō Mokuroku (Memorial Service List) No.2

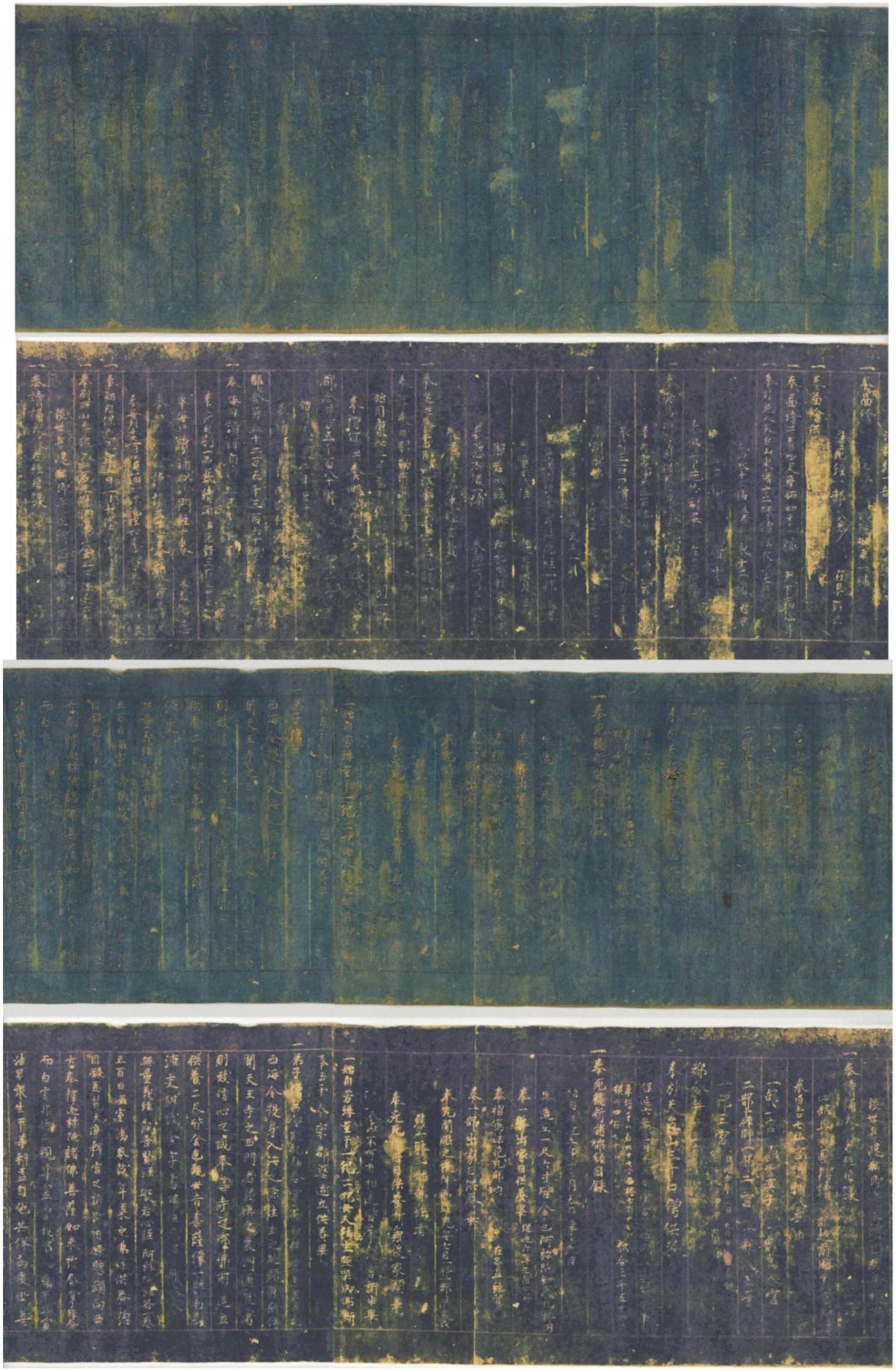
Original

Restored

Original

Restored

Figure A-2: Comparison of the original image and the restored image of Kuyō Mokuroku (Memorial Service List)



Memorial Service List-3

Original

Restored

Original

Restored

Figure A-3: Comparison of the original image and the restored image of Kuyō Mokuroku (Memorial Service List)

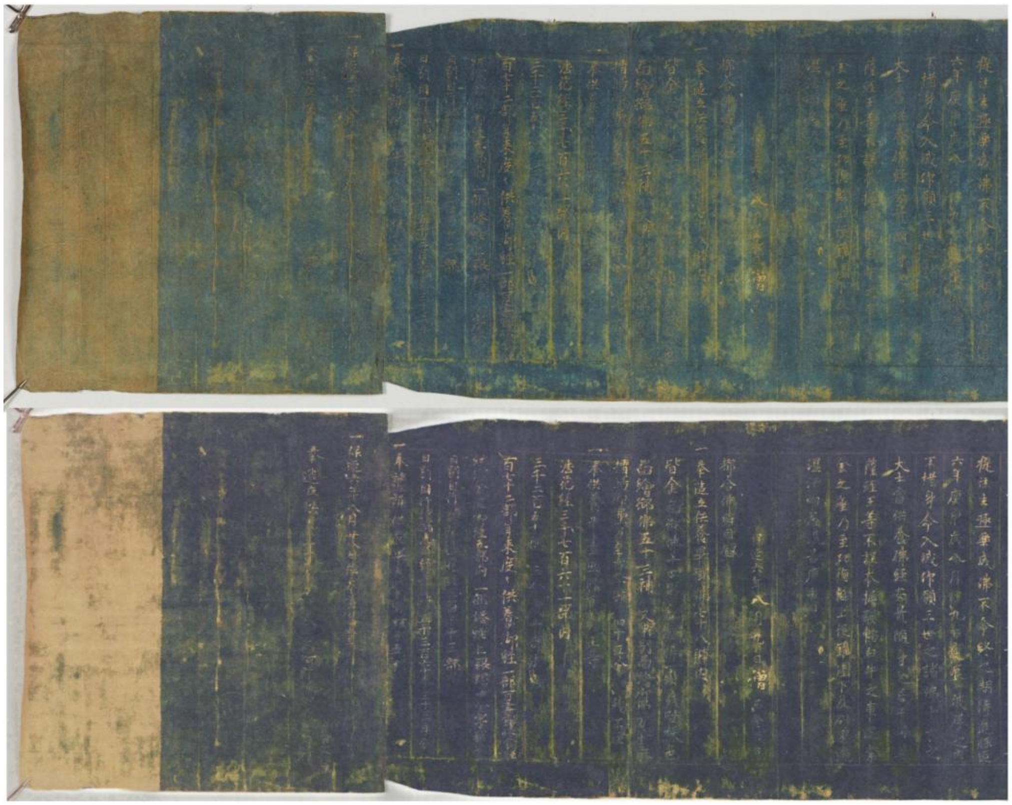


Figure A-4: Comparison of the original image and the restored image of Kuyō Mokuroku (Memorial Service List)

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