Rethinking Bhutanese Cultural Heritage Painting in the Age of AI

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Abstract

Bhutanese cultural heritage painting - thangka - holds significance as both an art form and a religious expression. Exploring thangka through artificial intelligence (AI) offers an opportunity to connect two distinct disciplines: traditional cultural heritage and emerging technology.

However, limited contemporary research has explored the application of AI to Bhutanese thangka, leaving a clear research gap that this study addresses. This study analyses the intersection of Bhutanese thangka art and AI through two Neural Style Transfer (NST) approaches: optimisation-based and diffusion-based. We applied the two approaches to four thangka schools relevant to Bhutanese thangka art. These included three Tibetan schools- Karma Gadri, Menri, and Khyenri- and the Bhutanese school. Each school was represented through its respective artistic style, which was applied to ordinary photographs used as content images.

The findings show that diffusion-based NST generally outperformed optimisation-based NST for Bhutanese thangka styles. Karma Gadri achieved the strongest balance between style transfer and content preservation, while other, more intricate thangka styles resulted in greater loss of content information and object identity.

The findings stress the need for specialised AI architectures, pointing to important directions for future research in the preservation and digital exploration of Bhutanese cultural heritage.

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Introduction

The rise of Artificial Intelligence (AI) has advanced the generation, analysis, and protection of information in numerous fields. Deep learning, a branch of artificial intelligence, has achieved remarkable success in computer vision, enabling tasks such as image classification (Yamini et al., 2023) and the precise recreation of artistic styles (Gatys et al., 2016).

Around the world, many traditional art forms face increasing challenges due to aging artisans, environmental deterioration, limited documentation, and the gradual decline of traditional craftsmanship. As societies become increasingly digital, researchers are exploring how AI can support the documentation, preservation, and revitalisation of cultural heritage without replacing the knowledge and skills of traditional artists.

AI provides complementary tools that empower human creativity by analysing artistic patterns, recreating stylistic elements, and assisting in the long-term preservation of culturally significant works (Colace et al., 2025; Paolanti et al., 2026). Little published research has focused specifically on Bhutanese thangka, underscoring a clear direction for future research.

Bhutan possesses a unique artistic heritage that is deeply intertwined with Mahayana and Vajrayana Buddhist traditions. Among its most distinctive cultural expressions is thangka, locally known as *lhazo*, a sacred painting tradition that combines religious philosophy, symbolism, and artistic precision.

Unlike many other forms of visual art, thangka paintings are not created solely for aesthetic appreciation but also serve as important educational, devotional, and meditative tools that communicate Buddhist teachings across generations (Shekede & Rickerby, 2013).

With recent advances in deep learning, techniques such as neural style transfer (NST) provide new possibilities for digitally preserving and studying these traditional artistic forms. AI-based models can reproduce stylistic elements while maintaining the structural content of new images by

learning the visual characteristics of thangka paintings. Such technologies offer valuable opportunities for cultural preservation, artistic education, and digital archiving, ensuring that Bhutan's artistic traditions continue to remain relevant in an increasingly digital world.

This article argues that neural style transfer can serve as a practical tool for generating Bhutanese thangka art. First, it examines the Buddhist philosophy that shapes thangka painting; second, it explains NST and its potential applications; and third, it considers how both relate to understanding Bhutan's rich artistic heritage.

We conducted an experiment using neural style transfer on thangka to generate new thangka-styled images to comprehend the compatibility and effectiveness of NST with thangka.

Buddhist Heritage and Thangka

Bhutan's artistic expressions are deeply influenced by religious philosophy, spiritual practice, and cultural values. Rather than depicting reality solely as the physical world, Buddhist philosophy views it as a dynamic interplay among wisdom, compassion, impermanence, karma, and the pursuit of enlightenment.

Consequently, religious art serves not merely as decoration but as a visual representation of these profound philosophical teachings. Central to this artistic tradition is thangka, one of the country's oldest and most respected forms of sacred painting.

A thangka is traditionally painted on cotton or silk, using natural pigments and mineral-based colours. Unlike ordinary paintings, every aspect of a thangka, including the proportions of figures, colour selection, hand gestures, symbols, and overall composition, is governed by strict iconographic guidelines derived from Buddhist scriptures. These established conventions ensure that each painting accurately communicates religious teachings while preserving centuries of artistic tradition (Yang & Fan, 2023).

Thangka paintings fulfil multiple roles within Bhutanese society. They are used as meditation aids, educational resources for teaching Buddhist philosophy, objects of devotion, and visual records of important religious figures and

historical narratives. Images of Buddhas, Bodhisattvas, protective deities, mandalas, and sacred symbols each conveys specific spiritual meanings that guide practitioners towards reflection and enlightenment. Through this symbolic language, thangka paintings communicate complex religious concepts in a visual form that remains accessible across generations.

