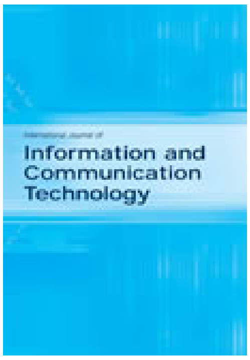

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A review of AI-driven art education: enhancing creativity through deep learning and digital image processing

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Abstract: Deep learning and digital image processing powered by artificial intelligence are now influencing art education. With AI, artists can now experiment with new styles and effects, thanks to CNNs, GANs and NST. Tasks such as edge detection, segmentation and super-resolution give rise to helpful approaches in creative learning. AI-assisted art is represented by platforms such as DeepDream and RunwayML. While AI offers fast and original feedback to improve learning, many are worried about who should get credit for the results, ethics and the loss of traditional abilities. We must deal with problems such as dataset bias, copyright and having too much trust in AI. By being careful with AI, it can connect rather than conflict with conventional art, while aiming for ethics, diverse sets and blended ways of teaching.

Keywords: AI in art education; deep learning in creativity; digital image processing; generative adversarial networks; GANs; neural style transfer; NST; ethical AI in art.

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1 Introduction

Artificial intelligence (AI) has led to the introduction of computational techniques to advance creativity, automate artistic processes, and offer intelligent feedback in art education (Zhang et al., 2022; Anantrasirichai and Bull, 2022;Ali Elfa and Dawood, 2023). Traditional art education is based on skill development through manual processes, which require many years of practice to master the basics of composition, colour theory, and brushwork (Alikulovich, 2021; Holtje, 2019). However, AI-driven tools using deep learning and digital image processing are changing the game entirely regarding how artists learn, create, and improve their work (Anantrasirichai and Bull, 2022; Monser and Fadel, 2023;Rani et al., 2023). Artistic learning with AI introduces interactive and accessible ways to learn through concepts like analysing artistic styles, generating new compositions, or helping in real-time image modifications (Fang and Jiang, 2024; Anantrasirichai and Bull, 2022;Chen et al., 2020). However, while this progress may provide opportunities to integrate AI into art education, there are also authorship, authenticity, bias, and ethical issues concerning its involvement with its creative expression by technology.

Recent progress in AI-assisted creativity has happened with contributions from deep learning, namely convolutional neural networks (CNNs), generative adversarial networks (GANs), and neural style transfer (NST) (Bao, 2024; Shen et al., 2024;Chavda et al., 2023). The CNNs are commonly used for artistic analysis, style recognition, composition evaluation (Santos et al., 2021), etc., while the GANs enable AI-generated artworks that imitate human creativity (Berryman, 2024). Seamless editing of art styles in images enabled by NST enables experimental learning in digital painting (Singh et al., 2021). It is supplemented by digital image processing techniques, such as edge detection, segmentation, histogram equalisation, and super-resolution, to enhance artistic workflow by refining image quality, improving visual aesthetics, and restoring historical artworks (Vijendran et al., 2024). As these AI-driven methodologies are applied more and more in art education, we see from AI-powered creative learning platforms to interactive museum exhibits. Nevertheless, the ethical implications of AI-generated art, the influence of

AI-generated art on traditional artistic skills, and the requirement of inclusive AI training datasets continue to be questions that need to be discussed.

In this study, we explore the integration of digital image processing and deep learning techniques with AI in prior art education, and the benefits and limitations of these techniques are examined. This research aims to help develop a structured framework for integrating AI into art curricula while maintaining artistic integrity, examining AI-driven tools, case studies, and ethical considerations. These findings will lend to current discussions of the potential positive uses of AI to complement, rather than replace, human creativity in art education.

1.1 Motivation and significance

This research is motivated by the fact that AI is widely adopted in artistic creation and education. Artists, educators, and students increasingly use AI-powered tools to automate repetitive tasks, experiment with new artistic styles, or enhance their creative workflows. AI in art education carries the following significance.

Figure 1 Role of AI in art education (see online version for colours)

AI-powered feedback mechanisms: the brushstrokes, composition, and colour balance are analysed in real-time to give feedback to students, which enhances the efficiency of learning. *Creative possibilities:* by leveraging GANs and NST, artists can expand the horizons of their creativity and create innovative works that would have been challenging to produce manually. AI-powered platforms can help improve accessibility by providing interactive learning to people with disability and those who do not have access to traditional art training. *Support artistic restoration:* digital image processing techniques help improve the quality of ancient and broken artworks, which helps digitalise the cultural heritage. AI tools enhance the learning of beginner artists by giving them real-time suggestions and automated refinements of art. While these advantages are present, there are still worries about AI dependency, bias in AI-created content, and the impacts of AI-helped art on old-school intelligible improvement. However, this study explores these issues by investigating how AI can be used responsibly and ethically in art education. The evolving role of AI in art education is depicted in Figure 1, which illustrates the key AI techniques and their applications in light of the goal of this thesis.

1.2 Research objectives

This study aims to evaluate the effect of AI on artistic learning to provide a rich analysis of the use of AI-driven techniques in art education. The key research objectives include:

- As a means of analysing deep learning and digital image processing in art education.
- Study on AI-driven image enhancement, AI-driven artistic style classification, and real-time feedback mechanism.
- The effect of CNNs, GANs, and NST on creativity learning.
- What kinds of AI-powered tools are available to support artistic training and creativity?
- Examine platforms like DeepDream, RunwayML, AI painting digital paint applications, etc.
- Digging through AI's role in Museums, Interactive Exhibits, and Digital Art Preservations.
- Studies in authorship, copyright concerns, and dataset bias in AI-assisted creative workflows.
- Considering the impact that AI-generated artworks can have on the progress of traditional art skills.
- As a proposal for a framework that facilitates the integration of AI into art education curricula.
- Conditions for AI assistance and human artistic practice.
- Aiding to make AI tools aid rather than substitute for regular art techniques.

The research covered in this study is summarised in Table 1.

Table 1 Key research areas in AI-based art education

Research focus	*Key questions addressed*	*Expected impact*
AI in artistic learning	How can AI improve artistic training?	Accelerated learning, real-time feedback
Digital image processing	How do AI techniques refine image quality?	Enhanced restoration, artistic transformations
Ethical considerations	Who owns AI-generated art? Is AI biased in artistic styles?	Development of fair-use policies
Hybrid learning models	How can AI and traditional techniques be balanced?	Sustainable AI integration in art curricula

1.3 Structure of the paper

In seven sections, this paper organises itself around a vital piece about integrating AI into art education. Section 2 provides the art history fundamentals in digital image processing with essential techniques like edge detection, segmentation, and super-resolution as potential applications to artistic education. Section 3 covers deep learning techniques of CNNs, GANs, and NST, introducing their theoretical foundations and how they are used to arouse artistic creativity. In Section 4, the authors examine case studies and applications of AI in art education by applying AI to real-world problems, such as AI-powered tools, digital restoration, and interactive museum exhibits. In Section 5, I examine AI's ethical challenges and considerations in art, considering topics like authorship, copyright concerns about our dataset being biased, and how we will be trained to use AI in the future. Section 6 looks at the future of AI diversity enhancement, AI-powered virtual art tutor development, and AI integration into hybrid learning models. It concludes in Section 7 with a summary of key findings and future research directions for the responsible and effective integration of AI in art education.

1.4 Summary

Advancements in using AI for art education create a lot of chances to increase creativity, increase access to learning, and enhance artistic learning. Nevertheless, there are some challenges while introducing these innovations, mainly regarding authorship, ethical issues, and dependency on the skills of AI tools. While this study attempts to balance technological developments and traditional artistic practice, it also comprehensively analyses AI in art education. This research aims to contribute to the structure of how to use AI in artistic training in ways that do not kill human creativity at the core of the artistic process. As the future of art education, we see AI's role as being used to heighten learning without diminishing the significance of traditional artistic methodology, enabling a space where human genius and computer smarts team up to broaden the limits of artistic expression.

