AI in Visual Arts: A Survey

[1]Mr Dontala KiranKumar, [2]Mrs Kandrathi Leela Pavani, [3]Mrs Meleti Sai Jyothi,
[4]Mrs Sivakumari Mekala, [5]Mr Galla Venkataswamy
[1]Assistant Professor, Department of CSE (AI&ML, DS)
Research Scholar - JNTU -GV, AITAM & AVANTHI INSTITUTE OF ENGINEERING & TECHNOLOGY
[2]Lecturer, Department of Computer Science, Govt.Degree College Chintapalli, A.S.R District
[3]Miracle Educational Society Group Of Institutions, Miracle City, Munjeru Village, Bhogapuram Mandal, Vizianagaram, 535216
[4]Government Degree College, Rampachodavaram, Devipatnam Road, Polavaram District, AP, India.
[5]Assistant Professor, Department of Computer Science (Data Science)
Raghu Engineering College (A), Dakamarri, Visakhapatnam

Abstract

Artificial Intelligence has emerged as a transformative force in the visual arts, reshaping creative processes, production techniques, and artistic expression. This survey presents a comprehensive overview of AI-driven methods applied in visual art generation, analysis, restoration, and curation.

Keywords: Artificial Intelligence, Visual Arts, Generative Model, Style Transfer, Digital Creativity

1. Introduction

Artificial Intelligence has emerged as a transformative force in the visual arts, profoundly reshaping creative workflows, production methodologies, and modes of artistic expression. With the rapid advancement of generative models, machine learning algorithms, and computer vision techniques, AI now plays a pivotal role in generating original artworks, analysing visual content, restoring historical pieces, and supporting data-driven curation practices. This survey provides a comprehensive overview of AI-driven methods across these domains, highlighting current capabilities, emerging trends, and their implications for the future of visual art.

2. Literature Review

1. The last 15 years moved from feature-manipulation (DeepDream, early CNN hacks) toward probabilistic and adversarial generative modelling (GANs) and then to scalable, controllable synthesis (StyleGAN family, BigGAN)

2. Image-to-image and unpaired translation (pix2pix, CycleGAN) enabled many practical art applications (style transfer, photo enhancement, domain transfer) used by artists and tools.

3. The 2020–2024 period introduced multimodal text↔image models (DALL·E, diffusion models, CLIP-guided methods) that changed workflows: artists can now generate and refine imagery via text prompts and semantic controls.

4. Parallel streams address restoration, inpainting, and curatorial automation — showing AI's role beyond image generation into conservation and curation.

5. Below is the more elaborate and year-wise review of the literature

(i) Goodfellow et al. (2014) introduced Generative Adversarial Networks (GANs), a novel framework where two neural networks—the generator and discriminator—compete to produce realistic data. This adversarial training paradigm became the foundation for modern generative art, enabling high-quality image synthesis, style transfer, and creative content generation.