Bhutanese thangka is documented as descending from Tibetan styles of thangka painting via the Drukpa Kagyu transmission in the 17th century, while developing regionally distinct characteristics (Luczanits & Namgyel, 2015). Hence, this research focuses on four thangka schools and their associated artistic styles: three Tibetan schools- Khyenri, Menri, and Karma Gadri- and the Bhutanese school.

Making a thangka is like a religious practice in its own right. Artists spend several years honing their skills not just in painting but also in Buddhism, iconography, and measurement. It is all about accuracy and precision, because a slight skewing of proportions or symbols could devastate the picture's religious meaning.

Thangka artists are trained through the Zorig Chusum, the 13 traditional arts and crafts, where Buddhist canons governing proportion, colour, and iconography are taught rigorously, and skill is built through repeated copying (Shekede & Rickerby, 2015).

There are challenges in maintaining thangkas. First, many paintings are susceptible to environmental degradation, including earthquakes (Bhutan lies in an active seismic zone), fire loss from butter lamps and wood-burning stoves, and light- and humidity-driven deterioration of organic pigments and glazes (Shekede & Rickerby, 2015).

Secondly, the number of professionally trained artists is limited in Bhutan. Hence, their skills are necessary for preserving thangka art in its original form. Modern technologies such as neural style transfer help revitalise and promote this tradition, recording various features of this art with greater precision.

Neural Style Transfer (NST) and AI Models

Neural style transfer is an AI technique that reproduces the artistic characteristics of a style image (e.g., a thangka painting) and transfers them onto the content of another image, generating a new image that retains the original content but adopts a different style. It keeps the subject or structure of one image while applying the colours, textures, patterns, and brushstrokes of another, such as a thangka painting.

Since its introduction by Gatys et al. (2016), NST has become an important technique in computational creativity and digital art. For instance, a photograph of a building used as the content image, combined with a Bhutanese mandala thangka as the style image, produces a new image that retains the building's structure while taking on the mandala's artistic style and visual characteristics.

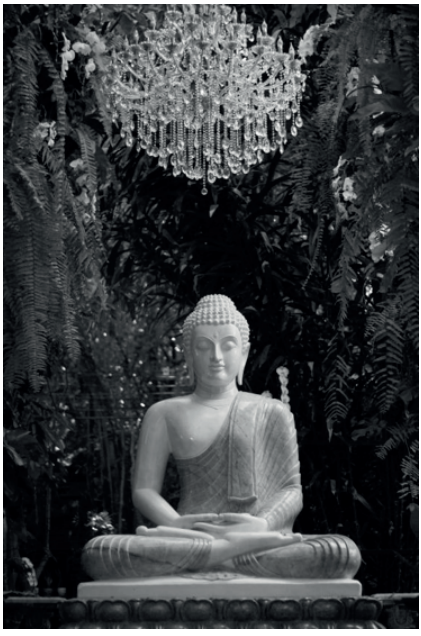


Figure 1: *A white Buddha statue image used as content image*



Figure 2: *Tibetan thangka of enlightened being by T. Tsem Rinpoche used as style image.*



Figure 3: *Diffusion-based NST output of an image combining the content of a Buddha image with the artistic style of a thangka painting. The transferred style is evident in the colour scheme, brushstroke characteristics, and linework, although some lines and strokes appear somewhat blurred. This indicates a limitation of the general diffusion architecture used, where stronger style transfer may result in partial loss of the original content details.*

This paper compares two approaches to performing NST. First, the optimisation-based method (Gatys et al., 2016) is used; it works by repeating a process of creating an image: A pre-trained AI model - one already trained on a large dataset beforehand, rather than built specifically for this task - nudges the pixel values of the content image until it takes on the target style while keeping the original composition.

Second, diffusion-based methods take a different approach, starting from an unstructured image and gradually refining it into a finished image. This process is guided by both the content and style images, resulting in a final stylised image (Ho et al., 2020). A diffusion- based method is considered the current state of the art and is used in numerous contemporary AI image-generation models (Rombach et al., 2022).

In the context of Bhutanese cultural heritage, NST provides a meaningful interpretation of the unique artistic qualities of thangka paintings while creating new images. As these two approaches belong to different periods in NST's development, comparing them allows this study to examine how the technique's practicality and output quality have evolved – from the foundational approach to the current techniques specifically for thangka paintings.