2 Fundamentals of digital image processing in art

Modern art education benefits from computational techniques for manipulating, enhancing, and transforming visual data that can be used in digital image processing. These techniques allow artists and students to experiment with new forms of artistic expression, automate tedious tasks, and hone their creative workflow (Wolberg, 1990; Jähne, 2005; Archana and Jeevaraj, 2024; Chanda and Majumder, 2011; Zhang et al., 2022). After the development of AI, existing image processing methods have evolved using deep learning, which increases efficiency and enlarges artistic possibilities.

This section looks at the basic information about digital image valuable processing in art education, including edge detection (Sun et al., 2022), image segmentation (Yu et al., 2023), histogram equalisation (Garg and Jain, 2017), super-resolution (Wang et al., 2020), and colourisation (Žeger et al., 2021). Moreover, the use of AI-driven image processing techniques is also examined, and the role that AI-empowered image processing tools play in artistic training and digital creativity is shown.

2.1 Essential image processing techniques

Mathematical operations on a digital image that change its properties, for instance, brightness, contrast, texture, or structure, define it as digital image processing (Zhou et al., 2010; Blackledge, 2005;Shih, 2017). Therefore, these techniques can help enhance the digital restoration of artistic compositions and provide a base of knowledge for future AI-based artistic applications.

2.1.1 Edge detection

This technique is used to detect edges, i.e., boundaries of objects in the image, by detecting the sharp intensity changes. It is beneficial in digital sketching, line art generation, and feature extraction for artistic analysis (Kyprianidis et al., 2012; Zhou et al., 2010; Yi et al., 2020). One of the most popular mathematical methods of edge detection is computing the main component of the gradient of an image.

$$G(x, y) = \sqrt{G_x^2 + G_y^2} \tag{1}$$

where G_x, and G_y, are the intensity gradients in the horizontal and vertical directions computed by convolving with edge detection kernels, e.g., the Sobel operator:

$$G_x = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix}, G_y = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix} \tag{2}$$

A finer edge detector like the Canny edge detector with Gaussian smoothing, gradient computation, and non-maximum suppression can be applied to achieve clean and well-defined edges (Setayesh, 2013; Hou and Wei, 2002;Grigorescu et al., 2004). An artistic image with edge detection applied to it is illustrated in Figure 2.

Figure 2 Edge detection applied to an artistic image (see online version for colours)

2.1.2 Image segmentation

Image segmentation is a process by which the divided parts are assigned into separate groups of the image so that an artist can perform on the individual part for compositional modification (Kyprianidis et al., 2012; Blaschke et al., 2004; Zhou et al., 2010). However, it is widely used for background removal, object separation, and digital painting (Lucchese and Mitra, 2001; Elhabian et al., 2008; Blaschke et al., 2004). Thresholding is a simple segmentation method in which a pixel value $I(x, y)$ is compared to a threshold T.

$$I'(x, y) = \begin{cases} 1, & \text{if } I(x, y) > T \\ 0, & \text{Otherwise} \end{cases} \tag{3}$$

K-means clustering is another, more elaborate segmentation method, which groups pixels into k clusters according to their colour and texture properties. Cluster the items to achieve the minimal intra-cluster variance.

$$J = \sum_{i=1}^{k} \sum_{j \in C_i} \left| x_j - \mu_i \right|^2 \tag{4}$$

where x_i, represents a pixel intensity, c_i represents a cluster, μ_i is the cluster's centroid. As shown in Figure 3, K-means segmentation separates elements in a piece of artwork so that a compositional refinement can be applied to them.

Figure 3 K-means clustering for image segmentation in artworks (see online version for colours)

2.1.3 Histogram equalisation

Histogram equalisation is a kind of image contrast enhancement technique that improves image contrast by redistributing the pixel intensities and enhancing the artistic details (Kaur et al., 2011; Zhu et al., 1999;Kong et al., 2013). From the cumulative distribution function (CDF), it depends on the transformation function $T(r)$.

$$T(r) = (L-1)\sum_{i=0}^{r} p(r_i) \tag{5}$$

where L is the number of intensity levels, $p(r_i)$ is the probability of a pixel having intensity r_i. Making subtle textures more straightforward to restore faded art is common, and histogram equalisation is used mainly for this. Histogram equalisation contrast improvement is shown in Figure 4.

Figure 4 Histogram equalisation on a classical painting (see online version for colours)

2.1.4 Super-resolution and image upscaling

Super-resolution techniques can be used to reconstruct images from low-resolution inputs and are so helpful for pixelated digital artwork as they can be used to restore the details of the artwork and enhance the art itself (Fatima, 2020; Wang et al., 2020; Dong et al., 2015a; Mol and Maheswari, 2021). However, traditional methods like bicubic interpolation estimate the missing pixel values but cannot restore fine details. Super-Resolution Convolutional Neural Networks (SRCNN) are deep learning approaches that allow mappings from low-resolution to high-resolution images (Kumar, 2020; Dong et al., 2014, 2015b).

$$Y = F(X) = W_3 * \left(\mathrm{ReLU}\left(W_2 * \left(\mathrm{ReLU}\left(W_1 * X + b_1\right)\right) + b_2\right)\right) + b_3 \quad (6)$$

where X is the input low-resolution image, Y is the high-resolution output, W_i and b_i are learned weights and biases of convolutional layers. AI super-resolution is shown in Figure 5 on a digital painting, which is a low-quality image.

Figure 5 AI-driven super-resolution in digital art (see online version for colours)

2.1.5 Colourisation and style transfer

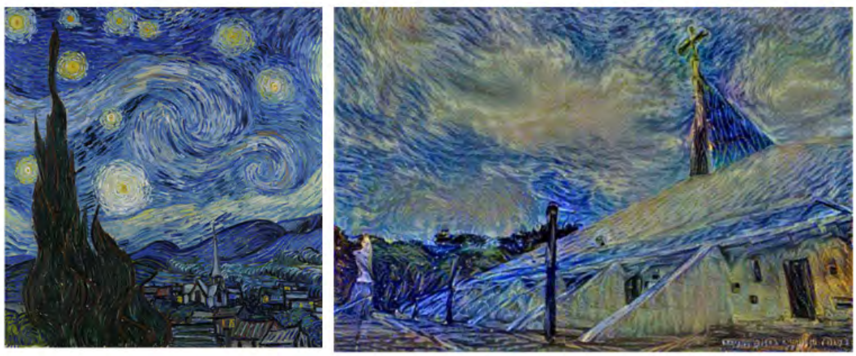
Colourisation involves predicting colours for greyscale images using AI-based deep learning models, and NST applies an artistic style of one image onto another (Kostrzewa, 2024). The NST is defined as the weighted combination of content loss, L_c, and style loss L_s:

$$L_{\text{total}} = \alpha L_c + \beta L_s \tag{7}$$

where $L_c = \sum_{i,j} \left(F_{ij}^{\text{generated}} - F_{ij}^{\text{content}} \right)^2, \ L_s = \sum_{i,j} \left(G_{ij}^{\text{generated}} - G_{ij}^{\text{style}} \right)^2.$

where F_{ij} denotes the feature maps extracted from a CNN, and G_{ij} refers to the Gram matrix representing style correlations. An example of a photograph transformed into the style of Van Gogh's Starry Night is also presented in Figure 6.