(ii) Gatys, Ecker, and Bethge (2015) proposed a **neural algorithm** of artistic style that separates and recombines content and style representations using deep convolutional neural networks. This work pioneered neural style transfer and became the basis for many popular art and image-editing applications.
(iii) Radford, Metz, and Chintala (2015) introduced **Deep Convolutional GANs (DCGANs)**, which adapted GAN architectures with convolutional layers to effectively model and generate realistic images. Their design principles significantly improved training stability and inspired a wide range of creative and artistic image-generation experiments.
(iv) Mordvintsev et al. (2015) introduced **DeepDream**, an early and highly visible example of neural image synthesis that visualised and amplified patterns learned by convolutional neural networks. It brought deep learning–based creativity to the public, influencing digital art and shaping interest in AI-generated imagery.
(v) Isola et al. (2017) proposed **pix2pix**, a conditional GAN framework for supervised image-to-image translation tasks such as edges-to-photos and labels-to-scenes. It demonstrated how paired data and adversarial learning could generate realistic, task-specific visual transformations.
(vi) Zhu et al. (2017) introduced **CycleGAN**, which enables image-to-image translation between domains without paired training data using cycle-consistency constraints. This approach made unpaired style transfer and domain adaptation practical and widely applicable in artistic and visual tasks.
(vii) Elgammal et al. (2017) proposed **Creative Adversarial Networks (CANs)**, extending GANs to encourage novelty by deviating from learned artistic styles while remaining aesthetically valid. This work was among the first to computationally model creativity, influencing AI-generated art and creative autonomy research.
(viii) Brock et al. (2018) introduced **BigGAN**, demonstrating that large-scale GANs with increased model capacity and batch sizes can generate extremely high-fidelity, realistic natural images. Their work showed that careful scaling and training stabilisation significantly improve image quality and diversity in generative models.
(ix) Yu et al. (2018) introduced a **contextual attention–based image inpainting** model that learns to fill missing regions by referencing and copying relevant features from surrounding image areas. This approach significantly improved structural consistency and visual realism in image restoration tasks.
(x) Karras et al. (2019) proposed **StyleGAN**, a style-based generator architecture that separates high-level attributes (such as pose and shape) from fine details (like texture and colour). This design enables fine-grained, intuitive control over generated images and set a new standard for photorealistic image synthesis.
(xi) Ramesh et al. (2021) introduced **DALL·E**, an autoregressive transformer model that generates images directly from natural language descriptions. It demonstrated strong compositional reasoning by combining multiple concepts, attributes, and styles in a single image based purely on text prompts.
(xii) Radford et al. (2021) proposed **CLIP**, a model that learns joint image–text embeddings by training on large-scale paired data. CLIP enables effective image–text alignment and is widely used to guide, rank, and curate generative models by evaluating how well images match textual descriptions.

3. Methodology

The methodology adopted in this survey is designed to systematically analyse, categorise, and synthesise research contributions related to Artificial Intelligence in the visual arts. The following steps outline the process used to develop this survey.
Step 1: Scope: The survey focuses on four major dimensions where AI has significantly influenced the visual arts

ecosystem: Art Generation, Art Analysis, Art Restoration, and Art Curation.

Step 2: Literature Search Strategy: A systematic search was conducted across major digital libraries, including: IEEE Xplore, ACM Digital Library, SpringerLink, Elsevier ScienceDirect, and arXiv (for the latest preprints).

Step 3: Selection Criteria

Peer-reviewed journal articles, conference papers, and high-impact preprints

Works directly related to computational models applied to artistic datasets

Models demonstrating contributions in creativity, analysis, or restoration

Step 4: Categorisation of Selected Studies

The selected literature was organised into thematic categories based on methodological contribution and application area:

- Generative methods
- Analytical and interpretive systems
- Restoration and enhancement frameworks
- Curation and cultural heritage technologies

Each work was examined for:

- Model architecture
- Dataset usage
- Evaluation methods
- Artistic or cultural relevance
- Technological novelty

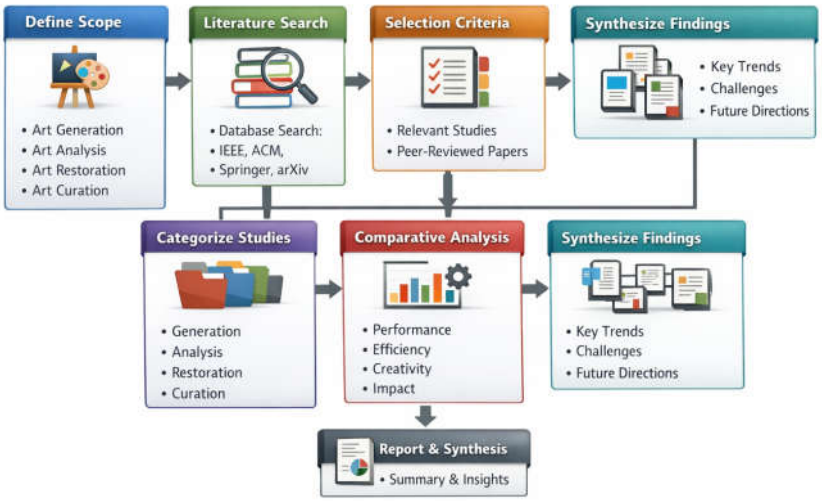

Fig 1: Survey Process Overview

Step 5: Comparative Analysis Framework

To ensure objectivity, the survey follows a comparative framework that evaluates methods based on:

- **Model Performance**: accuracy, realism, fidelity, aesthetic scoring
- **Computational Efficiency**: training time, scalability, resource usage
- **Creative Flexibility**: controllability, diversity, generalisation
- **Cultural Impact**: heritage preservation, ethical considerations

Step 6: Synthesis and Organisation of Findings
Insights from the reviewed literature were synthesised to highlight:

- Historical evolution of AI in the visual arts
- Core techniques and their advancements
- Application-specific strengths and limitations
- Cross-domain trends and interdisciplinary opportunities

The final survey is organised into sections covering generation, analysis, restoration, and curation, followed by ethical considerations, challenges, and future directions.

4. Results

The systematic application of the proposed methodology resulted in a structured synthesis of research on Artificial Intelligence in the visual arts across four major domains: generation, analysis, restoration, and curation. The literature review indicates that art generation is the most extensively explored area, driven by advances in generative adversarial networks, diffusion models, and text-to-image frameworks. These methods demonstrate high visual fidelity, stylistic diversity, and improved controllability.

Studies in art analysis primarily address artwork classification, style recognition, and aesthetic quality assessment. Deep learning models, particularly convolutional and vision transformer architectures, have achieved strong performance on benchmark datasets. However, limitations persist in capturing subjective aesthetic judgments and contextual artistic meaning.

In the domain of art restoration, AI-based techniques such as inpainting, colourisation, and super-resolution show significant potential for recovering damaged or degraded artworks. The results highlight improved structural coherence and visual consistency, although the reliance on data-driven reconstruction introduces concerns regarding historical authenticity.

Research on art curation and cultural heritage focuses on intelligent recommendation systems, large-scale digitisation, and semantic metadata enrichment. These systems improve accessibility and organisation of art collections, particularly within museums and digital archives, while emphasising interpretability and cultural relevance.

Domain	Key Techniques	Major Outcomes	Limitations / Challenges
Art Generation	GANs, Diffusion Models, Neural Style Transfer, Text-to-Image Models	High realism, stylistic diversity, controllability	High computational cost, evaluation of creativity
Art Analysis	CNNs, Vision Transformers, Aesthetic Models	Accurate classification and style recognition	Subjectivity in aesthetic judgment, limited contextual understanding
Art Restoration	Inpainting, Colorization, Super-Resolution	Improved recovery of damaged artworks	Risk of over-restoration, authenticity concerns
Art Curation	Recommendation Systems, Vision–Language Models	Enhanced organization and accessibility of collections	Bias in datasets, interpretability issues
Cross-Domain Trends	Multimodal Learning, Large-Scale Models	Interactive and co-creative workflows	Ethical, legal, and cultural challenges

Table 1: Summary of Key Findings in AI for Visual Arts

5. Discussion

The results reveal a clear transition from traditional rule-based approaches to data-driven and generative AI frameworks, reflecting the broader evolution of deep learning technologies. High-capacity generative models achieve superior aesthetic quality and creative flexibility but require substantial computational resources, limiting their scalability in some practical settings.

Comparative analysis shows that no single AI approach excels across all evaluation dimensions. While generative models prioritise creativity and realism, analytical and curatorial systems emphasise efficiency, explainability, and cultural sensitivity. Restoration frameworks must carefully balance technical enhancement with ethical responsibility to avoid altering artistic intent.