Significance of Thangka and the Study

This study demonstrates how modern AI techniques can appreciate traditional Bhutanese art. Rather than replacing conventional artistic practices like thangka painting practice, technologies such as neural style transfer and emerging diffusion models provide complementary approaches for digitally documenting, analysing, and reinterpreting traditional artistic styles.

This study shows that AI can be more than a tool for automation; it can also serve as a medium for cultural memory, creativity, and preservation. By bringing together Bhutan's traditional thangka art and modern generative technologies, the study opens a space where heritage is not only protected but also reimagined for future generations.

Findings

Diffusion-based NST outperformed optimisation-based NST across all four tested thangka schools- Karma Gadri, Menri, Khyenri, and the Bhutanese school- to varying degrees.

The optimisation-based method struggled to capture the distinctive styles of the different thangka schools, particularly their colours, textures, and patterns. Across the images and experimental runs, a consistent limitation was observed in preserving key content information and recognisable object identity from the original photographs.

In contrast, the diffusion-based method consistently produced better results, generating more visually coherent images that more closely reflected the distinctive styles of the respective thangka schools. However, style transfer quality varied across the four schools, as shown in the table below.

Table 1: Performance of diffusion-based NST across four thangka schools using their respective styles

Sl. No.	Thangka Style	Style Transfer	Object Identity Preservation	Content–Style Balance	Overall Performance
1	Karma Gadri	Very Strong	Strong	Very Strong	Balanced style and content transfer (best performance)
2	Menri	Very Strong	Moderate	Moderate	Strong stylistic transformation causes substantial content loss
3	Bhutanese	Strong	Moderate	Moderate	Strong stylistic transformation causes content loss
4	Khyenri	Very Strong	Weak	Weak	High style fidelity transformation reduced significant content loss

Using Bhutanese thangka paintings as the style image for NST effectively transfers distinctive artistic characteristics, including colour composition, brushwork, and decorative patterns.

Karma Gadri produced the most balanced results among the four thangka schools examined, preserving semantic information and object identity more effectively than the other schools. Among the other three styles, the generated images styled by Bhutanese thangka showed the closest resemblance to Menri, specifically signifying Menri's broader historical influence on Bhutanese thangka painting.

The effectiveness of NST depends on both the thangka style and the specific artwork style image selected. Variations in stylistic characteristics, such as colour palettes, patterns, textures, and compositional elements, can substantially influence the quality of the generated image.

Discussion

The comparison between methods confirms that diffusion-based NST is the stronger approach for thangka painting, consistent with its status as the current state of the art in image generation more broadly.

These findings indicate that further refinement of diffusion-based NST through architectural improvements may better balance style transfer and content reproduction. Such advancements could generate images that more closely resemble authentic Bhutanese thangka paintings while maintaining greater content coherence and cultural fidelity.

A limitation of this research was the limited availability of centralised thangka datasets, particularly for Bhutanese thangka, due to the scarcity of well-documented online sources and research on the subject. To work within this constraint, the second phase of the study ran three experiments across different, limited datasets.

This scarcity points to a need for dedicated data collection efforts, comparable to those already undertaken for Tibetan thangka (e.g., Li et al., 2025), which would meaningfully support future work, including training AI models specifically on thangka imagery.

Building on these findings, future research could focus on developing specialised diffusion-based NST architectures tailored to culturally rich and structurally complex artworks such as Bhutanese thangka. In addition, advanced AI approaches could help better understand, preserve, and digitally represent Bhutanese thangka. These developments could support the wider preservation and revitalisation of Bhutanese cultural heritage.

More broadly, this study points to the potential for integrating AI with cultural heritage work, suggesting that the two domains should be viewed not as independent disciplines but as complementary ones.

Rather than replacing traditional artistic practice like thangka, AI can serve as a supportive tool for analysing and digitally representing cultural heritage, which provides the context and direction needed to guide meaningful AI applications. This relationship illustrates how technological innovation and cultural heritage can reinforce one another, supporting the development

of AI systems that both respect and promote traditional art forms such as Bhutanese thangka painting.

Conclusion

This study's findings demonstrate that diffusion-based methodologies consistently outperform optimisation-based approaches on thangka, producing more visually coherent and aesthetically appealing images while achieving a better balance between style representation and content identity preservation.

However, the results also reveal that diffusion-based NST continues to struggle to preserve content information and object identity when transferring highly intricate thangka styles, highlighting opportunities for further methodological improvement.

The study is one of the first systematic evaluations of NST using Bhutanese thangka painting styles and contributes to the growing field of AI-assisted cultural heritage exposition. Future research should focus on developing specialised diffusion-based architectures that better balance semantic fidelity with the distinctive artistic characteristics of traditional thangka paintings.

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