Figure 6 NST applied to a digital portrait (see online version for colours)



2.1.6 AI-enhanced image processing in art

As AI progresses, the traditional image-processing methods artists use to complete their work have become AI-powered tools that help artists in their creative work Miller, 2019; Monser and Fadel, 2023). Key applications include real-time artistic enhancements through AI-assisted digital painting software such as Adobe Photoshop's Neural Filters (Ching and Mothi, 2025). Restoration tools that come from AI could reconstruct damaged artwork by predicting what has been lost (Ghaith and Hutson, 2024) – AI-generated composition suggestion feedback systems for art students in real-time (Attaluri and Mudunuri, 2025). Table 2 compares traditional image processing methods with AI-driven approaches.

Table 2 Traditional vs. AI-enhanced image processing in art

Processing type	*Traditional method*	*AI-enhanced method*
Edge detection	Sobel, Canny filters	AI-powered contour extraction
Image segmentation	Thresholding, K-means	Deep learning-based segmentation
Super-resolution	Bicubic interpolation	SRCNN, ESRGAN
Colourisation	Manual	AI-driven automatic colourisation

2.1.7 Summary

Digital image processing techniques have changed art education, allowing artists to define compositions, explore new styles, and restore historical artworks. Finally, AI-driven advances also enlarge these possibilities to include tools that make digital painting, image optimisation, and real-time artistic instruction. Art education can become an intersection of ancient and AI-driven approaches where human creativity and computational intelligence can work side by side in creating digital artistry.

3 Deep learning techniques in art education

Using computational techniques to enhance creativity, automate artistic processes, and supply intelligent support in artistic training has significantly influenced art education through deep learning (Zhang et al., 2022; Fan and Li, 2023). Typically, a computationally artificial autonomous tool, like those based on deep learning, enables a new way of exploring and learning within artistic practice, but traditional art education relies solely on skill development based on manual practice (Xu and Jiang, 2022; Gong, 2021;Marques et al., 2020). These techniques include convolutional neural networks (CNNs), Generative adversarial neural networks (GANs), and NST that not only help in automating the process of style classification but also in generating the AI artwork and mixing the different techniques of art (Singh et al., 2021; Jing et al., 2019;Sohaliya and Sharma, 2021;, Wang et al., 2024). These aren't replacements for human creativity; they're powerful tools that help creativity and learning become more interactive and manageable.

In this section, we investigate the key techniques that enable deep learning to become its art education by exploring its role in such a process. These techniques are discussed along with their mathematical foundations, and their use in digital painting, artistic analysis, and real-time feedback is discussed for students.

3.1 CNNs in artistic analysis

CNNs are widely used in art style classification, feature extraction, and composition analysis (Castellano and Vessio, 2021; Sandoval et al., 2019). First, they process hierarchical images, capturing low detail (edges and texture) and high artistic patterns. Multiple layers make up a CNN, the most important being.

Mathematical foundations of CNNs: both art style classification, feature extraction, and composition analysis use CNNs (Kumar et al., 2022; Gatys et al., 2016). They organise images hierarchically with the ability to capture coarse features (edges and textures) first, then finer features (shapes and textures with textures), and finally finer ones (patterns and textures with types of textures). A CNN consists of multiple layers, with the most important ones being:

- Convolutional layers, which apply filters to detect patterns:

$$O(x, y) = \sum_i \sum_j I(x-i, y-j)K(i, j) \tag{8}$$

Then $K(i, j)$, in our case, is the filter (or kernel), $I(x, y)$ is the input image, and $O(x, y)$, is the output feature map.

- Rectified linear unit (ReLU) activation functions introduce nonlinearity.

$$f(x) = \max(0, x) \tag{9}$$

- Max pooling, for instance, acts on the original data's dimensionality but lets through the essential features.

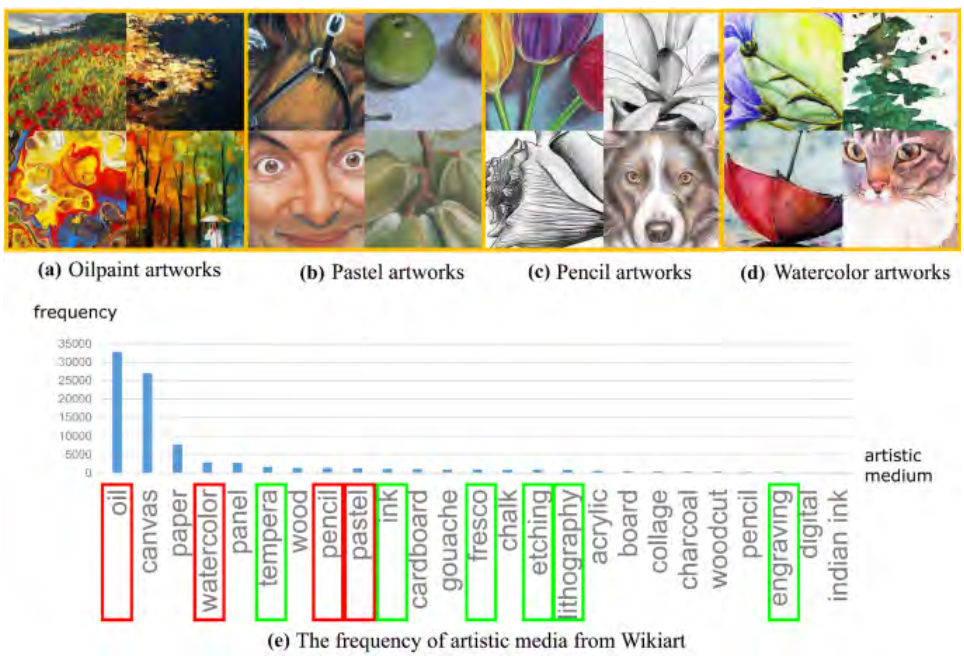
$$P(x, y) = \max_{i,j}\left(0(x+i,\ y+j)\right) \tag{10}$$

Applications in art education are several artistic training applications of CNNs:

- Artwork classification by style: AI models trained in famous paintings can categorise the artworks based on the style they typically paint.
- Texture and stroke direction: CNNs support students in understanding different brush techniques by analysing texture and stroke direction.
- Real-time artificial feedback: automate platforms with AI-based suggestions for enhancing composition.

Figure 7 depicts a CNN-based system to classify paintings into artistic styles.

Figure 7 CNN-based style classification of artworks (see online version for colours)



GANs in creative art: GANs are two neural networks that jointly explore a dynamic learning process. The generator (G) generates new images from random noise. The discriminator (D) predicts whether or not an image is real or artificial (Wang et al., 2017; Alqahtani et al., 2021;Dash et al., 2023). This adversarial relationship requires the Generator to improve with time, creating more realistic pictures. The above function mathematically explains this learning process.

$$\min_G \max_D V(D, G) = E_{X \sim p_{\text{data}}(x)}[\log D(x)] + E_{Z \sim p_z(z)}\left[\log\left(1 - D\left(G(z)\right)\right)\right] \tag{11}$$

where $p_{\text{data}}(x)$ represents the actual data distribution, $p_z(z)$ represents the distribution of random noise input to the generator, $G(z)$ generates new images from noise and $D(x)$ determines whether x is accurate or generated.

Applications in art education: since then, GANs have fundamentally changed AI-generated artwork, and there are numerous applications of GANs to help artists, educators, and historians (Cao et al., 2023; Bansal et al., 2024;Bengesi et al., 2024; Sims, 2024). These applications include:

- Genshakti creates unique digital paintings in various artistic styles, which can be used for wild and creative inspiration.
- GAN-based inpainting techniques reconstruct missing or damaged sections of historical paintings to preserve cultural heritage.
- GANs improve the workflow through artificial intelligence-assisted sketching, which turns rough sketches into finished compositions by GANs.

Table 3 compares different GAN architectures used in artistic applications.