Emerging trends indicate increased integration of multimodal models, combining visual and textual understanding to support interactive and co-creative workflows. Despite these advances, challenges related to dataset bias, evaluation of creativity, authorship, and copyright remain unresolved. Addressing these issues will be essential for the responsible and sustainable adoption of AI in the visual arts.

6. Conclusion

This survey highlights the transformative impact of Artificial Intelligence across visual art generation, analysis, restoration, and curation, demonstrating how data-driven and generative models have reshaped creative and cultural workflows. While AI continues to expand artistic possibilities and analytical capabilities, addressing challenges related to ethics, authenticity, and interpretability remains critical for the responsible integration of intelligent systems in the visual arts.

7. References

Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., Courville, A., & Bengio, Y. (2014). Generative adversarial nets. *Advances in Neural Information Processing Systems*, *27*, 2672–2680.

Gatys, L. A., Ecker, A. S., & Bethge, M. (2016). Image style transfer using convolutional neural networks. *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 2414–2423. https://doi.org/10.1109/CVPR.2016.265

Elgammal, A., Liu, B., Elhoseiny, M., & Mazzone, M. (2017). CAN: Creative adversarial networks generating “art” by learning about styles and deviating from style norms. *Proceedings of the 8th International Conference on Computational Creativity*, 96–103.

Isola, P., Zhu, J. Y., Zhou, T., & Efros, A. A. (2017). Image-to-image translation with conditional adversarial networks. *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 1125–1134. https://doi.org/10.1109/CVPR.2017.632

Zhu, J. Y., Park, T., Isola, P., & Efros, A. A. (2017). Unpaired image-to-image translation using cycle-consistent adversarial networks. *Proceedings of the IEEE International Conference on Computer Vision*, 2223–2232. https://doi.org/10.1109/ICCV.2017.244

Karras, T., Laine, S., & Aila, T. (2019). A style-based generator architecture for generative adversarial networks. *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 4401–4410. https://doi.org/10.1109/CVPR.2019.00453

Karras, T., Laine, S., Aittala, M., Hellsten, J., Lehtinen, J., & Aila, T. (2020). Analysing and improving the image quality of StyleGAN. *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 8110–8119.

Radford, A., Kim, J. W., Hallacy, C., Ramesh, A., Goh, G., Agarwal, S., … Sutskever, I. (2021). Learning transferable visual models from natural language supervision. *Proceedings of the 38th International Conference on Machine Learning*, 8748–8763.

Ramesh, A., Pavlov, M., Goh, G., Grey, S., Voss, C., Radford, A., … Sutskever, I. (2021). Zero-shot text-to-image generation. *Proceedings of the 38th International Conference on Machine Learning*, 8821–8831.

Rombach, R., Blattmann, A., Lorenz, D., Esser, P., & Ommer, B. (2022). High-resolution image synthesis with latent diffusion models. *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 10684–10695. https://doi.org/10.1109/CVPR52688.2022.01042

Liu, J., Chen, C., Yang, J., & Guo, Z. (2018). Image inpainting for irregular holes using partial convolutions. *Proceedings of the European Conference on Computer Vision*, 85–100.

Yeh, R. A., Chen, C., Yian Lim, T., Schwing, A. G., Hasegawa-Johnson, M., & Do, M. N. (2017). Semantic image inpainting with deep generative models. *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 5485–5493.

Strezoski, G., & Worring, M. (2017). OmniArt: Multi-task deep learning for artistic data analysis. *IEEE Transactions on Multimedia*, *21*(1), 188–200. https://doi.org/10.1109/TMM.2018.2859590

Saleh, B., & Elgammal, A. (2015). Large-scale classification of fine-art paintings. *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 558–565.

Pesenti, A., & Pica, G. (2020). Artificial intelligence and cultural heritage: Ethics, interpretability, and preservation. *Journal of Cultural Heritage*, *44*, 239–246. https://doi.org/10.1016/j.culher.2020.04.003