Table 3 Comparison of GAN architectures in artistic applications

GAN architecture	*Application in art*	*Key features*
Vanilla GAN	AI-generated paintings and textures	Basic adversarial training
DCGAN (Deep Convolutional GAN)	Improved art synthesis and digital painting	It uses convolutional layers for better feature extraction
CycleGAN	Style transfer and domain adaptation (e.g., converting sketches into paintings)	Transforms images between different styles without paired data
StyleGAN	Highly detailed and controllable artistic image generation	Enables fine-grained control over artistic elements
Pix2Pix	Sketch-to-image transformation and image in-painting	Requires paired data for training

Figure 8 shows an example of an AI-generated artwork created using GANs.

NST in art learning: NST is an image that combines another image's style and preserves the original's content (Jing et al., 2019; Singh et al., 2021; Li et al., 2020; Garg et al., 2023). It does this by optimising a loss function with content loss, L_c and style loss L_s combined.

$$L_{\text{total}} = \alpha L_c + \beta L_s \tag{12}$$

where $L_c = \sum_{i,j} \left(F_{ij}^{\text{generated}} - F_{ij}^{\text{content}} \right)^2$, $L_s = \sum_{i,j} \left(G_{ij}^{\text{generated}} - G_{ij}^{\text{style}} \right)^2$.

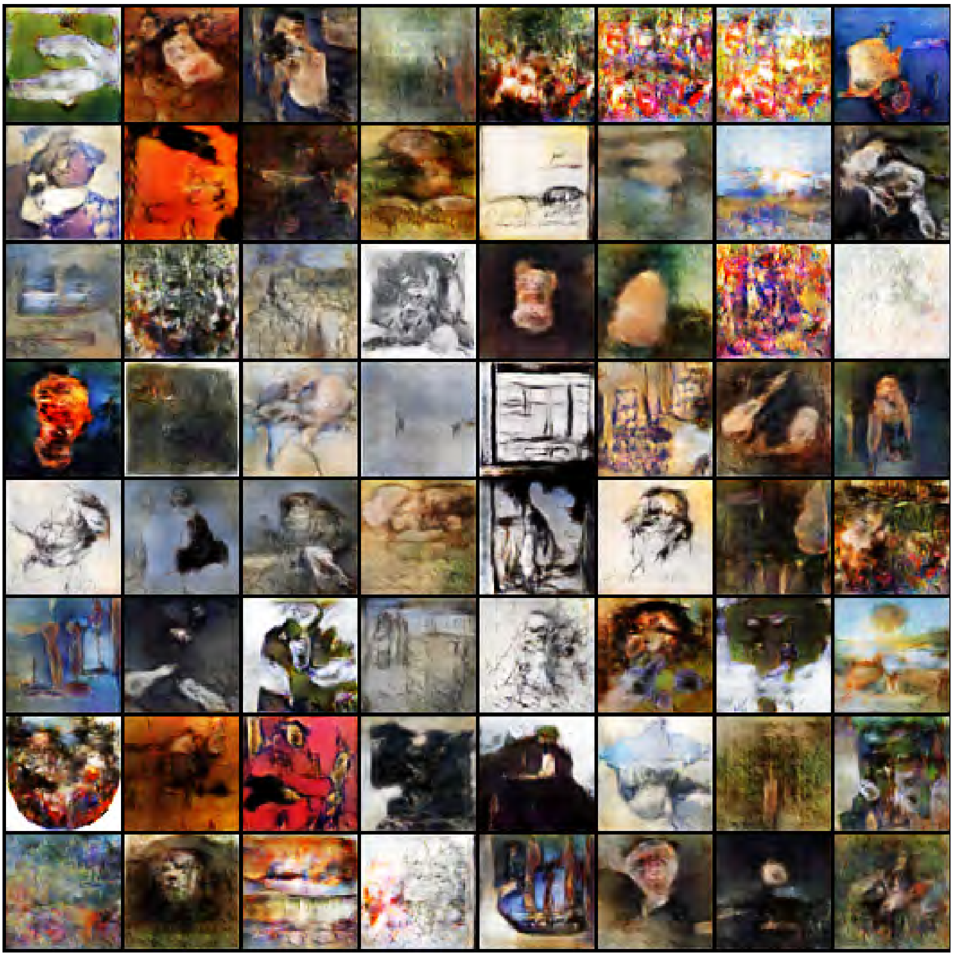
where F_{ij} denotes the feature maps extracted from a CNN, and G_{ij} refers to the Gram matrix representing style correlations.

Applications in art education are widely used for:

- AI-assisted art creation: students can check the conversion of the digital sketch into style according to Van Gogh, Picasso, or Monet.
- NST teaches artistic styles with a student's hands-on approach to discovering historical art movements.

- Visual stimulation: it facilitates visual stimulation among artists, allowing them to see their works in different styles and thus inspire from cross style. An image transformed using NST is presented in Figure 9.

Figure 8 AI-generated artwork using GANs (see online version for colours)



Future directions of deep learning in art education: with deep learning ever-growing, there has been an opportunity for deep learning to blend into art education both for educators and students. Several future research areas should be focused on before gaining the most of the benefits of AI while tackling ethical and artistic challenges.

Developing AI-powered art tutoring systems: run-time AI-driven feedback systems can analyse the student's artworks in real-time and provide personalised suggestions for improving composition, colour balance, and style. These systems can be used as virtual mentors to the students to help them polish their artistic skills through adaptive learning.

Enhancing ethical AI art guidelines: with AI-generated artwork becoming more commonplace, setting ethical attribution and ownership standards is most important. Putting some clear guidelines in place will help by defining authorship, preventing plagiarism, and approving the giving artists due recognition for their work in AI.

Figure 9 NST applied to a digital painting (see online version for colours)

Expanding AI training datasets for artistic diversity: one obvious limitation of the existing AI art models is that they are highly biased toward Western art styles due to the biased training datasets. Other research should be conducted to curate diverse datasets that include multicultural artistic traditions to enable the AI art generation to embody global artistic heritage.

Hybrid AI-traditional learning models: it should not replace fundamental artistic skills, and AI does not replace the manual labour of an artist as it can automate many things. The future learning models will combine AI assistance with traditional manual techniques so students will be well-versed technically and ingenuously. Table 4 summarises the future AI innovations in art education.

Table 4 Future AI innovations in art education

AI advancement	*Potential impact on art education*
AI-powered art tutors	Provides real-time feedback and guidance
AI art ethics guidelines	Defines authorship and ownership of AI-generated works
Multicultural AI training datasets	Reduces bias in AI-generated art
Hybrid AI-traditional learning	Maintains a balance between AI-assisted and manual art

Thanks to deep learning techniques such as CNNs, GANs, and NST, we can now teach new ways to analyse digital art, create art, and learn from digital art in interactive ways.

AI-based tools aid students in learning art styles, generating art of their own, and trying different artistic transformations. Nevertheless, the ethical concerns that come along with the responsible AI integration, the diversity of the dataset, and the fix of pumping the live people skills in the traditions of the art are yet to be addressed. With hybrid learning models, an ethical AI framework, and an advanced AI tutoring system, deep learning would continue to develop artistic possibilities. At the same time, human creativity in art education remains noble.

4 Case studies and applications

AI has overturned traditional art education learning, enabling students and artists to explore new creative possibilities. Tools created by AI aid in creating artwork, studying compositions, and reparation, among other things, while keeping learners notified of their progress in real-time. These advancements, in turn, allow the artistic training to be interactive, accessible, and data-driven. Various AI-based platforms and implementations, including deep learning models, digital image processing, and generative AI, are merging into art education.

This section shows the real-life application of AI through case studies on how AI is used in art education. The AI-integrated learning platforms, the AI-assisted creative learning aid, and the role of AI in museums and digital exhibitions fall under these. Many case studies demonstrate how AI enhances artistic exploration, skill enhancement, and curriculum development.

AI-integrated art learning platforms: it involves bringing AI's ability to create, modify, and analyse artworks, which is very helpful for artists and students who want to take art as their career (Miller, 2019; Mazzone and Elgammal, 2019; Hong and Curran, 2019). These platforms aim to give artists an additional tool to harness their creativity using deep learning models such as CNNs, GANs, and NST.

Case study (DeepDream by Google): Google's DeepDream is a tool based on a deep neural network that enhances image patterns to produce surreal and abstract artwork (Al-Khazraji et al., 2023; Dursun and Bakan, 2025;Somaini, 2023). It relies on convolutional layers to strengthen some visual features, which makes it highly appropriate for artistic distortions and texture generation. Gradient ascent is applied on a chosen layer of a pre-trained CNN (such as InceptionV3) till the activation of the highest possible features and pixels is maximised. Mathematically, this is expressed as:

$$I' = I + \alpha \frac{\partial I}{\partial \sum f_l(I)} \tag{13}$$

where I' is the transformed image, I is the original input image, $f_l(I)$ represents activations in the layer l, and α is the learning rate for modification. Application in art education:

- students use DeepDream to discover the textures and compositions AI can generate
- it provides a better understanding of CNN's feature extraction by intelligibly presenting how neural networks understand artistic elements
- as a result, it is often used in digital surrealism and abstract art made by AI.

DeepDream is demonstrated in Figure 10, where the results illustrate the hallucinogenic, intricate textures possible to create through processed initial artwork.

Figure 10 DeepDream image transformation (see online version for colours)

Case study (RunwayML – AI Tools for Artists): RunwayML is an AI creative toolkit for artists and students to easily add deep learning models into their creative workflows without requiring programming expertise (Ching and Mothi, 2025; Rossa, 2021). RunwayML is a popular tool for AI help with creation because it offers an intuitive interface and access to powerful AI techniques (Sunder, 2024; Friedman and Pollak, 2021;Muthazhagu et al., 2024). They can make AI more accessible to the art community by turning it into an application that allows users to use machine learning models for style transfer, object detection, and generative art.

- Pre-trained NST: applies artistic filters to images and videos using NST models; helps the users explore various visual aesthetics.
- Advanced generative models like StyleGAN are used to create outstanding AI paintings and illustrations (GANs for Art Generation).
- Body motion tracking: real-time tracking of human movement, used in interactive/ dynamic art installations that AI responds to.
- RunwayML tackles the frustrating issue of the technical barrier to AI creativity, enabling students to experiment with AI-generated art without understanding deep machine learning but still having a good amount of context around what makes it so and helping them become better creators moving forward.
- Real-time and interactive learning: enabling real-time artistic interactions that support students in comprehending how AI algorithms and artistic elements work.
- It is digital storytelling, empowering artists to combine the computer aid in creative expression with the traditional artistic way of creating multimedia projects.

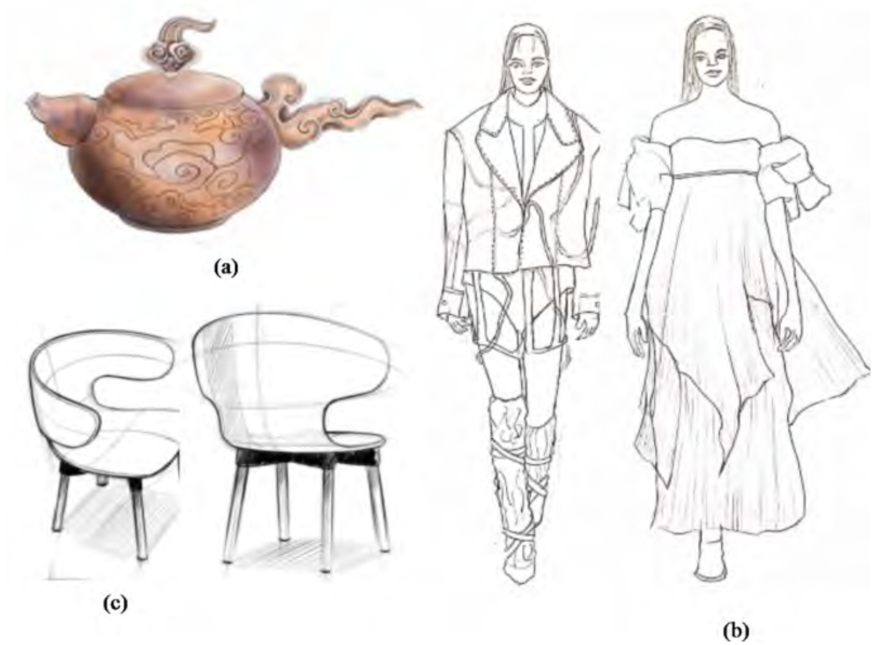
Table 5 compares RunwayML with other AI-driven art platforms.

AI-assisted creative learning programs: learning programs with AI are being built so that students can learn to sketch, do digital painting, and conceptualise (Ng et al., 2022; Gong, 2021; Zimmerman, 2018). Such programs allow real-time artistic feedback and automate various artistic enhancements, which simulate impressions of different painting styles.

Table 5 Comparison of AI art learning platforms

Platform	*Key AI technologies used*	*Educational applications*
DeepDream	CNN-based feature amplification	Understanding AI vision and artistic surrealism
RunwayML	GANs, NST, object detection	AI-assisted creative learning and experimentation
DALL·E	Transformer-based text-to-image generation	Conceptual art creation from textual descriptions

Figure 11 AI-assisted sketching process (see online version for colours)



Case study (AI-based sketching assistants): AI-assisted sketching applications use Deep learning to predict and polish hand-drawn sketches like Sketch-RNN and AutoDraw. Sketch-RNN is trained on large datasets of hand-drawn sketches to perform handwriting recognition using RNN (Xu et al., 2022; Bandyopadhyay et al., 2024;Bhunia et al., 2023). As one such model, it describes the sequential drawing process as a probability distribution over strokes.

$$p(S) = \prod_{t=1}^{T} p\left(S_t \,\middle|\, S_1, S_2, \ldots, S_{t-1}\right) \tag{14}$$

In which S_t is a stroke at time step t. The network generates vector-based sketches because they predict the next stroke from elements previously drawn. Application in Art Education is:

- AI helps students improve their digital sketching skills by learning composition techniques and refining their sketches.

- Automating rough conceptualisation: artists can use surprisingly fast to generate rough sketches for brain-storming ideas.
- It helps students learn stroke order and line weight distribution.

A rough hand-drawn image can be refined to a detailed sketch by a process aided by AI, as shown in Figure 11.

Case study (AI-powered image analysis in museums): AI-based image processing is being increasingly used in the analysis and restoration of historical works in museums and digital art exhibitions (Stoean et al., 2024; Zou and Lin, 2024; La Russa and Santagati, 2021). Using CNN-based models, AI can identify the artist of an unknown painting based on brushstroke patterns, colour distribution, etc. A deep art identification system was developed to classify paintings based on feature extraction.

$$F = W \cdot X + b \tag{15}$$

where F is the feature representation, W is the learned weight matrix, X is the input image tensor, b is the bias term. Impact on art education is as follows:

- Artwork with AI: particularly, AI explains artworks in great detail, enhancing the visitors' learning.
- Using inpainting techniques, AI reconstructs missing sections of aged paintings to restore them as Artwork Restoration.
- Forgery detection: brushstroke features are checked against known works to detect forgeries.

Figure 12 showcases an AI-assisted restoration of a Renaissance painting.

Figure 12 AI-powered artwork restoration (see online version for colours)

Real-time AI feedback in digital painting software: examples of AI-powered digital painting applications that give real-time artistic assistance include neural filters on Adobe Photoshop and Corel Painter AI (Ching and Mothi, 2025; Sari, 2024). These tools analyse an artist's brush strokes and suggest intelligent colour palettes, shooting, and composition options. AI Techniques Used in Neural Filters:

- Similar to integrating the above, they use CNNs to superresolve digital paintings to improve details and clarity.
- Portrait and face aware liquify: amends facial features in portraits while preserving realism using landmark detection.
- AI colourisation: using learned artistic patterns to convert greyscale images into colour, thus helping the artists explore different colour schemes.

Benefits in art education:

- AI-powered tools that can give instant feedback on digital paintings in composition, lighting, and shading will aid students in real-time learning.
- Artistic enhancements: AI helps polish all the small things, such as brushstrokes, texture, and colour balance, for artists to concentrate on creative expression.
- Students can create a hybrid AI and traditional techniques by integrating traditional painting methods and incorporating AI-driven changes.

The aids of AI-driven tools have changed art education by allowing new forms of creativity, genuine-time assistance in artistic direction, and intelligent learning environments. This section discussed the case studies summarised in Table 6.

Table 6 Summary of AI case studies in art education

Case study	*Key AI technique used*	*Application in art education*
DeepDream	CNN feature amplification	AI-generated surrealism
RunwayML	GANs, NST	AI-assisted creative learning
Sketch-RNN	RNN-based stroke prediction	AI-assisted digital sketching
AI in Museums	CNN-based artwork analysis	AI-driven art attribution

5 Challenges and ethical considerations

To that end, it has made art education creative learning to integrate AI in art education so that the students and artists are open to new artistic possibilities by using deep understanding and digital image processing. However, the issue that comes with advancements is that they create many challenges in terms of ethics. With AI-generated art, the question of authorship, inventiveness, and the protection of intellectual property rights are being asked. At the same time, the biases present in AI models influence the perception of art. In addition, as reliance on AI-powered tools continues to grow, there could be a risk to traditional skill-building in art education, and there is a need for a balance to be brought when integrating AI into art education.

This section examines the most critical problems and imaginary ethical questions around AI-led art education from the point of authorship and ownership issues, bias in AI output, the impact on traditional skills in the artistic field, and the ethical guidelines to prevent the spread of AI applications.

The question of authorship in AI-generated art: combining AI and human input makes AI-generated art even more forward-thinking than traditional art, as deep learning models work with human users together. First and foremost, the question arises: who owns the final artwork? If a user uploads an image to an AI tool that results in another artwork without the user's permission, who owns the artwork generated by the AI developer or the AI tool itself? Also, the extent of human involvement matters very much when it comes to establishing to whom the authorship belongs. Some AI models require significant curation and adjustment, while others produce results with minimal human hand. The process of AI-assisted artwork A can be mathematically represented as:

$$A = f(D, \theta, H) \tag{16}$$

where D represents the dataset used to train the AI model, θ denotes the model's parameters and learned features, H signifies human input in guiding or modifying the AI-generated content.

If H is minimal, the AI's role is dominant, and the question of ownership is ambiguous. Lack of legal clarity has also caused disputes regarding who owns AI-generated work courts, and policymakers are at odds with intellectual property rules for such creations.

Copyright laws today are not quite ready for AI-generated content as they have (for now) left us in the dark regarding ownership policies and fair use. Last year, a US federal court landmark ruling stated that AI-generated images without human intervention cannot be copyrighted. Of course, this constitutes debate when AI is used as a creative counterpart rather than a creator. Key Legal Concerns:

- Copyright infringement in AI training datasets – many AI models are trained on massive datasets where artworks are copyright-protected with no original artist's permission. Such generation raises ethical and legal issues about whether AI-generated art is original or derived from previous works.
- Fair use policies: given that AI can mimic other styles, there is legal ambiguity about whether AI-generated content incorporates derivative work.
- Attribution and licensing: how should the works produced with AI assistance be attributed and licensed? Are new licenses necessary? It is essential to establish proper attribution guidelines so you know who to attribute the human input to in AI-generated creations.

Table 7 outlines the varying legal approaches to AI-generated art across different regions.

Table 7 Copyright policies for AI-generated art by region

Region	*Copyright status*	*Legal considerations*
USA	No copyright for AI-only works	Requires significant human intervention
European Union	Partially recognised	The case-by-case basis for human involvement
Japan	AI-generated art is public domain	No formal laws addressing AI authorship
China	AI art can be copyrighted	Requires demonstration of human input

As depicted in Figure 13, an AI-generated artwork similar to an existing painting can induce a copyright clash.

Figure 13 AI-generated art vs. original artwork (see online version for colours)

Bias in AI-generated art: the quality and diversity of an AI art's training dataset are responsible for most of the reasons it is created the way it is. An AI model trained on a dataset with most Western artistic traditions will create output bias towards those styles while leaving behind non-Western and indigenous art forms. The problem is that AI-generated artwork might not be culturally diverse due to this dataset bias, keeping the imbalances in the current artistic realm. Finally, dataset bias B can be mathematically quantified as:

$$B = \frac{\sum_{i=1}^{n} W_i D_i}{\sum_{i=1}^{n} W_i} \tag{17}$$

where B represents the bias in the AI-generated output, D_i represents each dataset's influence on the AI model, and W_i is the weight assigned to each dataset, reflecting its prevalence in training.

The AI model will be restricted to creating instances of diverse artistic representation if most of the training data consists of Renaissance or Impressionist art. However, it limits the creative potential of AI, which is peculiar.

AI-generated art has been poking fun at the styles it uses to create art but has also been serving up gender, racial, and cultural stereotypes without asking for it. Key ethical concerns include:

- Dataset imbalance: many AI models underrepresent indigenous, Asian, African, and Latin American artistic traditions because datasets are imbalanced. Those involved thus turn into a Eurocentric bias, excluding global art heritage.
- Gender and racial stereotypes: if AI models are trained on biased datasets, their artwork may unwittingly portray ethnicity, culture, and identity along the lines of gender or racial stereotypes.

Figure 14 illustrates an AI-generated portrait that exhibits biases due to a skewed training dataset.

Figure 14 Bias in AI-Generated Portraits (see online version for colours)

To counter these issues, they should be forthcoming, trained, and provided with ethically sourced and much-varied datasets that reflect most artistic traditions.

The impact of AI on traditional artistic skills: with the advent of AI, which can automate most work, the worry now is students rely on AI too much on AI programs. While AI can help with the creative process, over-dependence on automation may be past basic, such as:

- Why would a student spend that much time sculpting a rough sketch when AI tools like Sketch-RNN can fill the gap for a student without real creativity?
- The benefit of AI colourisation vs. manual shading: as colourisation is based on AI, these tools take the art of applying colour theory and shading from the artists, which leaves smaller avenues for artistic exploration.

Figure 15 shows digital painting compared to manual, with the differences in skill development clearly shown in the display as AI is heavily involved.

Figure 15 AI-assisted art vs. traditional art (see online version for colours)

Integrating AI and manual artistic techniques in structured hybrid art learning models will help art educators use AI as an aid to learning traditional skills rather than replacing recommended strategies, including:

- Use of AI to encourage hybrid learning models: AI should be incorporated with the traditional art exercise to enhance students' technical and creative skills.
- Manual refinement of AI-generated outcomes: students should be educated on how to check and tweak AI-generated artwork so that they follow their artistic decision-making more.
- AI-assisted curricula: the curriculum should develop AI tools as enhancement tools instead of replacing the fundamentals of artistic techniques.

Table 8 outlines a balanced approach to integrating AI into art education.

Table 8 Balancing AI and traditional art education

AI feature	*Recommended use in education*	*Traditional skill preserved*
AI sketching assistants	Used for initial drafts	Freehand drawing
AI colourisation	Generates suggestions, not final work	Colour mixing and shading
AI style transfer	Teaches artistic styles interactively	Manual brushwork techniques

Ethical and regulatory frameworks for AI in Art: however, as AI-generated art gains more traction, there is a need to set proper guidelines for using AI-generated art responsibly and moderately. There are key concerns that regulatory frameworks, including transparency, diversity, and fair compensation, should address.

- Attribution and contributing: modifying the attribution in AI generative artworks to make clear how human and machine input contributed to the result.
- Including diversity in AI Training: to prevent AI models from being trained on datasets that exhibit the bias of favouring the Western or dominant art forms, AI models are being trained on sets of global artistic diversity.
- Recognition or compensation for artists of works that go into AI training datasets: Works that have gone into an AI training dataset should not be used without permission to create new AI outputs and owe nothing to the original artists.

So, these ethical considerations can establish a responsible AI artistic ecosystem based on AI developers and traditional artists.

Since AI will continuously improve in the art education field, AI for art education must have straightforward policies that governments and institutions create to regulate AI in art education while keeping ethical standards. Key policy areas include:

- Legal frameworks must determine who owns AI-generated artworks, separating AI-assisted pieces from AI-created ones.
- Regarding AI Use in education: a more appropriate use of AI would be its use to complement traditional learning rather than substitute fundamental manual artistic skills. Necessary policies should guarantee that AI improves creativity and not automate its creative expression.

- For ethical AI research: the training datasets must be valid in terms of being inclusive and fair so that the AI models do well regarding inclusivity, fairness, and cultural representation.

Strong ethical and regulatory frameworks for responsible AI integration into the art world can be developed by policymakers, which will bring innovation where fairness, diversity, and artistic integrity are embedded.

AI integration in art education has positive and negative effects. The key issues are summarised in Table 9, and proposed solutions.

Table 9 Summary of AI challenges and solutions in art education

Challenge	*Ethical concern*	*Proposed solution*
Authorship	Who owns AI-generated art?	Define legal frameworks for AI-assisted works.
Bias	AI favours mainstream styles	Train AI on diverse datasets
Skill degradation	Overuse of AI tools reduces manual skills	Implement hybrid AI-traditional learning models

Once they're addressed, AI can be responsibly introduced into art education, allowing for technological advances in the promise while still protecting artistic integrity.

6 Future directions

AI in art education is in its infancy but has widespread potential for development. With the continuous development of AI-powered tools, their roles in artistic training, creative exploration, and digital restoration will grow significantly. For AI to be beneficial and ethical, in addition to art education, ensuring that AI is done is a challenge that needs to be addressed. It includes ethical considerations, the diversity of an AI training dataset, a hybrid learning model, and an improved AI-based interactive learning environment.

This section outlines some key ways of realising AI in art education, like AI-driven art tutoring systems, ethical AI framework, better artistic diversity in AI models, hybrid learning approaches, and AI integration into virtual and augmented reality (VR/AR) environments.

6.1 Development of AI-powered art tutoring systems

In the future, AI-powered tutoring systems will be able to give personalised feedback to the students according to the student's own artistic style, learning prowess, and learning progress. These AI tutors will:

- Deep learning models analyse student artwork and determine brush strokes, colour balance, and composition.
- They provide real-time feedback on where things should improve, e.g., shading techniques, proportion adjustments, etc.
- Keep in mind how the student learns and adapts; gradually increase the complexity of the challenge as the student's skills develop.

Mathematically, an AI-driven feedback system can be formulated as:

$$S(A, P) = \sum_{i=1}^{n} w_i \left| F_i(A) - P_i \right| \tag{18}$$

where A is the student's artwork, P represents predefined artistic principles (such as contrast, perspective, and texture) F_i are extracted features from the artwork, and w_i are the weights assigned to each principle's importance.

It will allow the students to engage more of their artistic skills through adaptive learning in this kind of system while AI is an intelligent assistant and not just a passive tool.

Future studios powered by future AI will open up virtual art classrooms where students may collaborate, and AI can do the following:

- real-time artistic suggestions for students to paint or draw digitally
- it's a way to assist in colour selection and blending and get students to know colour theory through interactive examples
- it provides historical art insights explaining how the classical paintings were done using different techniques.

Figure 16 depicts an AI-driven virtual art classroom where AI tutors guide students in real-time.

Figure 16 AI-driven virtual art classroom (see online version for colours)

6.2 *Expanding ethical AI frameworks for art education*

One issue that must be addressed as AI-generated art becomes more common is for authorship, ownership, and AI biases to be ethical. Future research should be dedicated to developing international guidelines that would guarantee fairness and transparency of AI in art. These guidelines should cover:

- AI-generated artworks should have precise requirements for their attribution to differentiate them from human-created artworks.
- Artists' use in AI training datasets: using artists' work in AI training datasets should involve credit or financial remuneration to artists.
- Bias in generated artworks: generated artwork models should be trained on as much diversity in cultural and artistic styles as possible to avoid bias in generated artwork.

Table 10 outlines key ethical considerations and possible solutions for AI governance in art education.

Table 10 Proposed ethical guidelines for AI in art education

Ethical concern	*Proposed solution*
AI-generated art is mistaken for human-made art	Clearly label AI-generated content
Bias in AI-generated styles	Train AI models on diverse datasets.
Copyright disputes over AI art	Establish legal frameworks for AI-assisted works.
Lack of artist compensation for AI training data	Develop royalty-based licensing models

Implementing these will ethically incorporate AI-generated art into educational arenas while preserving artists' rights.

Improving AI models for artistic diversity: future AI systems should be trained by datasets containing works from different cultures, historical periods, and artistic movements. AI should instead favour Western-centric artistic styles instead of Western-centric artistic styles it favours.

- art traditions are drawn from the African, Asian, Latin American, and other underrepresented regions
- calligraphy and traditional brush techniques from different cultures
- some modern digital art styles are being developed in online creative communities.

Mathematically, a balanced dataset D for AI training can be represented as:

$$D = \sum_{i=1}^{n} w_i D_i \tag{19}$$

where D_i represents a distinct cultural or artistic style, and w_i is the proportional weight assigned to each style.

Future AI models will be better geared towards individual students' preferences and make suggestions unique to their artistic style. Reinforcement learning is how to do this as AI instructs the suggestions to improve after a user interacts. A reinforcement learning-based AI personalisation model can be represented as:

$$\pi^*(s) = \arg\max_a E\left[R(s, a) + \gamma V(s')\right] \tag{20}$$

where s represents the student's current skill level, a represents an artistic style or technique recommendation, $R(s, a)$ is the reward function based on student feedback, γ is the discount factor for future recommendations. Such models would enable an AI tutor to suggest exercises that reinforce what a student is strong in and what they are traditionally bad at, creating personalised artistic growth.

Hybrid learning models: combining AI with traditional art: AI provides huge tools but probably should not replace traditional art techniques. The next step in art education should be hybrid learning models, including the aid of AI, while preserving manual artistic skills. Educators should design courses that:

- experiment with AI to try out new styles while still working on their traditional techniques
- manually refine AI-generated works to retain students' drawing and painting abilities
- it'll encourage creative decision-making so as not to over-rely on AI-generated suggestions.

In the future, bright brushes and AI-assisted canvases will synthesise AI suggestions with actual brushstrokes to allow artists to:

- we will get real-time feedback on proportion, colour balance, and composition
- AI-produced drafts can be experimented with and changed manually to customise them further.

Table 11 compares AI-assisted and conventional learning.

Table 11 Comparison of AI-assisted vs. traditional art education

Learning approach	*Advantages*	*Challenges*
AI-assisted learning	Provides real-time feedback, automates repetitive tasks	Risk of skill degradation if overused
Traditional art learning	Develops fine motor skills, fosters deep creativity	Slower learning curve
Hybrid learning model	Combines AI efficiency with hands-on experience	Requires careful curriculum design

Figure 17 Hybrid AI-traditional art learning (see online version for colours)

Figure 17 shows how hybrid learning environments incorporating AI tools do not sacrifice traditional artistic values.

The world of AI in art education offers vast opportunities while demanding good practice. Key areas for future research and development are summarised in Table 12.

Table 12 Future research directions in AI-based art education

Future development	*Potential impact*
AI-powered virtual art tutors	Personalised feedback for students
Ethical AI guidelines	Ensures fairness in AI-generated art
Culturally diverse AI training models	Reduces biases in AI-generated artworks
Hybrid AI-traditional learning	Enhances creativity while preserving artistic skills
AI in virtual/AR art studios	Provides immersive, interactive artistic education

Addressing these areas will keep AI advancing artistic education, making creative expression more democratic, encouraging new generations of artists, and ensuring human creativity is central to the artistic process.

7 Conclusions

AI has revolutionised the field of art education with computational tools that enable creativity to be improved, artistic processes to be automated, and interactive learning capabilities. AI techniques, such as CNN, GAN, and NST, turn classical art education into the machinery to learn artistic through the following modalities: manual skill, manual skill creation, reference image creation, perspective drawing, finger tracing, handwritten drawing, and manual detailed drawing. Creative workflow is further enriched by digital image processing techniques such as edge detection, image segmentation, histogram equalisation, and super-resolution, allowing for precise artistic modifications. The exciting part of these advancements would be new possibilities for artists and students to go beyond conventional methods to do what they like.

While all of these have the potential to be beneficial, there are issues related to authorship, ethical concerns, bias in AI-generated art, and the role of traditional artistic skill preservation. The ownership of AI-assisted art remains legally ambiguous, so intellectual property frameworks are needed to specify the artist’s rights and the rights of the AI developers. In addition, if the training dataset of an AI model is biased, it is likely to intensify cultural and aesthetic homogeneity further rather than pushing the diversity of the arts. On the flip side, people fear that using AI tools too much may lead to weaker foundational artistic skills, so there has to be a hybrid learning model that blends AI assistance with established artistic training.

The principles of digital image processing and deep learning in art education have been studied in this work, and their real-world applications and the ethical challenges associated with them have also been discussed. In addition, it has suggested potential solutions, such as the creation of AI-assisted tutoring systems, the creation of ethical guidelines, and the generation of varied (in regards to gender, ethnicity, culture, etc.) AI training datasets AND the integration of hybrid learning AI traditional learning. Integrating AI in art education responsibly will assist in determining whether to incorporate it.

Key findings and contributions: the findings of this research highlight several key insights into the impact of AI in art education. AI serves as an assistive tool rather than a replacement for human creativity. Automating repetitive tasks, providing real-time feedback, and enabling more creativity in artistic learning. However, AI lacks human intuition, emotional depth, and creative intent, which are at the core of artistic expression.

New artistic possibilities are made possible through deep learning and image-processing technologies. CNNs now teach AI to analyse and classify art styles for artistic or historical knowledge. GANs bring algorithmic creativity and generate AI-created artwork. Continuing, digital image processing techniques such as super-resolution and colourisation with the help of AI are used during art restoration and enhancement.

While there are many advancements in the prevalence of AI-generated art, there are still some things you might not know about it that make it challenging regarding authorship, bias, and ethical considerations. AI models trained on imbalanced datasets can exacerbate biases by reinforcing Western art tradition bias. Additionally, there are disputes over copyright and intellectual property due to the lack of clear legal guidelines for AI-generated content ownership. Not relying on AI outputs too much may also lead to declining manual artistic skills.

In the future, the role of AI in art education will be balanced by AI in collaboration with traditional teaching of art. With hybrid learning models, students can access foundational skills while AI-enhanced creativity benefits. Artistic techniques will be customised in AI-powered personalised tutoring systems. Furthermore, adopting global ethical frameworks for AI-driven art will foster fairness, transparency, and inclusivity covered by the generated art.

These findings move the discourse on AI-assisted art education towards a broader discussion of responsible integration of AI.

Limitations of AI in Art Education: While artificial intelligence-based tools significantly improve artistic learning, there’s still a distance to its full potential. The primary challenge is the lack of emotional intelligence in the generated art by AI. AI’s artwork is based on what it has learned, not personal experiences or emotions. Unlike human artists, it is unaware of context or can infuse its artworks with deep personal meaning, an essential component of artistic expression.

A weakness of it is its reliance on high-quality training data. We need significant, high-quality, rich datasets for an AI model to produce good artistic outputs. Despite that, most current AI models are primarily trained on Western art styles, resulting in cultural biases in AI-generated works. It underrepresents diverse artistic traditions as well as different perspectives.

Further, computational and accessibility barriers to the adoption of AI in art education are significant. Unfortunately, many AI-powered artistic tools are resource-hungry and thus, less accessible in low-resource settings. Additionally, AI-created creativity depends on earlier data and cannot produce original items beyond what it’s learned.

Finally, there is a risk of excessive reliance on the aid of AI in the learning process. In my opinion, students are likely to depend on AI-generated suggestions, making it unlikely for them to acquire manual artistic ability and independent creative thinking. It begs the question of educators to design a curriculum that could balance hands-on artistic practice with AI-enhanced learning to keep using AI not as a substitute for traditional artistic development but as a complementary tool to aid artistic development.

Future research directions: many areas remain to be explored to ensure that responsible and effective AI is integrated into art education, given the changing role of AI in this field.

If the application of art collection services leads to the development of art tutoring by AI-powered personalised tutors, then one promising area will be explored. Real-time feedback systems will be able to learn how to process student artwork and provide customised artistic advice. Furthermore, it is beneficial to make AI tutors aware of the student's artistic styles and recommend things according to them to allow them to refine their unique creative expressions.

According to another critical research direction, making AI frameworks in art ethical and legal is the other important thing. Copyright laws and ownership policies regarding AI-generated art are necessary when AI-generated art is so common. Additionally, it is essential to develop guidelines on using the dataset to avoid AI models infringing on copyrighted artworks and providing fair artistic representation.

On the other hand we are also interested in bias mitigation in AI art models. Including in the training datasets diverse cultural and artistic styles can improve the reduction of the overrepresentation of Western art traditions. Furthermore, bias detection algorithms would be implemented to force AI-written art to represent various artistic points of view and traditions.

The other key research area is the integration of hybrid learning models that use AI in traditional art education. To ensure that curricula using AI-powered creativity are at once mighty and do not undermine foundational artistic training, it is critical to understand what this balance should be.

Finally, programs that utilise AI in virtual and augmented reality (VR/AR) art environments are a promising future in digital art education. Immersive VR/AR art studios where AI aids in real-time artistic assistance could revolutionise the learning experience. It could create environments beneficial for interactive learning; students can work with AI-generated art in dynamic and virtual settings. In Table 13, we summarise the key areas for further research in AI in art education, namely, to adopt a structured methodology for responsible AI in creative fields.

Table 13 Future research directions in AI art education

Research focus	*Potential impact*
AI-powered art tutors	Provides personalised real-time feedback to students
AI art ethics and copyright	Establishes fair use and legal protection for AI-generated art
Bias mitigation in AI art	Ensures diverse and representative AI-generated artworks
Hybrid AI-traditional learning models	Balances AI-assisted creativity with manual artistic skills.
AI in VR/AR art studios	Enhances immersive, interactive artistic education

Final thoughts: AI is changing how we learn to be creative, improving creative learning, streamlining artistic workflow, and democratising artistic exploration and inquiry. Despite this, AI-generated art's ethical, pedagogical, and legal problems must be addressed before use. AI should not be viewed as a replacement for human creativity but rather as an additional tool aiding artistic education, which preserves the humanity and individuality of personal expression. AI in art education has the potential to become a collaborative force rather than one of pure competition between technology and human creativity if we implement hybrid learning models, ethical AI frameworks, and inclusive set training datasets for AI. When used sensitively, AI can broaden the range of what art is and inspire this new generation of artists, retaining art's core values in the process.

Declarations

The authors declare that they have no conflict of interest.

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